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Applying an optimized low risk model for fast history matching in a giant oil reservoir

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Abstract

In this paper, the latest approaches for automated history matching (AHM) were applied to a real brown field having 14 active wells with multiple responses (production rate, bottom hole pressure and well block pressure) located in the south of Iran. A modified support vector machine was employed to create a proxy model incorporated based on design of experimental. Thereafter, all model parameters were adjusted to reproduce the observed history within the created proxy model. Accordingly, the proposed proxy model was successfully constructed using 1086 samples based on an R^2 coefficient of about 0.9 for the trained and test dataset. Finally, the process was optimized by two main algorithms to reach the best solutions, which are genetic and particle swarm optimization.

Keywords: Cubic centered face; fast history matching; Least square support sector; optimization.

1. Introduction

Scenario planning and production strategies for oil and gas reservoirs are highly dependent on the accuracy of the dynamic reservoir model and definite initial properties. History matching is one of the main important tasks in reservoir studies. Study evaluation and quality check of reservoir parameters depend on how fast and accurate history matching is done. In recent decades, compared with manual history matching, some techniques are introduced to achieve automatic matching, which is very advantageous. A study of methodologies for assisted history matching was done by Arief (2013). In this paper, the newest algorithms for proxy modeling were used for automated history matching.

The main components of automatic history matching are identification of uncertain reservoir parameters to be history matched, a definition of a suitable objective function, and a selection of a suitable optimization technique. There are some techniques (e.g.experimental designs) that can be used for parameter screening and sampling. After screening and selection of parameters (based on experience and sensitivity analysis), the obtained results are used as input to build a reliable proxy model.One of the main categories in the experimental design is the central composite design (CCD) (Arief, 2013; Bhark & Dehghani, 2014; Arwini & Stephen, 2011). Cubic centered face (CCF) is a type of the CCD which is acceptable with the principle of this study because of its coverage of all points and spaces. Regarding the acceptable results of the support vector machine (SVM) in function estimation (such as a proxy model), the appliance of this algorithm can be used in the field of oil and gas reservoir modeling (Suykens *et al*., 2002; Ahmadi & Bahadori, 2015).In this paper, a proxy model is introduced for reducing the run time of history matching and speed up the reservoir study. The acceptable outcomes of the presented optimized proxy model were applied in one of oil reservoirs.

2. Least square support vector machine (LS-SVM)

LSSVM is a modified support vector machine which maps nonlinear problems into multi-dimensional aspect space and solves the problem by decomposition into summations of some kernel functions. A simple format of a relationship which is used in LSSVM follows in Equation 1:

$$y(x) = w^T \varphi(x) + b \,, \tag{1}$$

where the function φ(x) takes the parameters into a high dimensional space to reduce the complexity and speed up the process, b is the bias value and w is a weight vector with similar dimension with the defined space dimension. The main LSSVM function results in

$$y(x) = \sum_{i=1}^{N} a_i \exp\left(-\frac{\|(x-x_i)\|^2}{\sigma^2}\right) + b \,, \tag{2}$$

where x and x_i are vectors of size p (number of parameters) and $\|(x-x_i)\|^2 = \sum_{k=1}^{p}(x_k - x_{k,i})^2$.

Kernel width parameters (σ^2) and regularization parameter (γ) affect the LSSVM the performance of generalization.

3. Optimization

Optimization algorithms, especially genetic algorithm (GA) and particle swarm optimization, are extensively utilized in different applied sciences and fields. For example, GA has been used to solve Problems related to parametric design of aircraft, robot trajectory generation and nonlinear dynamical systems.

3.1.1.Particle swarm optimization (PSO)
PSO, as a stochastic optimization technique, is

the model of the proposal of a group of birds and fishes (Wang & Qiu, 2013; Reynolds *et al*., 2015).

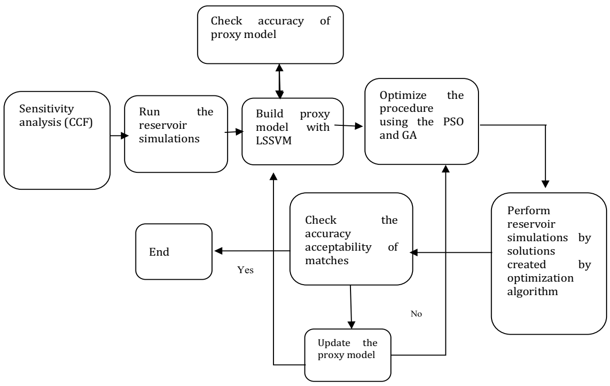

Fig. 1. Proposed algorithm for automated history matching

Research conducted by other authors shows that PSO is a very efficient method when compared to other optimization techniques (Reynolds *et al*., 2015).

3.1.2. Genetic algorithm (GA)

GA is one of the optimization techniques derived from the natural growth process. Generally, three kinds of regulations are utilized to get the procedure: selection, crossover, and mutation. This algorithm is one of the most popular methods for optimizing the procedure due to its simple and fast workflow. Lately, GAs are being extended particularly for history matching (Firoozjaee & Khamehchi, 2014).

4. Methodology workflow

As discussed in Section 2, several techniques are available for assisted history matching. These consist of at least three main factors: experimental design (screening parameters), proxy modeling, and optimization. However, in this work, the proposed workflow for automated history matching differs. (See Figure 1.) To save computational time and accelerating the simulation runs, LS-SVM (a proxy model) was applied for the substitution of the simulation model. Proxy construction was repeated many times in order to attain an acceptable model. Accordingly, all these main steps for automated history matching were analyzed and then tested in a real model. The criteria to verify the validity of the built model are Lambda, Sigma, errors and R2. The GA and PSO optimization techniques were applied to the proxy model to discover the best solutions. The same situations for both algorithms were employed. To find a solution for the matching problem, an objective function (OF) should be identified. In this case, the objective value for a function defines the divergence between the simulated value and observed data. The OF also considers the different time steps for parameters, if any.

5. Model description

The dimension of the reservoir under study is about 6.5×23 km. The exported up-scaled reservoir model is square shape, meauring 100×100 m. A 3D schematic view of the grid property of porosity is illustrated in Figure 2.

5.1. Selected parameters

With regard to the available information on the reservoir under study, 44 main parameters were considered for proxy generation.

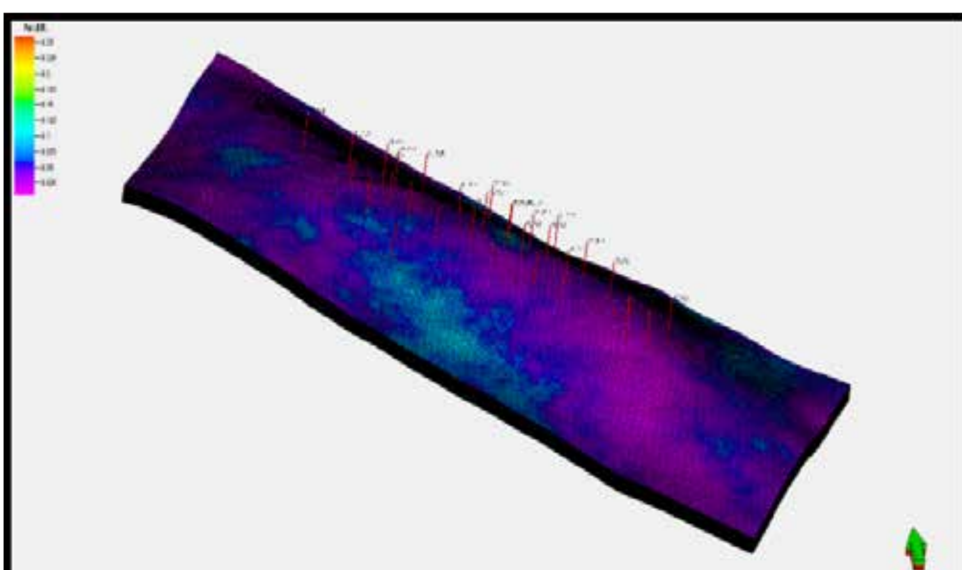

Fig. 2. 3D view of reservoir porosity

6. Results

6.1. Sample generation

For this study, 1086 runs were produced using the CCF design by means of the parameters defined in

Table 1. In Table 1, the 44 parameters used for the proxy generation are described. Maximum and minimum values were selected based on the information from nearby studied fields and reservoir engineering concepts. In this study all 1086 runs were succefully executed.

6.2. Proxy construction

Training, validation, and testing sets are three main steps for proxy generation. To reach these three steps, 70%, 15%, and 15% of the input data set (1086 samples) were defined, respectively. Based on the 1086 samples and the identified objective function, an acceptable proxy model was created. Figure 3 illustrates the comparison between the actual and predicted data from the proxy model for training tests.

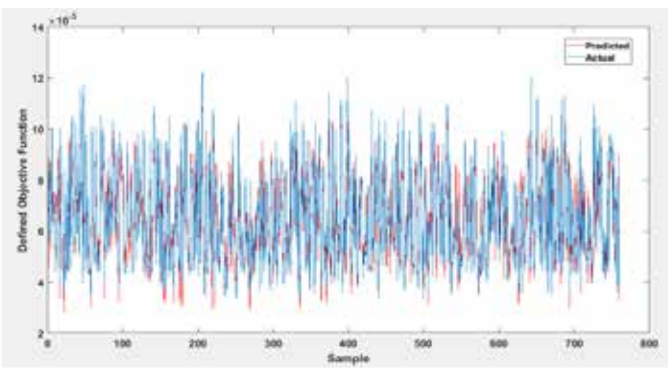

Fig 3. Comparison of actual and predicted data in a constructed proxy model

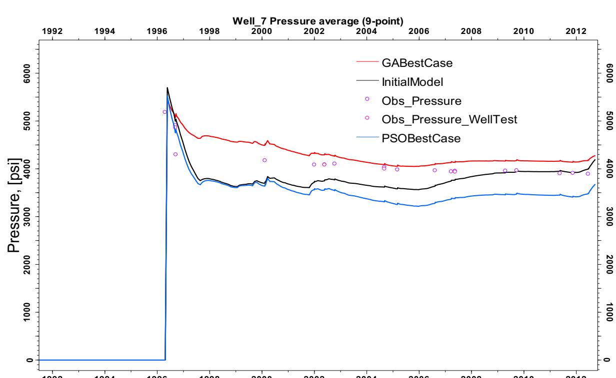

Fig 4. History matching results for average pressure (9-point) in well 7

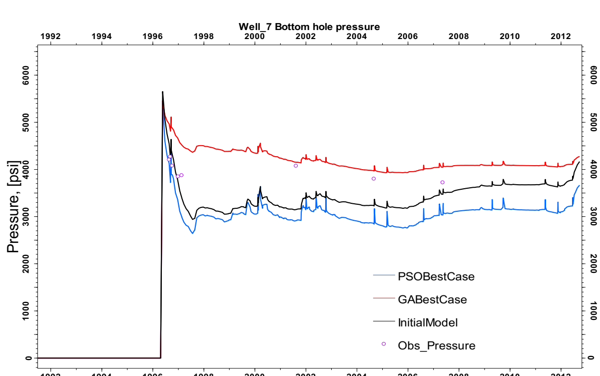

Fig 5. History matching results for bottom hole pressure in well_7

6.3. Optimization

The optimum control parameters are shown in Table 2. Hence GA exhibits a faster convergence with less computations.

Optimum intervals for all 44 parameters are shown in Table 3. These were selected based on reservoir engineering experience from the field. It sholud be noted that the value of the parameteres are entirely different for most parameters, revealing the solution diversity for history matching as an inverse problem.

6.4. Applying best solutions

In this section, the optimum solutions acquired by both optimization algorithms were run by a commercial sim ulator. Figures 4 to 7 demonstrate the results of the automatic history matching for both field scale and well scale. Using the discussed methodology, all wells that have observed data are

Table 1. Uncertain parameters used for sample generation, proxy construction and optimization

Factor	Parameter	Parameter name in the model	Min	Max
A	Compressibility(1/psi)	RockComp	2×10^{-6}	6×10^{-6}
B	Permeability Ratio	PermRatio	0.5	0.9
C	Aquifer Permeability (md)	AquPerm	1	200
D	Aquifer Porosity	AquPoro	0.1	0.2
E	Aquifer total compressibility (1/psi)	AquTotComp	2	8
F	Aquifer thickness (ft)	AquThick	300	400
G	Permeability Multiplier 1	PermMult1	0.5	3
H	Permeability Multiplier 2	PermMult2	0.5	3
J	Permeability Multiplier 3	PermMult3	0.5	3
K	Permeability Multiplier 4	PermMult4	0.5	3
L	Permeability Multiplier 5	PermMult5	0.5	3
M	Permeability Multiplier 6	PermMult6	0.5	3
N	Permeability Multiplier 7	PermMult7	0.5	3
O	Permeability Multiplier 8	PermMult8	0.5	3
P	Permeability Multiplier 9	PermMult9	0.5	3
Q	Permeability Multiplier 10	PermMult10	0.5	3
R	Permeability Multiplier 11	PermMult11	0.5	3
S	Permeability Multiplier 12	PermMult12	0.5	3
T	Permeability Multiplier 13	PermMult13	0.5	3
U	Permeability Multiplier 14	PermMult14	0.5	3
V	Well PI Multiplier1	WPIMULT1	1	15
W	Well PI Multiplier2	WPIMULT2	1	15
X	Well PI Multiplier3	WPIMULT3	1	15
Y	Well PI Multiplier4	WPIMULT4	1	15
Z	Well PI Multiplier5	WPIMULT5	1	15
A'	Well PI Multiplier6	WPIMULT6	1	15
B'	Well PI Multiplier7	WPIMULT7	1	15
C'	Well PI Multiplier8	WPIMULT8	1	15
D'	Well PI Multiplier9	WPIMULT9	1	15
E'	Well PI Multiplier10	WPIMULT10	1	15
F'	Well PI Multiplier11	WPIMULT11	1	15
G'	Well PI Multiplier12	WPIMULT12	1	15
H'	Well PI Multiplier13	WPIMULT13	1	15
J'	Well PI Multiplier14	WPIMULT14	1	15
K'	Well PI Multiplier15	WPIMULT15	1	15
L'	Well PI Multiplier16	WPIMULT16	1	15
M'	Well PI Multiplier17	WPIMULT17	1	15
N'	Well PI Multiplier18	WPIMULT18	1	15
O'	Well PI Multiplier19	WPIMULT19	1	15
P'	Well PI Multiplier20	WPIMULT20	1	15

Q'	Well PI Multiplier21	WPIMULT21	1	15
R'	Well PI Multiplier22	WPIMULT22	1	15
S'	Well PI Multiplier23	WPIMULT23	1	15
T'	Well PI Multiplier24	WPIMULT24	1	15

Table 2. Comparison of the solution for GA and PSO.

Optimization Method	Best Solutions – Objective Functions
GA	0.00003
PSO	0.00012

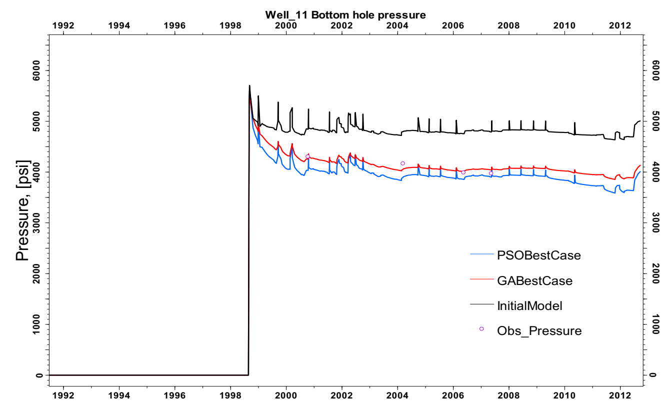

Fig 6. History matching results for bottom hole pressure in well 11

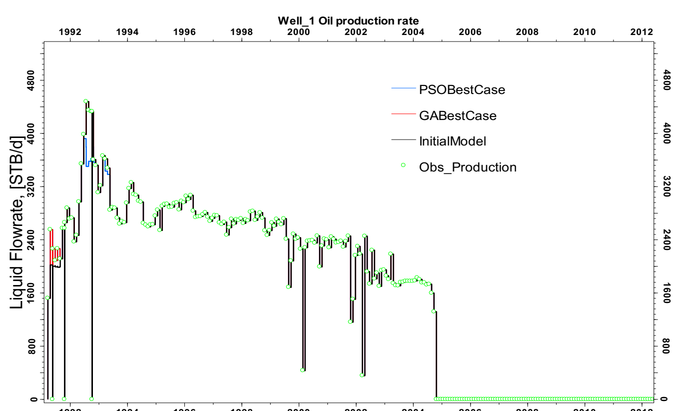

Fig. 7. History matching results for oil production rate in well 1

illustrated below with an acceptable match. As can be seen, the obtained solution has acceptable results.

7. Conclusions

In this study, a new methodology was applied to the analysis of one giant Iranian oil reservoir. The first step in the developed methodology is screening using CCF to generate samples for a proxy model. A large number of parameters (44) were used to generate the mentioned proxy model, and 1086 runs were conducted to prepare data for the LSSVM algorithm. The process of proxy generation was repeated many times to achieve

Table 3. Optimum parameters after implementation of an optimized proxy model.

Factor	Name	Min	Max
A	RockComp	2.22E-06	2.75E-06
B	PermRatio	0.51	0.86
C	AquPerm	10.46	98.38
D	AquPoro	0.10	0.12
E	AquTotComp	2.15E-06	3.81E-06
F	AquThick	305	349
G	PermMult1	0.71	2.76
H	PermMult2	0.71	2.76
J	PermMult3	0.71	2.76
K	PermMult4	0.58	0.67
L	PermMult5	0.54	0.70
M	PermMult6	0.71	2.82
N	PermMult7	0.71	2.87
O	PermMult8	0.54	0.76
P	PermMult9	0.54	0.57
Q	PermMult10	0.62	0.72
R	PermMult11	0.63	2.90
S	PermMult12	0.71	2.72
T	PermMult13	0.54	0.52
U	PermMult14	0.54	0.65
V	WPIMULT1	2.19	14.82
W	WPIMULT2	2.19	14.99
X	WPIMULT3	2.17	14.87
Y	WPIMULT4	2.19	14.92
Z	WPIMULT5	2.12	14.62
A'	WPIMULT6	1.24	1.10
B'	WPIMULT7	1.70	9.37
C'	WPIMULT8	1.56	1.06
D'	WPIMULT9	1.79	14.25
E'	WPIMULT10	1.29	1.48
F'	WPIMULT11	1.21	1.23
G'	WPIMULT12	1.50	10.90
H'	WPIMULT13	1.35	1.34
J'	WPIMULT14	1.82	12.18
K'	WPIMULT15	1.21	1.30
L'	WPIMULT16	1.21	1.28
M'	WPIMULT17	1.23	1.14
N'	WPIMULT18	1.80	14.37
O'	WPIMULT19	2.19	14.89
P'	WPIMULT20	1.21	1.12
Q'	WPIMULT21	1.73	9.51

R'	WPIMULT22	1.32	1.33
S'	WPIMULT23	1.26	1.41
T'	WPIMULT24	1.23	1.05

the appropriate proxy model parameters and criteria using a simplex optimization technique. Next, after providing validation criteria, the accepted proxy model was used instead of simulation software in order to get the best parameters using optimization methods. This was done by two important optimization algorithms: GA and PSO. The results demonstrated that GA produces more acceptable results in comparison to PSO. This study shows the capability of CCF, LSSVM and GA in the process of automatic history matching. All of this procedure was done using codes on a mathematical toolbox linked with a simulator and optimizer.

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تطبيق نموذج أمثل منخفض المخاطر للمواءمة التاريخية السريعة في خزان نفط عملاق

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الملخص

في هذا البحث، تم تطبيق أحدث طرق المواءمة التاريخية الآلية (AHM) على حقول جدباء حقيقية تحتوي على 14 بئر نشط مع استجابات متعددة (من حيث معدل الإنتاج، ضغط القاع وضغط كتلة البئر) تقع في الجزء الجنوبي من إيران. تم استخدام خوارزمية آلة متجة الدعم المُعدلة لإنشاء نموذج بروكسي مُدمج على أساس تصميم تجريبي. ومن ثم، تم ضبط كل معلمات النموذج لإعادة إنتاج التاريخ المرصود في نموذج بروكسي الذي تم إنشاؤه. وبالتالي، تم بناء نموذج بروكسي المُقترح بنجاح باستخدام 1086 عينة بناءً على معامل R2 لحوالي 0.9 من مجموعة البيانات المستخدمة في التدريب والاختبار. وأخيراً، تم تحسين هذه العملية من خلال خوارزميتين رئيسيتين للوصول إلى أفضل الحلول وهي الخوارزمية الوراثية وخوارزمية استمثال عناصر السرب.