Assisted History-Matching Based on Multiobjective Surrogate Reservoir Model for Tight Oil Reservoirs

Zhenzhen Dong¹, Weidong Tian¹, Yongzhi Yang², Tingkui Jiao³, Wenfeng Lv², Yongyi Zhou⁴, Jinghui Yang⁵ and Weirong Li¹, *

¹ Xi’an Shiyou University, China
² Research Institute of Petroleum Exploration and Development (RIPED), PetroChina
³ Research Institute of Petroleum Exploration and Development, Changqing OilField, PetroChina
⁴ Sinopec North China Petroleum Bureau, China
⁵ Institute of Petroleum Engineering Technology, SINOPEC Shengli Oilfield Company, China

*Corresponding author e-mail: weirong.li@xsyu.edu.cn

Abstract. History matching and quantifying uncertainty in hydrocarbon production forecasts are considered important steps in reservoir simulations and are key processes for providing crucial information for decision making in the development of oil and gas fields. However, history matching of unconventional reservoirs with complicated fracture system is very computationally expensive and time consuming, and most of the data used are subject to high uncertainty. In addition, the objectives of history matching are usually conflicting, such as improving match of oil rate will deteriorate match of water rate. Previous studies on assisted history matching have mainly focused on optimizing a single-objective function, where the production and pressure data are combined as a single misfit value. In this study, the proposed algorithm extends the application of the proxy model to deal with multiobjective optimization in the context of reservoir history matching. Then, the resulted proxy model were conducted to analyze history-matching quality and obtain uncertainty prediction. Result suggests that the multiobjective surrogate reservoir model scheme not only could obtain reliable history matches and provide accurate uncertainty estimation, but the complexity of gridded fractures is mitigated through the workflow. The benefit of using the multiobjective surrogate reservoir model is to obtain a various set of history matched models while reducing the number of expensive reservoir simulation runs. The proposed methodology might also be useful for reservoirs in which simulation models could not reflect the production history and for those with high uncertainties in reservoir characterization.

1. Introduction

History matching (HM) is one of the most significant activities in the development and management of oil and gas reservoirs. The main purpose of history matching is optimizing and verifying the simulation model of a reservoir by combining observations with characterization to obtain reliable prediction results.
History matched reservoir models are essential to ensure reliable production predictions and to obtain understanding of the geological and reservoir models. The on-site performance output forecast must be accurate because it affects the performance of the operator technically and economically.

In essence, HM is an inverse process. Most data used in HM are subject to uncertainty, which could be very large for the distribution of rock properties away from wells. To achieve an acceptable model, sometimes small changes may be made in the properties with higher uncertainty, such as fracture and reservoir properties, which are extremely difficult to measure directly and accurately with current experimental and diagnostic technologies (Mohamed et al. 2011). According to Wu and Aguilera (2013), permeability in tight oil and gas reservoirs is difficult to determine because laboratory-tested permeability cannot represent the permeability of a stimulated hydraulic fracture. Moreover, Wantawin et al. (2017), Yu et al. (2017, 2018), and Silpakorn et al. (2018) demonstrated the high uncertainty of fracture parameters, including effective half-length, conductivity, and fracture height. As a result, the production performance associated with any development strategies could not be forecasted exactly. However, a range of possible profiles can be calculated. Moreover, manually adjusting reservoir parameters through trial and error in classical HM makes the problem drearier and more time-consuming.

To improve the accuracy of the HM process, it is necessary to run full reservoir simulations for a few representative reservoir models. The set of reservoir models can quantify the uncertainty at a lower computational cost through the use of a robust proxy model for the full physics dynamic model. Thus, the efficacy of reservoir model selection hinges on the implementation of a fast proxy that can estimate the dynamic characteristics of all candidate models.

Moreover, a considerable number of optimization methods have been adopted for assisted history matching (AHM) (including gradient-based, hybrid, stochastic, and probabilistic methods) to determine the parameter space and reduce misfit (Romero et al. 2000). To overcome the deficiencies of gradient-based optimization methods, simulated annealing, evolutionary algorithms, evolution strategies, and other global optimization methods have been proposed, such as Particle swarm optimization (PSO) method, Data-driven proxy models (Shahkarami et al. 2018).

Recently, multiobjective optimization has been successfully applied to HM for reducing bias in uncertainty quantification by yielding more diversified reservoir models than those achieved by global optimization (Park et al. 2014; Min et al. 2015; Wantawin et al. 2017b). Most multiobjective optimization algorithms are based on Pareto optimality, in which no objective can be improved without worsening other objectives. Thus, exploring reservoir models well distributed along the Pareto-optimal front (POF) will guarantee the best unbiased uncertainty.

In this paper, an AHM workflow based on multiobjective optimization scheme using a proxy model is presented to finalize reservoir models conditioned to observed flow responses. Firstly, we give a review on the theory of the methods, including Latin hypercube sampling (LHS) for initial points, radial basis functions (RBFs) for generating the proxy model, multiobjective functions, Pareto optimality, and the embedded discrete fracture model (EDFM) method. Then, we illustrate the workflow/steps of the proposed algorithm. We also show application and validation of the proposed algorithm for a tight oil well.

2. Methodology

2.1. Latin Hypercube Sampling

The LHS design presented by McKay et al. (1979) aims to fill the space of the predictor by randomly choosing observed values with the same probability intervals in the input region. The design extracts samples from the interval [0, 1] of each input at all design points. In addition, just one observed value per interval [0, 1/n], [1/n, 2/n], ..., [(n-1)/n, 1] is assumed for the input for a sample with size n. More specifically, the boundary of [0, 1] of the LHS is considered the probability, and the points in the design are converted into the input probability distribution. According to the selected distribution, the model can distribute the sampling sites over the same probability area for each input.
2.2. Radial Basis Functions.
The RBFs proposed by Powell (1987) depend only on the gap between an observed value and set position c: \( \emptyset() = \emptyset(||x - c||) \). The regression model of the RBF can be expressed as follows:

\[
\hat{f}(x) = b_0 = \sum_{i=1}^{p} b_i \emptyset_i(x - x_i)
\]  

Thus, the approximate response surface can be obtained by using the weighted sum of the RBFs; each depends on the gap between target position x and sampled observed value xi. Subsequently, an ordinary least-squares approach can be used to train regression weight bi, and other variations of the subject can be applied to enhance the model fitting further. The fit can be improved by applying a relatively small quantity of RBFs, which include substitute centers such as c1, c2, …, cp instead of x1, x2, …, xp, with \( p' \ll p \). Another way is to enable the parameters in function \( \emptyset_i() \) to change according to the position.

2.3. Pareto Optimality and Dominance.
The aim in single-objective optimization is to achieve the global optimum. But the definition of optimality in multiobjective optimization is complicated, as the presence of conflicting objectives, in which improvements in one objective may worsen the others. Thus, the aim in multi-objective optimization is to find the trade-offs that exist between such conflicting objectives. Such a trade-off is obtained when a solution cannot improve any objective without degrading the other objectives. The solutions are referred as nondominated solutions, of which many may exist.

Pareto optimality represents a measure of efficiency in a multitarget environment, which includes several conflicting objectives that must be considered in the optimization process. If there is no other design that can enhance the output of either one of the target standards without lowering one or more of the other criteria, the design is considered Pareto-optimal.

Domination: A vector, \( x_1 \), dominates the other vector, \( x_2 \), if and only if, Eq. 2 is met:

\[
\forall i \in \{1, \ldots, m\} : f_i(x_1) \leq f_i(x_2) \quad \text{and} \quad \exists j \in \{1, \ldots, m\} : f_j(x_1) < f_j(x_2)
\]

Where the dominance of \( x_1 \) over \( x_2 \) is denoted as \( f(x_1) < f(x_2) \)

Pareto optimal. A vector, \( x^* \in F \), is Pareto-optimal if no solution vectors dominate it. The corresponding objective vector, \( f^*(x) \), is Pareto-optimal if x is Pareto-optimal (Mohamed et al. 2011).

Pareto-optimal set. This is the set which contains all the nondominated solutions for the multiple objective functions and can be expressed as Eq. 3.

\[
P^* = \{x^* \in F|\exists x \in F: x < x^*\}
\]

Pareto-optimal front. The POF is a set containing all the objective vectors corresponding to nondominated vectors,

\[
PF^* = \{f = (f_1(x^*), f_2(x^*), \ldots, f_j(x^*))|x^* \in P\}
\]

The solutions should converge along the POF and be sparsely distributed in the Pareto-optimal region to ensure diversity and a reasonable set of trade-off solutions based on the multiple objectives.

2.4. Multiobjective-Functions.
Assisted history matching has been presented use nonlinear optimization to minimize the least-squares fit between the simulated data and historical observed data. Eq. 5 defines the objective function in the least-squares sense. The subscripts t and i represent the number of observation data and number of objectives, respectively; N is the total number of observations; M is the total number of objectives; \( S_i,t \) and \( O_i,t \) are the simulated and observed data, respectively, representing oil rate, water rate, or reservoir pressure. Note that \( S_i,t \) is predicted by surrogate reservoir models (SRMs), as shown in Eq. 1, which was validated against historical data through reservoir simulation in this study. \( w_t \) is the
weighting factor. It is generally believed that the attribute and significance of measured data are distinct for certain parameters. In this study, all parameters were considered equally important, and the weight coefficients were equal.

\[ P_i = \sqrt{\frac{\sum_{t=0}^{N(t)} w(S_i - O_i)^2}{N}}, \quad i = 1, 2, \ldots, M \]  

(5)

2.5. Embedded Discrete Fracture Model

Recently, a generalized three-dimensional EDFM method for simulating fractured reservoirs with complex fracture geometries has been developed (Moinfar et al. 2014; Li et al. 2017). In this study, the UNConventional Oil and Gas Simulator (UNCONG) which is a in-house simulator was used. It is a composition reservoir simulator that tackles the difficulties of simulating shale oil, shale gas, and coalbed methane reservoirs. It is used to model fractured reservoirs with integrated state-of-the-art methods (for example, EDFM and multiple interacting continua) to calculate multiphase flows in fracture networks.

2.6. Multiobjective Surrogate Reservoir Model Algorithms

In the optimization phase, surrogate models (also known as proxy models) are adopted as an approximate substitution for expensive simulation models. The surrogate model is applied to find better solutions during the optimization phase. The substitution model as a replacement for real simulation models can greatly reduce calculation cost.

The majority of substitution algorithm procedures shown in Fig 1 comprise the following steps:

Step 1. Design an initial experiment.
Step 2. Perform expensive computation at the points selected in Step 1.
Step 3. Generate a SRM with RBFs for the simulation results from Step 2.
Step 4. Select a point for evaluating the next expensive function by using SRM.
Step 5. Evaluate the expensive function at the selected point in Step 4.
Step 6. Update the surrogate model with the new data points.
Step 7. Repeat Steps 4 to 6 until the procedure terminates.

Generally applied stopping standards are the greatest number of allowable function assessments, longest allowable central processing unit (CPU) computation time, or greatest quantity of unsuccessful iterative optimization tests.

Figure 1. Workflow for model.
3. Use of Multiobjective Surrogate Reservoir Model (MOSRM) in Calibration of Reservoir Modeling

We applied the MOSRM workflow as one of the surrogate model with the multiobjective optimization technique for HM and uncertainty quantification. We generated multiple HM models with MOSRM on a fractured tight oil reservoir model. The good HM models were run forward for the prediction period. Sensitivities of significant production variables (oil production and water production) for an additional 20 years were then calculated and used to calculate probability distribution and quantify the uncertainty on resources/reserves.

3.1. Reservoir Model Description

The fractured tight oil reservoir simulation was known to be very challenging, and standard HM methods had been very time consuming given a complex fracture system. The simulation model was 200×51×1 (X, Y, and Z axis, respectively), with the dimension of the reservoir being 6,000×2,040×60 ft in X, Y, and Z directions, respectively. A horizontal well with 58 hydraulic fractures is located in the center of the reservoir. The EDFM module in UNCONG was used to represent the 58 hydraulic fractures, as shown in Fig 2. The horizontal well has been operated at a fixed bottomhole pressure (100 psi). The reservoir and fluid parameters used in the work are listed in Table 1. The water and oil relative permeability curves of the fractures and matrix are presented in Fig 3.

![Reservoir model for horizontal well and 58 hydraulic fractures for tight oil reservoir.](image)

**Figure 2.** Reservoir model for horizontal well and 58 hydraulic fractures for tight oil reservoir.

| Parameter                        | Value                  | Unit    |
|----------------------------------|------------------------|---------|
| Reservoir dimension (X × Y × Z)  | 6,000 × 2,040 × 60     | ft      |
| Reservoir grid-block (X × Y × Z) | 200 × 51 × 1           | -       |
| Initial reservoir pressure       | 3,650                  | psi     |
| Well length                      | 4,560                  | ft      |
| Reservoir depth                  | 7,500                  | ft      |
| Number of fractures              | 58                     | -       |
| Oil viscosity                    | 0.95                   | mPa.s   |
| Water viscosity                  | 0.46                   | mPa.s   |
| Oil density                      | 45.0                   | lb/ft³  |

**Table 1.** Three Scheme comparing.
3.2. Parameterization

In the assisted history-matching, the varied properties probably are those that have the biggest effect on the predicted production in the HM period. In the uncertainty analysis, variables that have small effect in HM might be significant due to their effect on production performance in the predictive period. Two factors affect the influence of a parameter on the results: the sensitivity of the parameter and the range of uncertainty in the parameter value. During uncertainty analysis, each parameter in the simulation model should be considered. Considering the costs, some selection of parameters has to be made.

In this study, the tight oil reservoir model was characterized by six uncertain input parameters corresponding to fracture permeability, fracture height, fracture half-length, water saturation, matrix porosity, and matrix permeability. Table 2 lists the uniform range and the truth value for the six unknown parameters. Fig 4 shows three years of observed monthly oil and water rates that were simulated by the reservoir model and the truth values listed in Table 2.

![Figure 3](image1)

**Figure 3.** Relative permeability curves of gas, oil, and water flows of tight oil reservoir. (a) Relative permeability of water and oil. (b) Relative permeability of liquid and gas.

![Figure 4](image2)

**Figure 4.** Production data of the truth case. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production.
Table 2. Uncertain parameters and specific values used to generate oil and water rates.

| Parameter              | Distribution | Minimum | Maximum | Truth Case | Unit |
|------------------------|--------------|---------|---------|------------|------|
| Matrix porosity        | Uniform      | 0.02    | 0.08    | 0.055      | --   |
| Matrix permeability    | Uniform      | 0.05    | 0.25    | 0.09       | mD   |
| Water saturation       | Uniform      | 0.20    | 0.70    | 0.32       |      |
| Fracture half-length   | Uniform      | 200     | 900     | 450        | ft   |
| Fracture height        | Uniform      | 30      | 100     | 40         | ft   |
| Fracture permeability  | Uniform      | 500     | 1,200   | 950        | mD   |

3.3. History Matching

For MOSRM, the misfit was estimated with the least-squares equation shown in Eq. 5. The least-squares misfit in water rate at the producing horizontal well was considered to be the first objective, and the least-squares misfit in oil rate was treated as the second objective. Based on the six uncertain parameters shown in Table 2, a combination of 14 initial starting points obtained by the LHS method was used. After each condition was numerically simulated by running the simulator, the predicted oil and water production profiles of the 14 cases were compared with the observed data (Fig 5). Production data of the truth case was within the range predicted (Fig 5). Thus, the best HM solution could be determined within the given design space of the six uncertain parameters.

Figure 5. Production data from 14 simulation cases. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production. (Red dots represent the production data of the truth case. 14 lines are simulation results of 14 cases.)
Once the design space was determined by the LHS method, the initial RBF proxy model was built. Then, 2,000 points randomly generated for each variable were used in the RBF model to calculate misfit against observed data, and the points with minimal misfit value were chosen as new design points for the next expensive reservoir simulation. The MOSRM workflow was set to be terminated at the 100th iteration (100th reservoir simulation run). The quality of the proxy model was enhanced during the iterations, and the multiobjective optimization algorithm in the model selection yielded a diverse set of models.

The 100 selected samples for all the six variables are depicted in Fig 6. It is shown that the MOSRM approach seeks the response space and achieved a well distributed group of acceptable RSMs that approach the observed data (referred to black lines). Each variable converged around a certain value after 42 reservoir simulation runs, indicating that the MOSRM scheme has a fast convergence speed. Fig 7 compares the 100 predicted oil and water production profiles with the production data of the truth case (shown as red points). Evidently, the best HM solution was found and agreed well with the truth case.

**Figure 6.** Samples of six uncertain parameters for 100 solutions. (a) Porosity. (b) Permeability. (c) Fracture height. (d) Fracture half-length. (e) Fracture permeability. (f) Initial water saturation.
Figure 7. 100 HM solutions of oil and water production profiles compared with the truth case. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production. (Red dots represent truth case. 100 lines are 100 simulation results.)

The history matching results were summarized in Table 3. The misfit generated through the 100 iterations are presented with respect to the iteration numbers in Fig 8. A misfit value below 10 indicates a good model. The minimal misfit for each objective is below 0.1 (Fig 8a through 8d). The minimal cumulative misfit for the oil and water rates is below 0.05 (Fig 8e), indicating the best match.

Moreover, Table 4 compares the six uncertain parameters that correspond to the minimal cumulative misfit (referred to as the best HM solution) with the truth values used to generate the production profile of the truth case. They were found to be in good agreement.

Table 3. Performance of MOSRM.

| Algorithm | Total number of simulations | Number of solutions with M<10 | Number of Pareto | Minimum total fitting error |
|-----------|-----------------------------|------------------------------|------------------|-----------------------------|
| MOSRM     | 100                         | 75                           | 18               | 0.05                        |
Figure 8. Misfit with respect to iteration number through MOSRM. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production. (e) Total misfit for both water and oil production.

MOSRM reported a set of nondominated solutions (18 models) populating the repository, that refers to the estimated POF. The solutions in the full envelop are given in the POF chart obtained with MOSRM, shown as Fig 9. The optimal Pareto set involves the solutions that are equivalent to different validations of the reservoir models.

Figure 9. POF plot of MOSRM (size of Pareto=18).

3.4. Uncertainty Analysis
Uncertainty can be quantified by generating multiple reservoir models, performing HM for each model, and then simulating future production with each. A refined approach estimates the probability of the parameters with a set of stochastic realizations and AHM with data uncertainty. This approach is very
expensive and requires additional resources to match multiple models rather than fine-tuning the match of a single model.

An alternative way to estimate uncertainty in the future performance of producing reservoirs is based on the recognition that once the values of the reservoir parameters have been tuned to get an acceptable HM. It is probable to slightly perturb these values and still get an acceptable match. If the same perturbations are conducted in the prediction period, a number of possible predicted production profiles is obtained. In addition, a linear perturbation analysis can be used to obtain confidence intervals for the production prediction if the perturbations are sufficiently small.

To capture various acceptable models is significant to consider a range of geological scenarios and, thus, cause more divergent prediction qualities and more realistic uncertainty estimates rather than to find solutions that lead to similar forecasts. In this study, 75 models/cases with misfit values below the threshold of 10 (indicating good quality), shown in Fig 8e, were chosen to perform further uncertainty analysis. The production prediction profile for an additional 20 years of the 75 good models is shown in Fig 10. It indicates that MOSRM obtained a wide realistic estimate of uncertainty that captured the simulated truth indicated earlier in Table 2.

![Predicted oil and water production. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production.](image)

**Figure 10.** Predicted oil and water production. (a) Water rate. (b) Oil rate. (c) Cumulative water production. (d) Cumulative oil production.

Statistical analysis was performed to generate the probability distribution (PDF) and cumulative probability distribution (CDF) of the predicted oil and water production, which are presented in Fig 11. The cumulative oil productions after another 20 years were found to be 710.2, 772.6, and 785.4 Mbbl, and the expected oil recoveries were found to be 14.2%, 15.4%, and 15.7% (P10, P50, and P90, respectively). In addition, the cumulative water productions after another 20 years were found to be 93.5, 102.8, and 107.2 Mbbl (P10, P50, and P90, respectively). MOSRM performed a 10% and 11% error difference in oil rate and water rate, as shown in Fig 11b and 11d, respectively.
4. Conclusions
This research work investigated an MOSRM optimization scheme that combines the innovative, nonintrusive EDFM method to conduct HM, production prediction, and uncertainty estimation for a tight oil reservoir with a complex fracture system. The complexity of gridded fractures is mitigated through the workflow. MOSRM is applied to analyze reservoir simulations in which conflicting objectives lead to identification of more possible scenarios, and to obtain uncertainty prediction envelopes. The results suggest, for the tight oil reservoir with the specified objective functions, that
1. The MOSRM approach could efficiently improve HM (as indicated in Table 3).
2. MOSRM is very competitive in achieving a well distributed combination of good fitting reservoir model (referred to Figures 5 and 6).
3. MOSRM has a fast convergence rate (as shown in Figures 5 and 7).
4. The benefits of using the MOSRM is evident in obtaining a diverse set of acceptable HMs while reducing the efforts of expensive reservoir simulations.

In a word, the MOSRM scheme provides flexibility in optimizing conflicting objectives simultaneously, obtains reliable HM solutions, gives a more accurate uncertainty estimation, and has a fast convergence rate.

5. Nomenclature
P10, P50, P90 = values for which the probability is 10, 50, or 90% that the value will not be exceeded, indicated by the 10th, 50th, or 90th percentile on a cumulative probability plot.
Acknowledgments
The authors are grateful for financial support from the National Science and Technology Major Project (Grant No. 2016ZX05016-005 and 2016ZX05016-001), the Major Project of China National Petroleum Corporation (Grant No. RIPED-2020-JS-50214) and (Grant No. RIPED-2020-JS-50215), the project of Sinopec North China Petroleum Bureau (Grant No. 290018276) and project of Petroleum Engineering Technology Institute of SINOPEC Shengli Oilfield (Grant No. 290018276).

References
[1] A Castellini, H Gross, Y Zhou, J He, W Chen, An iterative scheme to construct robust proxy models, ECMOR XII-12th European Conference on the Mathematics of Oil Recovery, 2010
[2] Bhark, E. W. and Dehghani, K. 2014. Assisted History Matching Benchmarking: Design of Experiments-Based Techniques. Presented at the SPE Annual Technical Conference and Exhibition, Amsterdam, 27–29 October. SPE-170690-MS.
[3] Boxiao Li, Eric W. Bhark, Stephen J. Gross, Travis C. Billiter, Kaveh Dehghani, Best Practices of Assisted History Matching Using Design of Experiments, SPE 191699, SPEJ, 24(4), Aug 2019
[4] Cheng, H., Dehghani, K., and Billiter, T. C. 2008. A Structured Approach for Probabilistic-Assisted History Matching Using Evolutionary Algorithms: Tengiz Field Applications. Presented at the SPE Annual Technical Conference and Exhibition, Denver, 21–24 September. SPE-116212-MS.
[5] Gong, W., Duan, Q., Li, J., Wang, C., Di, Z., Ye, A., ... & Dai, Y. (2016). Multiobjective adaptive surrogate modeling - based optimization for parameter estimation of large, complex geophysical models. Water Resources Research, 52(3), 1984-2008.
[6] He, J., J. Xie, W. Wen and X.-H. Wen, Improved Proxy For History Matching Using Proxy-for-data Approach And Reduced Order Modeling, SPE Western Regional Meeting, 2015
[7] Kim, J., Kang, J. M., Park, C., Park, Y., Park, J., & Lim, S. (2017). Multi-objective history matching with a proxy model for the characterization of production performances at the shale gas reservoir. Energies, 10(4),579.
[8] Lee, S.H., Lough, M.L., and Jensen, C.L. (2001). Hierarchical modeling of flow in naturally fractured formations with multiple length scales. Water Resources Research, 37(3), 443-455.
[9] Li, L. and Lee, S.H. (2008). Efficient field-scale simulation of black oil in a naturally fractured reservoir through discrete fracture networks and homogenized media. SPE Reservoir Evaluation & Engineering, 11, 750-758.
[10] Li, W., Dong, Z., and Lei, G. 2017. Integrating Embedded Discrete Fracture and Dual-Permeability Methods to Simulate Fluid Flow in Shale Oil Reservoirs. Energies 10(10):1471-1480.
[11] Mckay, M. D., Beckman, R. J., Conover, W. J. 1979. A Comparison of Three Methods for Selecting Values of Input Variables in the Analysis of Output from A Computer Code. An Introduction to Copulas 21: 239 – 245.
[12] Min, B., Park, C., Jang, I.S., et al. 2015. Development of Pareto-Based Evolutionary Model Integrated with Dynamic Goal Programming and Successive Linear Objective Reduction. Appl. Soft Comput. 35: 75-112.
[13] Moinfar, A., Varavei, A., Sepehrnoori, K., and Johns R.T. 2014. Development of an Efficient Embedded Discrete Fracture Model for 3D Compositional Reservoir Simulation in Fractured Reservoirs. SPE Journal 19(2): 289–303.
[14] Mohamed, L., Christie, M., and Demyanov, V. 2011. History Matching and Uncertainty Quantification: Multi-objective Particle Swarm Optimization Approach. Paper presented at the SPE EUROPEC/EAGE Annual Conference and Exhibition, Vienna, Austria, 23-26 May. SPE-143067-MS.
[15] Park, H. Y., Datta-Gupta, A., and King, M.J. 2014. Handing Conflicting Multiple Objectives Using Pareto-Based Evolutionary Algorithm During History Matching of Reservoir
[16] Powell, M. 1987. Radial Basis Functions for Multivariable Interpolation. Clarendon Press.

[17] Romero, C. E., Carter, J. N., Gringarten, A. C., and Zimmerman, R. W. 2000. A Modified Genetic Algorithm for Reservoir Characterization. Paper presented at International Oil and Gas Conference and Exhibition in China, Beijing, China, 7-10 November. SPE-64765-MS.

[18] Shahkarami, A., Mohaghegh, S.D., and Hajizadeh, Y. 2018. Assisted History Matching using Pattern Recognition Technology. International Journal of Oil, Gas and Coal Technology 17(4): 56-70.

[19] Silpakorn D., Yu,W., Pavel Z., and Kamy S. 2018. Application of Assisted-History-Matching Workflow Using Proxy-Based MCMC on A Shale Oil Field Case. Journal of Petroleum Science and Engineering 167(2018):316–328.

[20] Wantawin, M., Yu, W., and Sepehrnoori, K. 2017a. An Iterative Work Flow for History Matching by Use of Design of Experiment, Response-Surface Methodology, and Markov Chain Monte Carlo Algorithm Applied to Tight Oil Reservoirs. SPE Reservoir Evaluation & Engineering 20(3): 613–626.

[21] Wantawin, M., Yu, W., and Sepehrnoori, K. 2017b. An Iterative Response-Surface Methodology by Use of High Degree-Polynomial Proxy Models for Integrated History Matching and Probabilistic Forecasting Applied to Shale Gas Reservoirs. SPE Journal 22(6): 2012–2031.

[22] Wu, P. and Aguilera, R. 2013. Uncertainty Analysis of Shale Gas Simulation: Consideration of Basic Petrophysical Properties. Paper presented at SPE Unconventional Resources Conference Canada, Calgary, Canada, 5–7 November. SPE-167236-MS.

[23] Yu, W., Wu, K., Sepehrnoori, K., and Xu, W., 2017. A Comprehensive Model for Simulation of Gas Transport in Shale Formation with Complex Hydraulic-Fracture Geometry. SPE Reservoir Evaluation & Engineering 20(3): 547–561.

[24] Yu,W., Sutthaporn T., Kamy S., and Miao, J. 2018. An Automatic History-Matching Workflow for Unconventional Reservoirs Coupling MCMC and Non-Intrusive EDFM Methods. Paper presented at 2018 SPE Annual Technical Conference and Exhibition. Dallas, Texas, 24-26 September. SPE-191473-MS.

[25] Yeten, B., Castellini, A., Guyaguler, B. et al. 2005. A Comparison Study on Experimental Design and Response Surface Methodologies. Presented at the SPE Reservoir Simulation Symposium, Houston, 31 January–2 February. SPE-93347-MS. https://doi.org/10.2118/93347-MS

[26] X.-H Wen and W. C. Chen, Some practical issues on real time reservoir updating using Ensemble Kalman Filter, SPEJ, June, 2007, 12(2), 156-166.

[27] X.-H Wen and W. C. Chen, Real time reservoir updating using Ensemble Kalman Filter: The confirming approach, SPE 92991, SPEJ, Nov., 11(4), 431-442, 2006

[28] X.-H. Wen, S. Lee and T. Yu, Simultaneous integration of production data and 4-D seismic data, Math. Geology, Vol 38 (3), 2006.

[29] X.-H. Wen, T. Yu, and S. Lee, Coupling SSC/GA to integrate production data in geostatistical reservoir modeling, Geostat 2004, Banff, 2004.