Oil Well Productivity Computation Based on a Brain-Inspired Cognitive Architecture

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ABSTRACT

This paper aims to mitigate the negative effect of production data errors on the curve of inflow performance relationship (IPR). To this end, the author proposed a brain-inspired productivity computation method for oil wells based on Shannhan's brain-inspired cognitive architecture. The architecture consists of two interacting sensorimotor loops. In the proposed method, the IPR parameters were fitted in the inner loop, and the fitting results were considered in the productivity computing in the outer loop. Then, the proposed model was applied to compute the oil productivity of a real oil well, compared with other common methods, and verified through numerical simulation. The results show that the new method can predict well productivity more accurately than the contrast methods. Suffice it to say that this research puts forward a simple and reliable method for IPR curve drawing.

Key Words: Brain-inspired Intelligence, Productivity, Inflow Performance Relationship (IPR), Brain-inspired Cognitive Architecture, Nonlinear Least Squares Fitting

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Introduction

The countries all over the world are competing to explore brain science and brain-inspired intelligence. Relevant research programs have been launched in the US, the EU and China, such as the China Brain Project in 2016 (Poo *et al.*, 2016; Zhu *et al.*, 2016; Wang *et al.*, 2016).

Focusing on the multi-scale structure of brain tissue and its relationship with various cognitive functions and diseases, the brain science pursues the physiological understanding of the cognitive mechanism of human behaviours. The brain's multi-scale structure and its cognitive mechanism are utilized in brain-inspired intelligence research to create intelligent frameworks, algorithms and systems mimicking the information processing mechanism in human brain, that is, the study of brain-inspired intelligence aims to simulate the brain in learning, cognition and reasoning based on the full understanding of brain structure and functions.

In some respects, brain-inspired intelligence bears strong resemblances to human-like intelligence. With the development of deep learning and artificial neural networks (ANNs), great progress has been made in the research of brain-inspired intelligence, especially in the area of pattern recognition. One of the most attractive research directions for brain-inspired intelligence is the neuroscience-based brain-inspired computing, which operates on an intelligent computing model with a similar structure to the brain.

The oil industry is an important field for the application of brain-inspired intelligence. As the key to the manufacturing industry, petroleum accounts for a large percentage of the world's

energy consumption and becomes a top concern in many countries. It is significant to ensure the efficient and economic exploitation of this valuable natural resource. In view of the above, this paper presents a brain-inspired productivity model for oil wells through the abstraction and simulation of the brain's cognition mechanism, aiming to make accurate prediction of oil well productivity based on the production data.

Shanahan's brain-Inspired cognitive architecture

Referring to the structure of the human brain (e.g. basal ganglia, amygdala, and thalamus cortex), Shanahan combined the global workspace theory and internal simulation into a two-loop model (Fig. 1) that reflects the interaction between the system and the outside world (Shanahan, 2006; Qu, 2012). The outer sensorimotor loop is responsible for sensing and decision-making, and the inner loop for internal simulation.
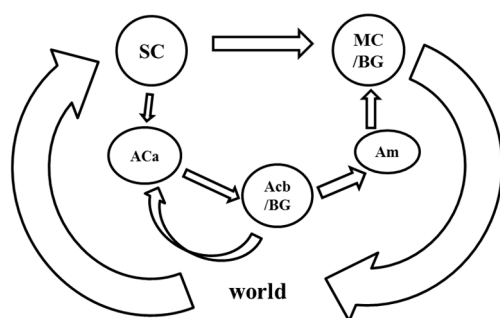
Figure 1. Shanahan's brain-inspired cognitive architecture

Fig. 1 Shanahan's brain-inspired cognitive architecture

In Shanahan's model, the cognitive activity is accomplished through the two-loop architecture. Without the intervention of cognition, the outer loop receives stimuli from the outside world and makes an immediate reaction by a certain rule, and collects the response of the external environment to the reaction. The inner loop rehearses these external stimuli, reaction and response in memory, and modulates the reaction rule of the outer loop based on the rehearsal results.

The two loops have different functions. The outer loop reflects passive and immediate reaction of the body to external stimuli without the intervention of cognition, while the latter makes active and gradual adjustment to the reaction rule through scenario analysis, aiming to correctly respond to similar stimuli in future. In

light of these, it is possible to identify two main features of brain cognition:

(1) In the human brain, the immediate reaction to external stimuli is random is random initially, and the environmental response to the reaction is not necessarily favourable.

(2) The environmental response becomes more favourable with the increase of external stimuli, thanks to the inner loop's modulation of the outer loop after collecting and analysing previous scenarios.

The abovementioned brain-inspired cognitive architecture was taken into consideration in the subsequent discussion on the computation of oil well productivity.

Computation of oil well productivity

Productivity, a key parameter of oil production, lays the basis for design optimization of the production plan, artificial lift and surface pipe network, and plays a crucial role in the analysis on production system. The parameter is often estimated by inflow performance relationship (IPR). Many popular productivity models are grounded on the IPR curve (Vogel, 1968; Standing, 1970; Fetkovich, 1973; Jones et al., 1976; Solomon et al., 1990; Wiggins, 1994; Wiggins et al., 1996; Guehria, 2000; Zhong et al., 2007).

The earliest studies on the IPR tackled the single-phase flow in circular, homogeneous reservoirs with sealed boundaries. Later, Jones, Blount, Glaze, et al. described the relationship between production rate and bottom hole flowing pressure with quadratic equations. In 1968, Vogel put forward an empirical IPR for solution gas drive reservoirs under the bubble point pressure, after discovering that the productivity data of various reservoir shapes, seepage features and oil properties share a similar dimensionless two-phase IPR curve. The empirical IPR can be expressed as:

$$\frac{q}{q_{max}} = 1 - 0.2\left(\frac{P_{wf}}{P_r}\right) - 0.8\left(\frac{P_{wf}}{P_r}\right)^2 \qquad (1)$$

where q is the production rate; q_{max} is the maximum flow rate (absolute open flow rate); P_r is the static reservoir pressure; P_{wf} is the bottom hole flowing pressure.

Due to its high practicality, Vogel's solution has been extensively applied to determine the IPR curve of solution-gas drive reservoirs. Nevertheless, the solution fails to yield accurate results on damaged wells, because Vogel

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ignored skin effects by assuming the target well is intact. To solve the problem, Standing and Harrison modified Vogel's solution for wells with varied degrees of damage: the single-phase IPR and two-phase IPR of solution-gas drive wells were combined, considering the single-phase flow when the bottom hole flowing pressure was above the bubble point pressure. In this way, the application scope of Vogel's solution was expanded to the wells in under-saturated reservoirs.

The computation of oil well productivity can be viewed as a cognitive problem that can be simulated according to Shanahan's brain-inspired cognitive architecture. As shown in Fig. 2, bottom hole flowing pressure is taken as the external stimulus, the IPR computing method as the reaction rule, test data points as the correct stress reaction of the brain's memory to the external environment, and the fitting of the IPR with the test data points as the operation of the inner loop.
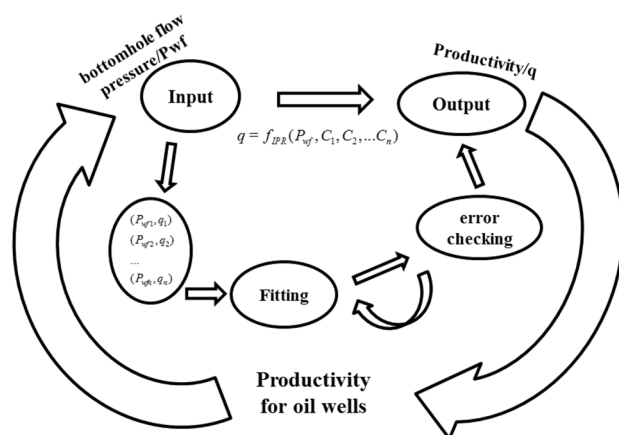
Figure 2. Productivity cognitive architecture

The first step to building the above brain-inspired productivity computing model is to fit the parameters in IPR calculation. Several data points (e.g. the production rate and bottom hole flowing pressure under the steady state) are needed to draw the IPR curve by the above solutions. For solving unknown parameters, the number of data points must be the same with that of unknown parameters.

Taking Standing's solution for instance, one data point is required to calculate the maximum flow rate in advance. Two other data points are needed, if the reservoir static pressure and the flow efficiency are unknown due to data unavailability of well testing or nearby wells. In other words, three data points are necessary for

computing the maximum flow rate, the reservoir static pressure and the flow efficiency.

In many cases, there are more available data points than unknown parameters. Then, the dataset must be processed to ensure the uniqueness of the solution to the equations. Two methods are commonly used for dataset processing: selection of the optimal data point and mathematical processing of the whole dataset. Despite the ease of implementation, the first method is in lack of computing accuracy owing to the errors arising from the complex and stochastic selection standard. What is worse, many information on oil well production is wasted as the unused data are abandoned in this method. By contrast, the second method solves the unknown parameters using all the data points.

In addition, Fetkovich (1973) proposed an IPR determination equation by extending gas well testing method to oil wells. The equation reveals a linear correlation between the flow rate and the delta pressure square in log-log plots. Thus, the linear least squares method can be used to solve a number of unknown parameters with an even greater number of data points. Nonetheless, the Fetkovich method is limited by the following constraint: the reservoir static pressure must be known and lower than the bubble point pressure.

Based on field data, the author developed a productivity computation method for IPR determination under unknown reservoir static pressure and flow efficiency.

Defects of conventional productivity computing methods

As stated above, several known data points must be available before determining the IPR using field data on oil production. If there are fewer data points than unknown parameters, the IPR can be obtained either by selecting the optimal data point for calculation from the dataset or determining all unknown parameters for calculation through fitting with all data points in the dataset. Using the measured data points in a test well (Tab.1), both of these methods are adopted to determine the IPR in this research. By the first method, the single-phase production index (PI) was combined with two-phase Vogel's solution, and two data points were selected to determine the IPR through ten rounds of computations. By the second method, the reservoir pressure and PI were obtained by the least squares method based on single-phase PI.

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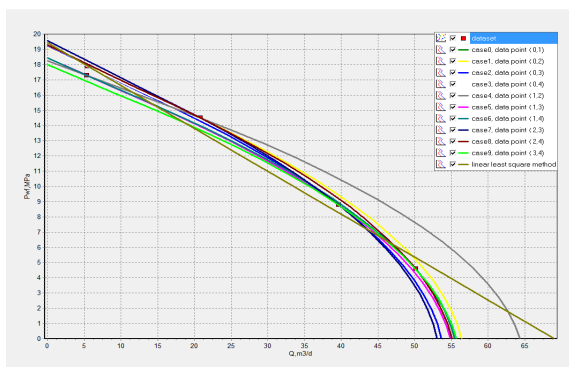
Figure 3. IPR curves determined by the two methods

Table1. Data points (Bubble point pressure:15.1MPa)

NO.	P_{wf}，MPa	Q_o，m^3/d
1	17.8	5.4
2	17.3	5.3
3	14.5	20.8
4	8.8	39.6
5	4.6	50.1

Table 2. Test plan and method

NO.	Description	Static reservoir Pressure	PI	maximum flow rate
Case 1	Using data point(1,2)	-14.5	-0.167	-
Case 2	Using data point(1,3)	19.1	4.54	56.4
Case 3	Using data point(1,4)	19.2	4.29	53.7
Case 4	Using data point(1,5)	19.1	4.43	55.1
Case 5	Using data point(2,3)	18.3	5.55	64.3
Case 6	Using data point(2,4)	18.4	4.66	54.8
Case 7	Using data point(2,5)	18.4	4.72	55.5
Case 8	Using data point(3,4)	19.6	4.12	53.1
Case 9	Using data point(3,5)	19.3	4.37	55.1
Case 10	Using data point(4,5)	17.9	4.91	55.7
Case 11	Using linear least square method	19.4	3.55	69

The test plan and results are displayed in Tab.2 and Fig.3, respectively.

As shown in Fig. 3 and Tab. 2, the curve shape remained similar from case 2 to case 10, while the results were vastly different. The similarity in shape is attributed to the adoption of the same computing model, while the difference in results to the use of different data points. The biggest differences in reservoir pressure, the PI and the maximum oil production rate were observed between cases 8 and 10 (1.7MPa), cases 5 and 8 (1.43), and cases 8 and 10 (11.2 m^3/d), respectively. However, no rational results were obtained in case 1 based on data points 1 and 2.

These results reflect a nonnegligible impact of data point selection on the computing results. On the one hand, each measured data point carries the current dynamic information of oil well productivity; on the other hand, the data points differ greatly in measuring error, and thus result in the lack of solution (case 1).

Since the selection standard for the optimal data point varies from person to person, the calculation results could be quite different. For instance, the result of case 11 is undesirable despite the utilization of all data points. This is because the method, designed for single-phase flow, cannot depict the two-phase flow in the reservoir correctly.

As the static reservoir pressure is unknown, it is impossible to solve all unknown parameters by the least squares method. Thus, the Fetkovich method was not used in the above test plan. This is a common problem in actual calculation. For example, when calculating the IPR for lifting design in practical production, there are no reliable data to determine the precise static reservoir pressure or flow efficiency at the current time.

Therefore, this paper presents a multi-point productivity model capable of determining the current reservoir parameters in oil well productivity calculation with a limited amount of production data, and obtaining highly accuracy IPR curve.

Parameter fitting model in inner loop

To create the productivity model, Standing's flow efficiency method for two-phase flow was expanded to single-phase flow. The resulting model can be expressed as:

$$
f(P_{wf}) =
\begin{cases}
FEJ(\overline{P}_r - P_{wf})...(P_{wf} \geq P_b) \\
FEJ(\overline{P}_r - P_b) + \dfrac{FEJP_b}{1.8}\left[1 - 0.2\dfrac{P_{wf}}{P_b} - 1.6(1-FE)\dfrac{\overline{P}_r P_{wf}}{P_b^2} - 0.8FE\dfrac{P_{wf}^2}{P_b^2}\right] \\
\quad + \dfrac{(1-FE)JP_b}{1.8}\left[1 - 0.2\dfrac{\overline{P}_r}{P_b} - 0.8(1-FE)\dfrac{\overline{P}_r^2}{P_b^2}\right]....(P_{wf} < P_b)
\end{cases}
\tag{2}
$$

Where FE is the flow efficiency; J is the single-phase PI; P_b is the bubble point pressure. The IPR curve obtained by this equation is smooth, as long as both flow efficiency and $\overline{P_r}/P_b$ approximate 1.

In total, there are three unknown parameters in Eq. 2, namely FE, J, and P_r. Let $D=\{(q_1, P_{wf1}), (q_2, P_{wf2}),..., (q_n, P_{wfn})\}$ ($n>3$) be a dataset with n sets of data points. Then, the following group of nonlinear equations are valid:

$$\begin{cases} f(P_{wf1},\overline{P_r},J,FE)=q_1 \\ f(P_{wf2},\overline{P_r},J,FE)=q_2 \\ ... \\ f(P_{wfn},\overline{P_r},J,FE)=q_n \end{cases} \qquad (3)$$

These nonlinear equations are overdetermined and insolvable. However, there is a possible solution by minimizing the sum of squared errors, according to the nonlinear least squares fitting method (Yao *et al.*, 2012; Shi *et al.*, 2016; Cai *et al.*, 2012; Liu *et al.*, 2016; Zhang, 2012; Feng *et al.*, 2016; Cannistraro *et al.*, 2016). Specifically, all the data points in D were fitted with a set of undetermined coefficients, $C=(\overline{P_r},J,FE)^T$ according to Eq. 2. If the sum of squared errors is the minimum (Eq. 4), then C is the least squares solution of the group of nonlinear equations.

$$\|R\|=\sum_{i=1}^{n}\left[q_i-f(P_{wfi},\overline{P_r},J,FE)\right]^2=\min \qquad (4)$$

To obtain the solution, the Taylor series expansion was performed to locally linearize Eq. 2. Then, the extremum was calculated through the following steps. First, set the initial value $C_0=(P_{r0},J_0,FE_0)^T$. Then, expand $f(P_{wf},C)$ at C_0, using linear terms only:

$$f(P_{wf},\overline{P_r},J,FE)\approx f(P_{wfi},\overline{P_{r0}},J_0,FE_0)+\frac{\partial f}{\partial \overline{P_r}}\Delta\overline{P_r}+\frac{\partial f}{\partial J_0}\Delta J+\frac{\partial f}{\partial FE_0}\Delta FE \qquad (5)$$

Substitute Eq. 5 into Eq. 4, and we have:

$$\|R\|=\sum_{i=1}^{n}\left[q_i-f_0-\frac{\partial f}{\partial \overline{P_r}}\Delta\overline{P_r}-\frac{\partial f}{\partial J_0}\Delta J-\frac{\partial f}{\partial FE_0}\Delta FE\right]^2 \qquad (6)$$

where f_0 is $f(P_{wf},\overline{P_{r0}},J_0,FE_0)$. According to the necessary conditions for extreme value:

$$\begin{cases} \frac{\partial R}{\partial \overline{P_r}}=0; \frac{\partial R}{\partial J}=0; \frac{\partial R}{\partial FE}=0 \end{cases} \qquad (7)$$

Since $C=C_0+\Delta C$, Eq. 7 can be rewritten as:

$$\begin{cases} \frac{\partial R}{\partial \Delta\overline{P_r}}=0; \frac{\partial R}{\partial \Delta J}=0; \frac{\partial R}{\partial \Delta FE}=0 \end{cases} \qquad (8)$$

Find the partial derivatives of Eq. 6 for every unknown parameter, and substitute them into Eq. 8. After rearrangement, we have:

$$A\Delta C = Q - F \qquad (9)$$

For simplicity, transform Eq. 9 into Eq. 10:

$$A^T A\Delta C = A^T(Q-F) \qquad (10)$$

where,

$$A=\begin{bmatrix} \frac{\partial f_1}{\partial \overline{P_r}} & \frac{\partial f_1}{\partial J} & \frac{\partial f_1}{\partial FE} \\ \frac{\partial f_2}{\partial \overline{P_r}} & \frac{\partial f_2}{\partial J} & \frac{\partial f_2}{\partial FE} \\ ... & ... & ... \\ \frac{\partial f_n}{\partial \overline{P_r}} & \frac{\partial f_n}{\partial J} & \frac{\partial f_n}{\partial FE} \end{bmatrix}\in R^{3\times n}$$

$$\frac{\partial f_i}{\partial \overline{P_r}}=\begin{cases} FEJ....(P_{wfi}\geq P_b) \\ \frac{10}{9}FEJ-\frac{J}{9}-\frac{8}{9}(1-FE)J\left[FE\frac{P_{wfi}}{P_b}+(1-FE)\frac{\overline{P_r}}{P_b}\right]....(P_{wfi}<P_b) \end{cases}$$

$$\frac{\partial f_i}{\partial J}=\begin{cases} FE\left(\overline{P_r}-P_{wfi}\right)...(P_{wfi}\geq P_b) \\ FE\left(\overline{P_r}-P_b\right)+\frac{FEP_b}{1.8}\left[1-0.2\frac{P_{wfi}}{P_b}-1.6(1-FE)\frac{\overline{P_r}P_{wfi}}{P_b^2}-0.8FE\frac{P_{wfi}^2}{P_b^2}\right] \\ +\frac{(1-FE)P_b}{1.8}\left[1-0.2\frac{\overline{P_r}}{P_b}-0.8(1-FE)\frac{\overline{P_r}^2}{P_b^2}\right]....(P_{wfi}<P_b) \end{cases}$$

$$\frac{\partial f_i}{\partial FE}=\begin{cases} J\left(\overline{P_r}-P_{wfi}\right)...(P_{wfi}\geq P_b) \\ J\left(\overline{P_r}-P_b\right)+\frac{JP_b}{1.8}\left[1-0.2\frac{P_{wfi}}{P_b}-1.6(1-2FE)\frac{\overline{P_r}P_{wfi}}{P_b^2}-1.6FE\frac{P_{wfi}^2}{P_b^2}\right] \\ +\frac{JP_b}{1.8}\left[-FE+0.2FE\frac{\overline{P_r}}{P_b}+1.6(1-FE)\frac{\overline{P_r}^2}{P_b^2}\right]....(P_{wfi}<P_b) \end{cases}$$

$$\Delta C=\left(\Delta\overline{P_r},\Delta P_b,\Delta J,\Delta FE\right)\in R^4$$
$$Q=\left(q_1,q_2,...,q_n\right)\in R^n$$
$$F=\left(f_1,f_2,...,f_n\right)\in R^n$$

Set the convergence accuracy ε and solve Eq. 10. If $\|\Delta C\|<\varepsilon$, terminate the calculation;
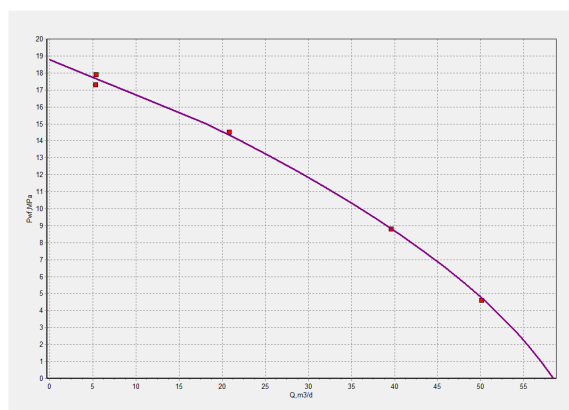
otherwise, set $C=C_0$ and recalculate until meeting the convergence condition.
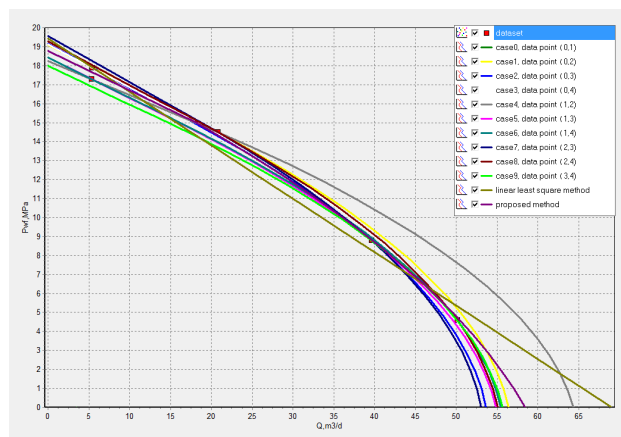
Case study

The oil production rate and its corresponding bottom hole flowing pressure of a production well were measured through a well test (Tab. 1).

Figure 4. IPR curve obtained by the proposed model

Table 3. Results of the proposed productivity model

Method	Static reservoir pressure, MPa	PI	Maximum flow rate, m³/d	FE
Proposed productivity model	18.8	3.55	58.4	0.892

Figure 5. IPR comparison between the proposed productivity model and the aforementioned conventional methods

According to the fluid physical properties in the block, the bubble point pressure of the well is 15.1MPa. Then, the IPR was determined by the method proposed in this paper. The results are displayed in Fig. 4 and Tab. 3. Fig. 5 is an IPR comparison between the proposed productivity model and the methods introduced above.

Finally, the proposed model was verified through numerical simulation with the data points $P_{wf}=13.0$MPa and $Q_o=26$m³/d). The results are shown in Tab. 4. It can be seen that the proposed model achieved a high computing accuracy: the relative error of the static reservoir pressure was 1.1% and the relative error of the production rate was only 0.4%.

Table 4. Simulation results

NO.	Static reservoir Pressure, MPa	Relative error,%	Production rate, m³/d	Relative error,%
exact solution	18.6	/	25.99	/
Brain-inpired productivity model	18.8	1.1	25.89	0.4
Case1	-14.5	178	4.6	82.3
Case2	19.1	2.7	27.1	4.3
Case 3	19.2	3.2	25.94	0.2
Case4	19.1	2.7	26.57	2.2
Case5	18.3	1.6	28.51	9.7
Case6	18.4	1.1	24.78	4.7
Case7	18.4	1.1	25.03	3.7
Case8	19.6	5.4	26.52	2
Case9	19.3	3.8	26.87	3.4
Case10	17.9	3.8	23.96	7.8
Case11	Using linear least square method	19.4	3.55	69

Conclusions

This paper presents an oil well productivity computation method based on a brain-inspired cognitive architecture. The architecture, consisting of two interacting sensorimotor loops, realizes prediction and other cognitive functions through the internal simulation of the interaction with the external environment. In the proposed method, the IPR parameters were fitted in the inner loop. The fitting results were considered in the productivity computing in the outer loop after achieving the threshold value.

The brain-inspired productivity computation model fully reflects the dynamic production features of oil wells, thanks to the integration of the whole spectrum of production data. With a high prediction accuracy, this model can guide the design of production engineering project, well production optimization, and well performance analysis.

Acknowledgements

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