Research Article

History Matching and Production Prediction of Steam Drive Reservoir Based on Data-Space Inversion Method

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Recently, a data-space inversion (DSI) method has been proposed and successfully applied for the history matching and production optimization for conventional waterflooding reservoir. Under Bayesian framework, DSI can directly and effectively obtain posterior flow predictions without inverting any geological parameters of reservoir model. In this paper, we integrate the numerical simulation model with DSI method for rapid history matching and production prediction for steam flooding reservoir. Based on the finite volume method, a numerical simulation model is established and it is used to provide production data samples for DSI by the simulation of ensemble geological models. DSI-based production prediction model is then established and get trained by the historical data through the random maximum likelihood principle. The posterior production estimation can be obtained fast by training the DSI-based model with history data, but without any posterior geological parameters. The proposed method is applied for history matching and estimating production performance prediction in some numerical examples and a field case, and the results prove its effectiveness and reliability.

1. Introduction

Steam flooding is an effective way for heavy oil development. The effective and efficient history matching and production performance prediction can help to judge the development stage and carry out phased adjustment for more oil recovery of steam flooding reservoir.

In order to obtain accurate performance prediction of steam flooding reservoir, many scholars have established a large number of analytical, empirical models and numerical method in the past decades. Marx and Langenheim [1] firstly proposed an empirical model to calculate production performance for steam flooding. Neuman [2] constructed a mathematical steam flooding model considering gravity overlap, which promoted the development of theoretical studies of steam flooding process. Jones [3] established a simplified production prediction model, and it can simulate the oil pro-

duction rate under a certain steam injection rate. Due to the complexity of the flow during steam flooding process, it is difficult to predict reservoir outputs by these models when the production situation changes frequently.

Based on reservoir geological model, the numerical simulation method can generate reservoir outputs by simulating underground fluid flow, which has higher calculation accuracy. Pope and Aydelotte [4] proposed a new numerical simulation method based on the theory of phase separation flow and the principle of conservation of energy and matter. The relevant calculation results showed the distribution characteristics of temperature field, pressure field, and saturation field of steam flooding reservoir. Chen and Liu [5] divided the steam drive reservoir into four regions and established the steam flooding prediction model (SFPM). Fu et al. [6] established steam propagation front model under different well patterns by considering steam overlap and heat loss of

top and bottom layers. Coats et al. [7] proposed a three-dimensional numerical simulation model of steam flooding based on the implicit condensation scheme of finite difference.

History matching is the core of the numerical simulation of real reservoirs [8–15]. By automatically adjusting grid parameters (porosity, permeability, etc.) through repeated numerical simulation, this technique can provide accurate reservoir geological model. However, there are hundreds of thousands of parameters of reservoir model that need to be inverted by history matching, which leads to the high cost of calculation. In the past few decades, many effective algorithms including Kalman and parameterization algorithms have been developed for historical matching, which have achieved good results. However, these algorithms did not work well when applied into steam flooding reservoir. Because the phase change often disappears in the numerical simulation process of steam flooding, it needs more small time step to get the solution in accordance with the physical meaning. Thus, more number of time steps is necessary to simulate the whole production stage of steam flooding reservoir, which leads to low calculation efficiency. Therefore, shortening the number of numerical simulation or finding a surrogate prediction model is the main direction to improve the efficiency of history matching for steam flooding reservoirs.

As a data-driven method, machine learning can solve any reservoir simulation problem with input-output link and provide reservoir prediction quickly by building learning model through a large number of data training [16]. Sibaweihi et al. [17] employed learning models for the short-term forecast of NPV with regard to the redistribution of steam. The model parameters are updated continuously by using a moving horizon approach that considers selected prior data including real-time measurements. Otherwise, Kubota and Reinert [18] applied two machine learning algorithms including linear regression and long short-term memory (LSTM) networks to forecast oil rate in a field driven by water and steam injection. Specially, no geological model and/or numerical reservoir simulators are needed in this method. Albinhassan and Wang [19] conducted reservoir characterization based on seismic spectral variations. Wang [20] used the group method of data handling for porosity prediction. Generally, similar to proxy model, the machine learning can improve greatly the prediction of the production performance. But such methods ignore the physics of reservoir and consequently fail either by generating “nonphysical” output solutions or when presented with data not anticipated in the training data set.

Recently, Sun et al. [21–23] developed a new approach for history matching known as data-space inversion (DSI). Under Bayesian framework, the DSI can directly provide posterior production performance account for the historical data without inversion of reservoir geological parameters and repeated numerical simulation. Only a set of prior reservoir model simulations is needed; the DSI can generate posterior estimates based on the maximum likelihood principle along with uncertainty quantification. It is worthy to mention that the calculation efficiency of DSI is high because

the dimension of history matching variables is related to production data instead of reservoir parameters. At present, the DSI method has been successfully applied to conventional reservoir for history matching and production optimization, but not to steam flooding reservoir, and the DSI method is expected to resolve the low-efficiency problem of history matching of steam flooding reservoir.

This paper intends to apply the DSI method to the steam flooding reservoir which is more difficult than the conventional water drive reservoir in history matching, and we avoid using the commercial numerical simulator and independently develop a simple and efficient steam drive reservoir numerical simulator which only considers the water components so that we can better construct an integrated DSI-based history matching module for steam flooding reservoir. Therefore, we add the above statements to the Abstract and Introduction to present the main objective of this work and progress.

This paper proceeds as follows. In Section 2, the numerical simulation technique and the relevant calculation results of a simple example including pressure, temperature, and production performance are simply analyzed. In Section 3, we briefly introduce the principle of the DSI and some improvements. History matching and posterior production estimates for one-dimensional and two-dimensional numerical examples and a real field case are presented in Section 4. From the results of those numerical examples, the proposed method shows its adaptability and reliability and gets good achievements without high computational cost. Concluding remarks are finally stated.

2. Numerical Simulation of Steam Flooding Reservoirs for Data Preparation

By injecting a large amount of steam into the formation, steam flooding can heat heavy oil and reduce oil viscosity and displace more oil compared with waterflooding. In this section, we will introduce the numerical simulation method constructed by the finite volume method and apply it for providing data samples for DSI.

2.1. Finite Volume-Based Discretization of Governing Equations. The numerical model of steam flooding involves three-phase flow, heat conduction, heat convection, and phase change. The governing equation in continuous form can be stated as the following:

$$\left(\frac{\partial(\rho_o \phi S_o)}{\partial t} \right) + \frac{\partial(\rho_o u_o)}{\partial x} = \rho_o q_o, \quad (1)$$

$$\left(\frac{\partial(\rho_g \phi S_g)}{\partial t} \right) + \frac{\partial(\rho_g u_g)}{\partial x} = \rho_g q_g - q_c, \quad (2)$$

$$\left(\frac{\partial(\rho_w \phi S_w)}{\partial t} \right) + \frac{\partial(\rho_w u_w)}{\partial x} = \rho_w q_w + q_c, \quad (3)$$

$$\begin{aligned}
& \nabla(\lambda_c \nabla T) - \nabla \left(\rho_w h_w \frac{kk_{rw}}{\mu_w} \nabla p \right) - \nabla \left(\rho_o h_o \frac{kk_{ro}}{\mu_o} \nabla p \right) \\
& - \nabla \left(\rho_s h_s \frac{kk_{rs}}{\mu_s} \nabla p \right) \\
& = \frac{\partial}{\partial t} \left[(1 - \phi) \rho_R C_R T + \phi \rho_o S_o h_o + \phi \rho_w S_w h_w + \phi \rho_g S_g h_g \right] \lambda_c \\
& = \phi (s_w \lambda_w + s_o \lambda_o + s_s \lambda_s) + (1 - \phi) \lambda_r,
\end{aligned} \tag{4}$$

where λ_{cw} , λ_{co} , λ_{cs} , λ_{cr} , and λ_c represent the thermal conductivity of water phase, oil phase, gas phase, oil layer, and comprehensive, respectively; h_w , h_o , and h_s denote the heat content of water phase, oil phase, and gas phase; c_r is the specific heat capacity of rock in oil layer; T is the temperature of reservoir; ρ_o , ρ_w , and ρ_s represent the density of water phase, oil phase, and gas phase.

In this paper, the implicit scheme of quantity of condense steam is adopted. Combining Equation (1) with Equation (2) and adding the phase equilibrium equation, they are

$$\left(\frac{\partial(\rho_w \phi S_w)}{\partial t} \right) + \frac{\partial(\rho_w u_w)}{\partial x} + \left(\frac{\partial(\rho_g \phi S_g)}{\partial t} \right) \tag{5}$$

$$+ \frac{\partial(\rho_g u_g)}{\partial x} = \rho_w q_w + \rho_g q_g,$$

$$p_s(T) - p = 0, \quad \text{if } s_g > 0. \tag{6}$$

Then, we apply the finite volume method to discretize Equations (1), (4), (5), and (6) and adopt the fully implicit scheme to solve these [24]. When the capillary force is ignored, they are

$$\begin{aligned}
& -\rho_{w,sc} \sum_{j=1}^n \left\{ G_{ij} \lambda_{w,ij} \left[(p_i - p_j) - \frac{\rho_{w,sc} \mathcal{G}}{B_{w,ij}} (D_i - D_j) \right] \right\}^{t+\Delta t} \\
& - \rho_{g,sc} \sum_{j=1}^n \left\{ G_{ij} \lambda_{g,ij} \left[(p_i - p_j) - \frac{\rho_{g,sc} \mathcal{G}}{B_{g,ij}} (D_i - D_j) \right] \right\}^{t+\Delta t} \\
& + \rho_{w,sc} Q_{w,sc}^{t+\Delta t} + \rho_{g,sc} Q_{g,sc}^{t+\Delta t} \\
& = \frac{\Delta V_i}{\Delta t} \rho_{g,sc} \left[\left(\frac{\phi s_{g,i}}{B_{g,i}} \right)^{t+\Delta t} - \left(\frac{\phi s_{g,i}}{B_{g,i}} \right)^t \right] \\
& + \frac{\Delta V_i}{\Delta t} \rho_{w,sc} \left[\left(\frac{\phi s_{w,i}}{B_{w,i}} \right)^{t+\Delta t} - \left(\frac{\phi s_{w,i}}{B_{w,i}} \right)^t \right],
\end{aligned} \tag{7}$$

$$\begin{aligned}
& - \sum_{j=1}^n \left\{ G_{ij} \lambda_{o,ij} \left[(p_i - p_j) - \frac{\rho_{o,sc} \mathcal{G}}{B_{o,ij}} (D_i - D_j) \right] \right\}^{t+\Delta t} \\
& + Q_{o,sc}^{t+\Delta t} = \frac{\Delta V_i}{\Delta t} \left[\left(\frac{\phi s_{o,i}}{B_{o,i}} \right)^{t+\Delta t} - \left(\frac{\phi s_{o,i}}{B_{o,i}} \right)^t \right],
\end{aligned} \tag{8}$$

$$\begin{aligned}
& - \sum_{j=1}^n \left\{ \frac{\rho_{w,sc}}{B_{w,ij}^{t+\Delta t}} h_{w,ij} G_{ij} \left[(p_i^{t+\Delta t} - p_j^{t+\Delta t}) + \frac{\rho_{w,sc} \mathcal{G}}{B_{w,ij}^{t+\Delta t}} (D_i - D_j) \right] \right\} \\
& - \sum_{j=1}^n \left\{ \frac{\rho_{o,sc}}{B_{o,ij}^{t+\Delta t}} h_{o,ij} G_{ij} \left[(p_i^{t+\Delta t} - p_j^{t+\Delta t}) + \frac{\rho_{o,sc} \mathcal{G}}{B_{o,ij}^{t+\Delta t}} (D_i - D_j) \right] \right\} \\
& - \sum_{j=1}^n \left\{ \frac{\rho_{g,sc}}{B_{g,ij}^{t+\Delta t}} h_{g,ij} G_{ij} \left[(p_i^{t+\Delta t} - p_j^{t+\Delta t}) + \frac{\rho_{g,sc} \mathcal{G}}{B_{g,ij}^{t+\Delta t}} (D_i - D_j) \right] \right\} \\
& - \sum_{j=1}^n \lambda_{c,ij}^{t+\Delta t} G_{ij}' (T_i^{t+\Delta t} - T_j^{t+\Delta t}) + \rho_g h_g Q_{s,si}^{t+\Delta t} \\
& + \rho_o h_o Q_{o,si}^{t+\Delta t} + \rho_w h_w Q_{w,si}^{t+\Delta t} \\
& = \frac{\Delta V_i}{\Delta t} \left[((1 - \phi) \rho_R C_R T)_i^{t+\Delta t} - ((1 - \phi) \rho_R C_R T)_i^t \right. \\
& + (\phi \rho_o S_o h_o)_i^{t+\Delta t} - (\phi \rho_o S_o h_o)_i^t + (\phi \rho_w S_w h_w)_i^{t+\Delta t} \\
& \left. - (\phi \rho_w S_w h_w)_i^t + (\phi \rho_s S_s h_s)_i^{t+\Delta t} - (\phi \rho_s S_s h_s)_i^t \right],
\end{aligned} \tag{9}$$

$$p_s(T^{t+\Delta t}) - p^{t+\Delta t} = 0, \quad \text{if } s_g^{t+\Delta t} > 0. \tag{10}$$

In addition, there is still an auxiliary equation to calculate the enthalpy of wet steam, that is,

$$h_s = x h_s + (1 - x) h_w, \tag{11}$$

where x is the steam quality, h_s is the enthalpy of the dry steam, and h_w is the enthalpy of water.

The basic variables in this simulation model are temperature, pressure, gas-phase saturation, and water saturation. All equations including Equations (7), (8), (9), and (10) are solved in closed and implicit form. Since the steam flooding reservoir involves the phase change process from steam to hot water and then to steam, we use adaptive-time-step Newton iterative technique and automatic differential method to solve the above equations. In order to make the simulation result converge to the physics, we reduce the initial time step and increase the grid size, which will reduce the computational cost. The low computational efficiency is the key problem in history matching of steam flooding reservoirs. Therefore, the DSI method will be introduced to solve this problem in the next section.

2.2. A Simple Computational Test. To test the performances of the above numerical simulation model, we conduct a heterogeneous two-dimensional reservoir model developed by steam flooding; the permeability profile is shown in Figure 1. The reservoir model has one layer which is divided into $15 \times 15 \times 1$ cells. The number of grids is 15×15 . There is a steam injection well in the lower left corner of the reservoir and a production well in the upper right corner of the reservoir. The original reservoir pressure and temperature are 6 MPa and 50°C, respectively. The producer is controlled by bottom hole pressure, 3 MPa. The steam injection rate is 150 t/d, steam temperature is 310°C, and steam quality is 0.8. The simulation time of this reservoir model is 300 d.

Figure 2 shows the calculated distribution of temperature and gas-phase (steam) and water saturation at 300 days. It shows that steam only exists in the grid of the injector while the water saturation has increased for most grids. This

FIGURE 1: One-dimensional steam drive reservoir model and its randomly generated permeability distribution.

FIGURE 2: Computational results at the 300th day.

illustrates that the injected steam has been condensed into hot water at the original reservoir temperature. Only when the temperature of steam injection well is high enough, the

corresponding temperature and pressure relationship of saturated steam in Equation (10) can be satisfied, and then, steam can disappear in the grid. In addition, it can be found

FIGURE 3: One-dimensional steam drive reservoir model and its randomly generated permeability distribution.

FIGURE 4: The plot for production data of initial models.

that although the water saturation of many grids has increased, the temperature of the grid has not significantly increased, which shows that the heat carried by hot water is very limited, so the existence of steam is of great significance to the effect of steam flooding. At the same time, it also shows that the effect of steam flooding will be better after the reservoir temperature rises to a certain degree after long-term steam huff and puff.

3. The DSI-Based Method of History Matching and Production Prediction

The DSI method is based on a large number of prior geological model simulations. For steam flooding reservoir problem, we sample geological parameters of reservoir based on Kriging interpolation and then generate N_r prior models

with different physics and same scheme. Let $\mathbf{m}_i \in \mathbb{R}^{N_m \times 1}$ ($i = 1, 2, \dots, N_r$) and $\mathbf{d}_i \in \mathbb{R}^{N_d \times 1}$ represent the model parameters and its production data under simulation, respectively. The vector of $\mathbf{d}_i$ contains production data from both historical period, $\mathbf{d}_{i,h} \in \mathbb{R}^{N_h \times 1}$, and forecast period, $\mathbf{d}_{i,p} \in \mathbb{R}^{N_p \times 1}$, that is in the form of

$$\mathbf{d}_i = \left(\mathbf{d}_{i,h}^T, \mathbf{d}_{i,p}^T \right)^T = g(\mathbf{m}_i), \quad (12)$$

where $g(\cdot)$ is the numerical simulation procedure. The prior ensemble production data of models can be expressed as

$$\mathbf{d} = (\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_{N_r}). \quad (13)$$

Our goal is to predict production performance via the

FIGURE 5: The comparison of results from the presented method and real model.

FIGURE 6: Average relative errors vs. the number of initial models.

historical production data. Let $\mathbf{d}_{\text{obs}} \in R^{N_h \times 1}$ denote the historical production data of reservoir. Actually, there exist observation errors between the true model simulation of reservoir and the historical data; the vector of error can be stated as

$$\varepsilon = \mathbf{d}_{\text{true}} - \mathbf{d}_{\text{obs}}, \quad (14)$$

FIGURE 7: Two-dimensional steam drive reservoir model and its randomly generated permeability distribution.

where $\varepsilon \in R^{N_h \times 1}$ is assumed to be Gaussian variables with covariance $\mathbf{C}_D \in R^{N_h \times N_h}$ and mean zero; $\mathbf{d}_{\text{true}} \in R^{N_h \times N_h}$ denotes the “true” data from a field. Under Bayesian

FIGURE 8: Daily and cumulative oil production data sets of the production well at the upper left corner.

FIGURE 9: Daily and cumulative oil production data sets of the production well at the upper right corner.

framework, the likelihood of $\mathbf{d}$ via $\mathbf{d}_{\text{obs}}$ is

$$p(\mathbf{d}_{\text{full}}|\mathbf{d}_{\text{obs}}) = \frac{p(\mathbf{d}_{\text{obs}}|\mathbf{d}_{\text{full}})p(\mathbf{d}_{\text{full}})}{p(\mathbf{d}_{\text{obs}})} \propto p(\mathbf{d}_{\text{obs}}|\mathbf{d}_{\text{full}})p(\mathbf{d}_{\text{full}}). \quad (15)$$

And the likelihood of $\mathbf{d}_{\text{obs}}$ via $\mathbf{d}$ is

$$p(\mathbf{d}_{\text{obs}}|\mathbf{d}_{\text{full}}) = p(\boldsymbol{\varepsilon} = \mathbf{H}\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}}) \propto \exp\left(-\frac{1}{2}(\mathbf{H}\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}})^T \mathbf{C}_{\mathbf{D}}^{-1}(\mathbf{H}\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}})\right), \quad (16)$$

where $\mathbf{H} \in R^{N_h \times N_d}$ is to extract data points belonging to the historical period and it contains 0 and 1. In this paper, $\mathbf{d}$ is assumed to be Gaussian variables with covariance $\mathbf{C}_{\mathbf{d}} \in$

$R^{N_d \times N_d}$ and mean $\mathbf{d}_{\text{prior}}$; the prior likelihood of $\mathbf{d}$ is

$$p(\mathbf{d}_{\text{full}}) \propto \exp\left(-\frac{1}{2}(\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}})^T \mathbf{C}_{\mathbf{d}}^{-1}(\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}})\right). \quad (17)$$

The production data obtained from prior models can be regarded as the sampling of each random variable in $\mathbf{d}$. Thus, $\mathbf{d}_{\text{prior}}$ and $\mathbf{d}$ can be calculated by

$$\mathbf{d}_{\text{prior},i} = \frac{1}{N_r} \sum_{k=1}^{N_r} \mathbf{d}_{ik}, \quad (18)$$

$$\mathbf{C}_{\mathbf{d}} = \frac{1}{N_r - 1} \sum_{i=1}^{N_r} [(\mathbf{d} - \mathbf{d}_{\text{prior}})(\mathbf{d} - \mathbf{d}_{\text{prior}})].$$

FIGURE 10: A simple well network description of the field reservoir model.

The deviation of $\mathbf{d}$ is

$$\Delta \mathbf{d} = (\mathbf{d}_1 - \mathbf{d}_{\text{prior}}, \mathbf{d}_2 - \mathbf{d}_{\text{prior}}, \dots, \mathbf{d}_{N_r} - \mathbf{d}_{\text{prior}}). \quad (19)$$

The formula of covariance $\mathbf{C}_d$ can be written in a more concise matrix form, that is,

$$\mathbf{C}_d = \Phi \Phi^T, \quad (20)$$

where the basis matrix $\Phi = \Delta \mathbf{d} / \sqrt{N_r - 1}$. Based on Equations (13), (15), and (17), $p(\mathbf{d}_{\text{full}} | \mathbf{d}_{\text{obs}})$ becomes

$$p(\mathbf{d}_{\text{full}} | \mathbf{d}_{\text{obs}}) \propto \exp \left(-\frac{1}{2} \left[(\mathbf{H} \mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}})^T \mathbf{C}_D^{-1} (\mathbf{H} \mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}}) + (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}})^T \mathbf{C}_d^{-1} (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}}) \right] \right). \quad (21)$$

The random maximum likelihood (RML) method is introduced to maximize $p(\mathbf{d} | \mathbf{d}_{\text{obs}})$ and posterior production performance is

$$\hat{\mathbf{d}}_{\text{full}} = \min_{\mathbf{d}_{\text{full}}} \left(\left[(\mathbf{H} \mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}})^T \mathbf{C}_D^{-1} (\mathbf{H} \mathbf{d}_{\text{full}} - \mathbf{d}_{\text{obs}}) + (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}})^T \mathbf{C}_d^{-1} (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}}) \right] \right). \quad (22)$$

The above optimization problem can be solved by the optimization algorithm. However, in the actual problem, the dimension of $\mathbf{d}$ may be large, resulting in the calculation being very time-consuming and even difficult, which significantly reduces the efficiency of the optimization calculation. Therefore, it is necessary to reduce the dimension of the independent variable of the objective function in the above optimization problem.

Let

$$\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}} = \Delta \mathbf{d} \boldsymbol{\eta} = \Phi \boldsymbol{\xi}, \quad (23)$$

where $\boldsymbol{\xi} = \sqrt{N_r - 1} \boldsymbol{\eta}$. Therefore,

$$\begin{aligned} (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}})^T \mathbf{C}_d^{-1} (\mathbf{d}_{\text{full}} - \mathbf{d}_{\text{prior}}) \\ = \boldsymbol{\xi}^T \Phi^T (\Phi^T)^{-1} \Phi^{-1} \Phi \boldsymbol{\xi} = \boldsymbol{\xi}^T \boldsymbol{\xi}. \end{aligned} \quad (24)$$

TABLE 1: Physical properties of the field reservoir.

Property	Value
Initial reservoir pressure (MPa)	25
Initial reservoir temperature (°C)	50
Steam temperature (°C)	300
Steam quality (fraction)	0.85
Permeability (D)	4
Oil compressibility (MPa ⁻¹)	1.00×10^{-4}
Water compressibility (MPa ⁻¹)	1.00×10^{-4}
Rock compressibility (MPa ⁻¹)	1.45×10^{-4}
Oil viscosity at 50°C (mPa·s)	400
Water viscosity (mPa·s)	1.0

The optimization problem in Equation (22) can be stated as

$$\hat{\boldsymbol{\xi}} = \min_{\boldsymbol{\xi}} \left(\left[(\mathbf{H} \Phi \boldsymbol{\xi} + \mathbf{H} \mathbf{d}_{\text{prior}} - \mathbf{d}_{\text{obs}})^T \cdot \mathbf{C}_D^{-1} (\mathbf{H} \Phi \boldsymbol{\xi} + \mathbf{H} \mathbf{d}_{\text{prior}} - \mathbf{d}_{\text{obs}}) + \boldsymbol{\xi}^T \boldsymbol{\xi} \right] \right). \quad (25)$$

We introduce the SPSA algorithm to solve the optimization problem in Equation (25) to generate the optimal $\hat{\boldsymbol{\xi}}$ and calculate the posterior production prediction of steam flooding reservoir through

$$\mathbf{d}_{\text{full}} = \Delta \mathbf{d} \boldsymbol{\eta} = \Phi \boldsymbol{\xi} + \mathbf{d}_{\text{prior}}. \quad (26)$$

4. Numerical Examples

4.1. One-Dimensional Example. In this section, a simple one-dimensional steam flooding reservoir model is established (shown in Figure 3), with a steam injection well in the middle and a production well at both ends. The heterogeneous permeability field is randomly generated by Kriging interpolation, and the steam injection rate and well spacing are obtained by random sampling. A total of 400 prior models are obtained, and its production data of producer are obtained by the abovementioned numerical simulation method. The porosity of each model is 0.3 and the initial oil saturation is 0.85 and the initial reservoir production

FIGURE 11: Results of history matching and production prediction of the field reservoir mode.

pressure is 5 MPa. The lifetime of this reservoir is set as 250 days. The first 200 days are used for history matching, and the last 50 days are used for production prediction.

The oil production rate and cumulative oil production curves of the prior model set are shown in Figure 4. It can be seen that the oil production rate curve calculated by the proposed simulation method presents typical production characteristics of steam flooding. First, the oil production rate will decrease due to the decrease of formation pressure. Then, when the crude oil is heated, the oil viscosity will decrease and the oil production rate will increase. Last, because of the decrease of formation pressure and the influence of steam and hot water channeling, the production rate also will decrease.

One of prior models is randomly selected as the real model, and the remaining prior models are used as the prior sample data to form the data space. DSI is then performed for history matching via the history data and generate posterior production performance. In Figure 5, it can be seen that the calculated value is consistent with the real model data in

the historical and forecast period. Because there is no repeated the numerical calculation, the calculation time only cost 5.2 s except for the prior model simulations.

We also explore the variation of the average relative error with the number of prior models. As shown in Figure 6, when the number of initial models increases, the relative error will decrease. The relative error can be reduced to less than 5% when the number of initial models is only 400. Since the calculation cost of this method is mainly dependent on numerical simulation of prior models, it is necessary to have good-quality initial models to further improve the efficiency of history matching and production prediction.

4.2. Two-Dimensional Example. The two-dimensional heterogeneous model developed by steam flooding is defined on a $32 \times 32 \times 1$ grid. The grid size is set to be $10 \text{ m} \times 10 \text{ m} \times 10 \text{ m}$. Figure 7 shows the permeability field of this model. For this reservoir model, a steam injector is located in the center and four producers are located in four corners of this square reservoir. We also generate 500 prior models, and

physical properties of these models are consistent with the above one-dimensional case. The true model is randomly selected. The lifetime of this reservoir is to be 500 days. The first 150 days are applied for history matching, and the last 350 days are used for production prediction.

Firstly, the prior sample data is obtained by numerical calculation of a prior ensemble of models. Then, the posterior production performance is obtained by the DSI algorithm. Taking two producers in the upper left corner and the upper right corner as examples, the prior production performance data are shown in the grey curves in Figures 8 and 9. The calculated results (red curve) based on this method can well match the data of real model (blue curve). In addition, under the condition of 500 prior models, the average relative error of history matching and prediction results of oil production rate is less than 5%, and the average relative error of cumulative oil production is less than 1%.

4.3. A Field Case. This is an offshore heavy oil reservoir with nearly homogeneous geological properties without edge-bottom water. As shown in Figure 10, a connected well network with one injector and seven producers is used to simply describe the reservoir model, and the main physical properties of this field are shown in Table 1. All producers are controlled by a nearly constant flow rate 40 m³/d, and the average steam injection rate is 250 t/d. The oil production data from the first 150 days are the observed data to be matched.

Figure 11 shows the oil production rate curves of four producers close to the injector simulated by 500 initial models, as well as the historical matching of the actual observation data by the presented method. It can be seen that the overall accuracy of history matching and production performance prediction are good, and the results of producer 1 from observed data and this method are almost identical. In addition, it can be seen that the wells near the steam injection wells are more prone to steam channeling.

5. Conclusions

Throughout the whole paper, several key conclusions are obtained:

- (1) This paper presents a numerical simulation model of steam flooding reservoir based on finite volume method. In this model, the quantity of condensed steam is treated implicitly. Combined with the phase equilibrium equation, the fully implicit solution is performed to solve temperature, pressure, and saturations simultaneously by using the Newton iteration technique
- (2) Combined with the numerical simulation method of steam flooding reservoir and DSI algorithm, we establish an efficient method for fast history matching and production prediction for steam flooding reservoir. Importantly, it can update directly predictions through the history data without repeating simulation process and updating reservoir geological parameters
- (3) Three examples including a real field case show that the proposed method possesses enough accuracy for history matching and production prediction. Otherwise, the relative error will decrease with the increase of the number of initial models. Only a few prior models are needed to meet the requirements of field applications

Data Availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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