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Original Article

Fractured reservoir history matching improved based on artificial intelligent

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In this paper, a new robust approach based on Least Square Support Vector Machine (LSSVM) as a proxy model is used for an automatic fractured reservoir history matching. The proxy model is made to model the history match objective function (mismatch values) based on the history data of the field. This model is then used to minimize the objective function through Particle Swarm Optimization (PSO) and Imperialist Competitive Algorithm (ICA). In automatic history matching, sensitive analysis is often performed on full simulation model. In this work, to get new range of the uncertain parameters (matching parameters) in which the objective function has a minimum value, sensitivity analysis is also performed on the proxy model. By applying the modified ranges to the optimization methods, optimization of the objective function will be faster and outputs of the optimization methods (matching parameters) are produced in less time and with high precision. This procedure leads to matching of history of the field in which a set of reservoir parameters is used. The final sets of parameters are then applied for the full simulation model to validate the technique. The obtained results show that the present procedure in this work is effective for history matching process due to its robust dependability and fast convergence speed. Due to high speed and need for small data sets, LSSVM is the best tool to build a proxy model. Also the comparison of PSO and ICA shows that PSO is less time-consuming and more effective.

1. Introduction

Numerical reservoir simulation could provide the ability to understand the real reservoir behavior. To propel the simulated data to the real data, it is necessary to carry out the history matching operations and tune the reservoir parameters [1]. The main stages of the history matching process involve selecting parameters, defining the mathematical model, defining the objective function, sensitivity analysis and stop conditions. The major problems in history matching are: 1) generally, history matching is done manually and due to the enormous number of data used, a desired result is not achieved.; 2) it would be difficult to adjust the parameters to obtain the match due to the large number of reservoir parameters; 3) optimization algorithms used in the history matching process, optimize the problem locally; Thus when there are several minimums an acceptable solution is not provided; and 4) typical history matching procedure works for one simulation model and does not have the ability to work with several number of models. To solve the problems mentioned above, different techniques of automatic history matching were offered. In the proper procedure, one of the most important activities to achieve an acceptable result is to improve the optimization algorithms to achieve global minimum [2].

In this paper, two of the most famous global optimizers in the literature are employed: the PSO and ICA. These two algorithms need large number of objective function evaluation for optimization but each function evaluation needs a full simulation run

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which is time consuming. In order to reduce the function evaluation time, we use proxy models. Proxy models are alternatives to the reservoir simulation model. A good proxy model should have the following features [3,4]: (1) is acceptable imitation of nonlinear behavior of the actual model; (2) has a simple application; and (3) its construction is straightforward. A number of proxy models are used for reservoir simulation by different authors and each proxy model has been used for a particular reservoir and application [5]. Proxy models can simplify the process of finding the optimal values of reservoir parameters to reach the history matching by speeding up the calculations. This is more important for fractured reservoir because of its complex behavior.

History matching of fractured reservoirs poses more challenges compared to conventional reservoirs in two main areas: the number and type of history matching parameters, and the increased computational cost. For example, in the single porosity model, relative permeability and k_v/k_h(k_v: vertical permeability; k_h: horizontal permeability) are used as matching parameters in the match of water cut and gas production, whereas the matching parameters in the dual porosity model are fracture porosity, shape factor and k_{fv}/k_{fh} (k_{fv}: fracture vertical permeability; k_{fh}: fracture horizontal permeability). The dual porosity models have longer execution time than the single porosity models because of the large number of parameters. Also, the inter-porosity flow between the matrix and fracture poses additional challenge arising from the matrix–fracture interactions because it requires extensive computation. The doubling of the number of computational cells and significant non-linearity that leads to much smaller time-steps and more computations per time-step increase the computations required to evaluate the dual porosity model compared with an equivalent single porosity model. A partial representation of the fracture networks or describing them in a simplistic way in reservoir models due to scarcity of fracture data or lack of necessary numerical tools is one of the challenges of the fractured reservoir history matching.

Considering the importance of proxy application in the history matching, many studies have been carried out in this area. Cullik et al. [6] conducted the history matching using a nonlinear proxy and global optimization. They used the neural networks as a proxy model and showed that the required number of simulation runs to obtain a good history match can be reduced by the neural network. Yu et al. [7] used the genetic programming as a proxy model for history matching. Zhang et al. [1] provided an automatic history matching based on improved genetic algorithm. They showed that the rate of convergence of the automatic history matching can be significantly increased by the improved genetic algorithm. Rammay et al. [8] used the Adaptive Neuro-Fuzzy System (ANFIS) as a proxy to reservoir simulator. They combined ANFIS and Differential Evolution (DE) algorithm to reduce the number of simulation runs and the expensive simulation time. Maschio et al. [9] replaced the flow simulator by proxy models created by artificial neural network (ANN) to make possible the application of the sampling method in the history matching. They used Markov Chain Monte Carlo (MCMC) sampling and combined it and ANN. Goodwin [10] appraised the limitations of random walk MCMC. They showed that a combination of MCMC and proxy models provide a more reliable probabilistic uncertainty quantification and a suitable ensemble of deterministic reservoir models. He et al. [11] proposed the proxy-for-data approach. In this paper, the aggregated mismatch was calculated by the data values predicted by proxies. They also reduced the number of proxies needed by use of reduced order modeling.

In this paper, use of Least Square Support Vector Machine (LSSVM) as a nonlinear proxy model is proposed and a history match workflow with strong and nonlinear LSSVM proxy model to improve the history matching process is presented. One of the Iranian fractured reservoir simulation model and its history data is used as the case study.

2. LSSVM for function approximation

Considering the high performance of the support vector machine (SVM) in function approximation, the application of this algorithm has caused a significant growth in the field of oil reservoir modeling. SVM as a learning organization takes the nonlinear problems into high dimensional feature space and solves the problem through the kernel functions. Accordingly, SVM forecasts the functions so that the desired functions are developed on the subset of support vectors [12]. A version of SVM for regression is called support vector regression (SVR).

The purpose of SVR is to find a function f(x) that has at most ε deviation from the actually obtained targets $y^{(i)}$ for all the training data, and is as flat as possible simultaneously. In the case where f(x) is a linear function of the form $f(x) = \omega^T x + b$, the resulting primal optimization problem is shown in the following form [13]:

$$\text{minimize } \frac{1}{2}\omega^T\omega + C\sum_{i=1}^{m}(\varepsilon_i + \varepsilon_i^*)$$
$$\text{subject to } \begin{cases} y^{(i)} - \omega^T x^{(i)} - b \le \varepsilon + \varepsilon_i \\ \omega^T x^{(i)} - y^{(i)} + b \le \varepsilon + \varepsilon_i^* \\ \varepsilon,\ \varepsilon_i,\ \varepsilon_i^* \ge 0 \end{cases} \tag{1}$$

- $\omega^T\omega$ controls the trade-off between the complexity and the approximation accuracy of the model.
- $\varepsilon_i, \varepsilon_i^*$ are slack variables that measure the error of the up and down sides, respectively.
- C controls the trade off between the error and margin.

This optimization problem can transformed into the dual problem, which is easier to solve, and its solution is given by

$$f(x) = \sum_{i=1}^{n_{SV}}(\alpha_i - \alpha_i^*)k(x_i, x) \tag{2}$$

subject to $0 \le \alpha_i^*, \alpha_i \le C$ where α_i^* and α_i are called the lagrangian multipliers are in Eq. (2), which satisfy the equalities $\alpha_i^*\alpha_i = 0$, $\alpha_i > 0$ and $\alpha_i^* \ge 0$ and n_{SV} is the number of Support Vectors (SVs) and the kernel function

$$K(x, x_i) = \sum_{j=1}^{m} g_i(x)g_i(x_i) \tag{3}$$

In order to reduce complexity and increase computing speed, modified SVM as LSSVM is offered [14]. LSSVM as a function approximation is to estimate a function y(x) from a given training set of N samples $\{x_i, y_i\}_{i=1}^{N}$ in which $x_i \in R^N$ (N dimensional vector space) as input data and $y_i \in r$ (one dimensional vector space) as corresponding output data [15]. LSSVM suggests the following equation to estimate y(x) [15]:

$$y(x) = w^T\varphi(x) + b \tag{4}$$