

**OIL
GAS** **EUROPEAN MAGAZINE**
INTERNATIONAL EDITION OF
ERDÖL ERDGAS KOHLE

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September, 3/08



Reducing Uncertainty in Reservoir Modelling Through Efficient History Matching

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Abstract

Inverse methods play an important role when the characterisation of spatial distribution of petrophysical properties is necessary. Using the inverse procedure it is possible to reduce the uncertainty in reservoir characterisation by integrating different types of data combining probabilistic (geostatistical simulation) and physically-based (reservoir fluid simulation) modelling.

One characterises the distribution of field permeability in oil reservoirs through the geostatistical history matching procedure. First of all, a set of equiprobable realizations of the reservoir properties is generated using direct sequential simulation (DSS). The field permeability is obtained and updated iteratively with successive co-simulations, preserving geological continuity, until a realization that matches both the stochastic model (variogram and histogram) and production data (i. e. fluid rate) is found.

The algorithm proposed shows the ability to produce a good match with a small number of simulations.

Key words: reservoir characterisation; data integration; geostatistical co-simulation, history matching.

1 Introduction

Reservoir characterisation is still a challenge in the petroleum industry. Spatial distribution of petrophysical properties, which is probably the most important information to evaluate reservoir productivity, is inaccessible owing to physical (the formations are located thousands of meters below the earth) and economical (sample collection is quite expensive) constraints. In addition, the methods frequently used to infer reservoir properties are uncertain and time consuming. In the last decades, several works have proposed new algorithms based on inverse modelling to improve reservoir characterisation by reducing uncertainty (see [1–16]). It is common to present the general inverse procedure to study a physical system as follows (see e. g. [11, 13, 15, 17, 18]): (1) parameterization of the system; (2) forward mo-

delling; and (3) inverse modelling. All history matching techniques proposed in the literature are based on inverse modelling (Fig. 1) and this work is not an exception.

Starting with data on a few wells data and seismic information, a stochastic model is defined to represent the reservoir geological continuity. In a second stage, the stochastic model is perturbed (e. g. permeability perturbation) with regard to spatial continuity until a stochastic realization that considers static and reservoir production data is found. This realization is termed history matched. Therefore, history matching corresponds to an inverse algorithm in which an objective function is iteratively minimized as much as possible. History matching is an algorithm that evolved from ground water hydrology and represents today a fundamental tool for reservoir characterisation. There are several different inverse algorithms (history matching procedures) available in the literature i) pilot point method [33]; ii) zonation method [19]; iii) self-calibrated method [20]; iv) gradual deformation method, GDM [9, 11, 21, 22]; and v) regional probability perturbations [13, 14, 15, 23].

Türeyen [24] states that “most history matching techniques arbitrarily change permeability near wells or between wells with little or no regard to the prior model of geological continuity”. It is fortunately worth noting that all of the above mentioned algorithms, and the one proposed in this work, perform history matching with regard to geological continuity and production data.

This work deals with the problem of defining the reservoir permeability field. The author proposes a history matching procedure in which the permeability field perturbation is carried out without any prior data transformation, since stochastic realizations are obtained by direct sequential simulation and co-simulation.

2 Regional Perturbation Algorithm

This section presents the proposed regional perturbation algorithms for history matching performance, which is based on the following general procedure, as depicted in Figure 2.

The algorithm includes two main stages: (1) stochastic simulation by direct sequential simulation and co-simulation as proposed by Soares [25] to simulate continuous variables (e. g. porosity and permeability) and recently synthesized in [26], and (2) deterministic simulation to obtain the forward fluid flow by using a multiphase simulator – Eclipse 100 [27]. Eclipse 100 is a commercial multiphase, three dimensional finite differences simulator used to solve the mass conservation equation of fluids in porous media according to Darcy’s law:

$$\frac{\partial(\phi\rho_i s_i)}{\partial t} = \nabla \cdot \left[\frac{\rho_i k k_{ri}}{\mu_i} (\nabla p_i - \rho_i g) \right] + q_i \quad (1)$$

with q the fluid flow, k the absolute permeability of the formation, g the gravity acceleration and the subscript i refers to the attributes of each phase: saturation (s), pressure (p), density (ρ), porosity (ϕ), viscosity (μ), flux (q) and relative permeability (k_r).

To make the algorithm easily understandable one presents flowcharts describing each step of the procedure (Figs. 2 and 4). Figure 2 shows the general principle of the algorithm and Figure 4 depicts the specific regional perturbation algorithm applied to the case study presented in application examples.

According to this general process, depicted in Figure 2, several history matching “sub-procedures” can be drawn, either global or regional perturbation algorithms.

Regarding the criteria to evaluate the history matching performance, both numerical and graphical criteria were considered to provi-

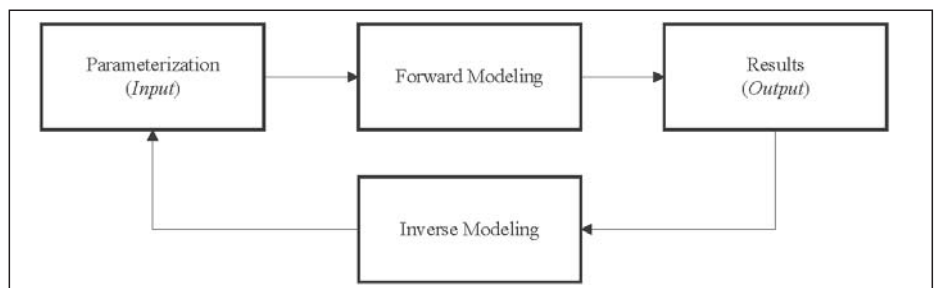


Fig. 1 General procedure to model a physical system

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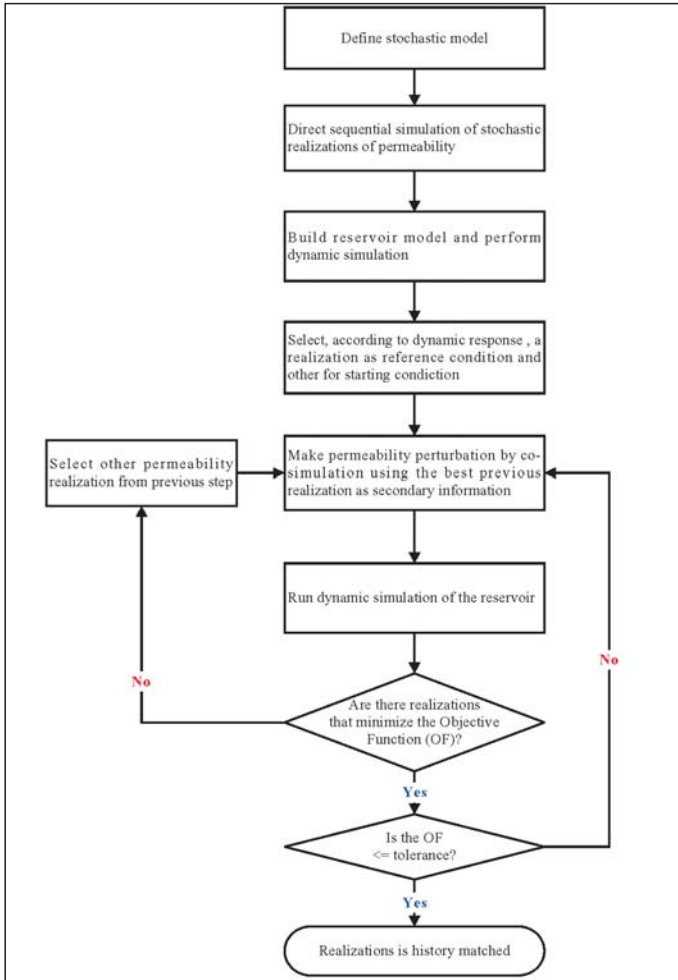


Fig. 2 General workflow of the algorithm

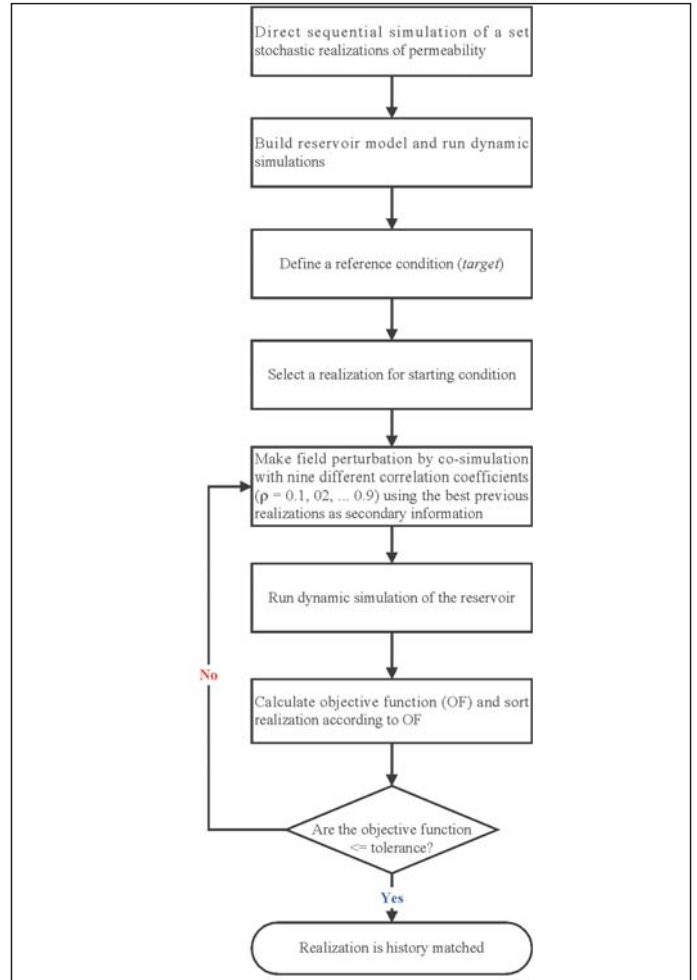


Fig. 4 Diagram of the proposed history matching algorithm

de a good overall indication of the method's capabilities. In this article, the accuracy criteria concern the watercut (also called fractional water flow, f_w). Although, other dyna-

mic data such as pressure [11], cumulative oil production and oil rate [28, 29] can also be used, watercut is used more frequently [13, 24, 30, 28].

Usually one tries to obtain reservoir properties (e. g. permeability and porosity) by matching the observed information through a mathematical model. This process entails the minimization of an objective function (OF):

$$OF = \min \sum_{i=1}^n (R_{t,obs} - R_{t,sim})^2 \quad (2)$$

where: i and n indicate the beginning and end of time series used for optimisation, and $R_{t,obs}$, $R_{t,sim}$ are measured and simulated variables at the well. The sum of squared residuals objective function has the peculiarity of giving greater weight to large errors and lesser weight to small errors. This was the main reason to select Eq. (2) as the objective function in this work.

One uses Eq. (2) in conjunction with »lag time (i. e. water breakthrough time, Lag)« to select the best realizations in each iteration of the algorithms. The lag time is here defined as the time from the beginning of reservoir dynamic simulation until the rise of the watercut (f_w) curve in the producer well. Therefore, one considers the best realization in each iteration as the one that minimizes both Eq. (2) and lag time when compared with the true watercut curve. The latter (i.e. computed Lag) has prevalence over Eq. (2). These regional perturbation algorithms re-

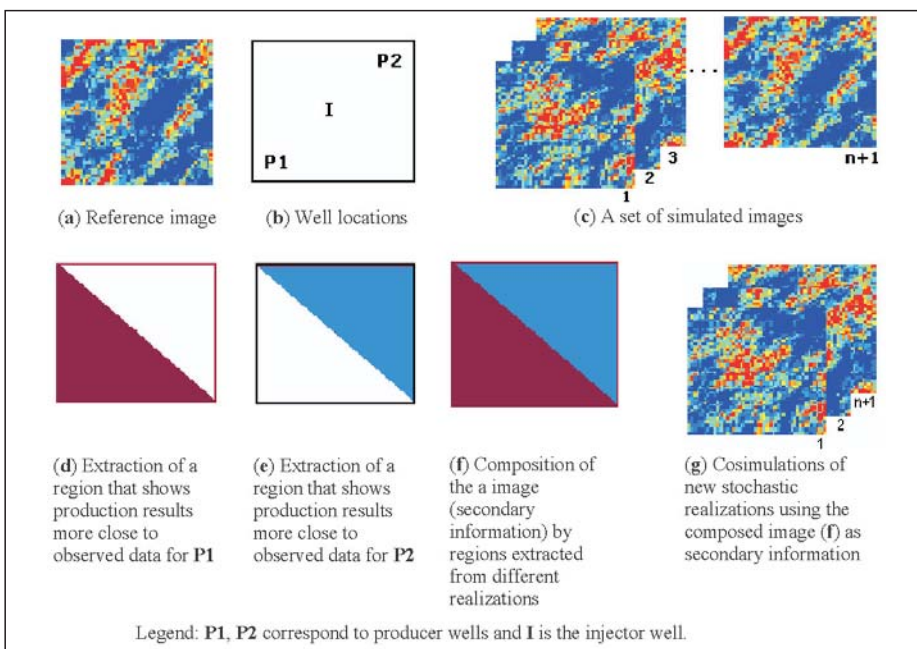


Fig. 3 Illustration of the building process of the secondary information to use in cosimulations (for a case of two regions). Note: Reservoir regions can be defined from geological information, streamlines, sensitivity coefficients or expert opinion of reservoir engineer (Milliken et al., 2001; Hoffman and Caers, 2005)

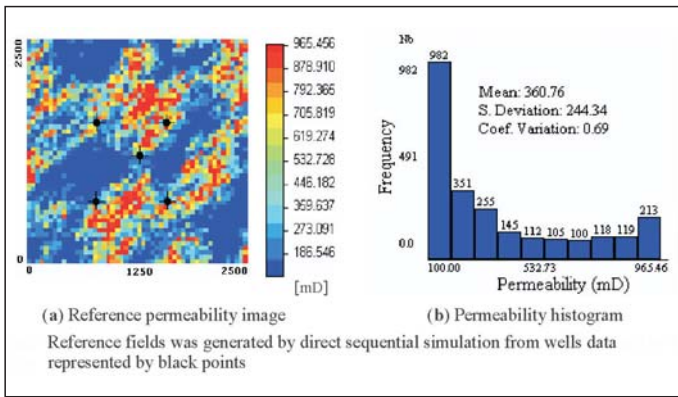


Fig. 5 Reference permeability field of the synthetic case study

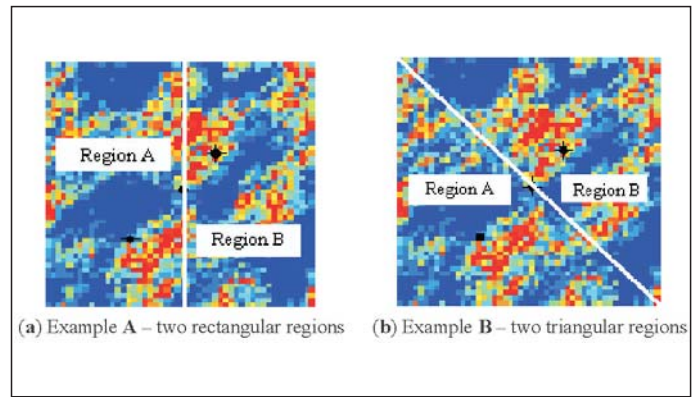


Fig. 6 Definition of the two regions to be considered

quire multiple producer wells (at least two) since each region is characterised by its well production information. The perturbation is called regional because the realization (stochastic permeability image) used as secondary information, to constrain the next stochastic realizations obtained by co-simulation, is built with regions extracted from different equally likely realizations (Fig. 3) from the previous step, like a puzzle. This composed image (i. e. secondary information) is a mixture of the best regions extracted from different previous realizations. After obtaining the composed image, perturbations are made by multiple co-simulations according to the procedure depicted in Figure 4. As mentioned before the perturbations are fortunately made with regard to geological continuity (spatial variability and histogram) of permeability, since [25 (p. 920–921)] in direct co-simulation “only the primary variable variogram and the correlation coefficient (ρ) XXXbetween primary and secondary variable are needed”.

This process is repeated until one single stochastic realization leads to results that minimize simultaneously the optimization criteria (equation 2 and Lag) for all producer wells in the reservoir.

- The real novelty of the proposed algorithm concerns the direct simulation of reservoir properties without data transformation.
- In summary, the approach depicted in Figure 4 follows the general outline:
 - A first set of stochastic realizations of reservoir permeability is calculated by Direct Sequential Simulation
 - A deterministic flow simulator is run to

obtain the equivalent dynamic reservoir responses and the comparison between the responses of simulated permeability fields and real production data is calculated. This is the aim of history matching and usually consists of the minimization of the objective function

- Selection of best responses according to the objective function, and composition of a secondary image for the next co-simulation step of the iterative process. Note that several correlation coefficients ($\rho = 0.1, 0.2, \dots 0.9$) are used simultaneously in each co-simulation step to generate multiple equally likely realizations.

Direct sequential co-simulation generates the next iteration set of permeability fields constrained to the composed secondary image and local co-regionalization models [25]. According to the proposed algorithm, steps ii) and iii) are repeated until the objective function of the equation 2 and Lag reaches a desirable minimum.

The examples presented in the next section follow strictly the procedure as described above.

3 Application Examples

This section describes two synthetic cases used to demonstrate and validate the proposed algorithms and the results obtained for different inverse algorithms are presented mainly by graphics to provide an easy understanding.

3.1 Synthetic reservoir description

The reservoir is composed of a single layer

of grid blocks. The grid blocks are square with uniform thickness (10 m). All tests were done with a constant porosity equal to 0.20. Both examples considered (Fig. 6) correspond to a permeability field characterised by a spherical and anisotropic variogram as depicted in Figure 5.

3.2 Results and Discussion

This algorithm was tested with the stochastic model depicted in Figure 5. The reservoir is composed of three wells of which one is injector (I) and two are producers (P1, P2), with the following locations in grid blocks: I (25, 25); P1 (15, 15); and P2 (32, 32).

Regional perturbation is considered in each iteration of the algorithm until a single image, that globally (i. e. simultaneously for all producer wells) reproduces the production data, is found. Subsequently this single image (i. e. not composed) is used as secondary information to obtain new realizations.

To implement the algorithm, two regions (Fig. 6) are considered. Therefore this example refers to regional perturbation in which two regions and three wells are considered. The same starting condition (Fig. 7) is considered for the examples (I and II) in Figure 6, and both results are presented in parallel to facilitate comparative analysis. Figures 7 to 14 show the results obtained from starting realization until matched solution.

The dynamic responses for both producer wells before and after the history matching are shown in Figure 14, which also shows that a good convergence (match) is obtained with the application of the proposed regional perturbation algorithm. It is possible to see

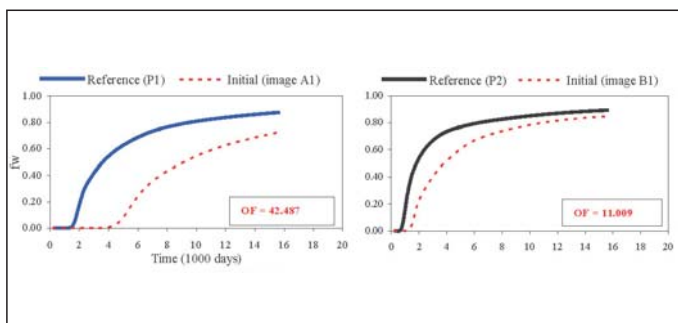


Fig. 7 Reference and starting condition for both examples (I and II)

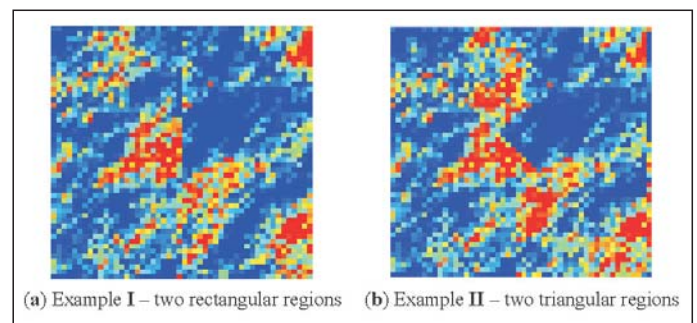


Fig. 8 Secondary information (image) composed from different realizations

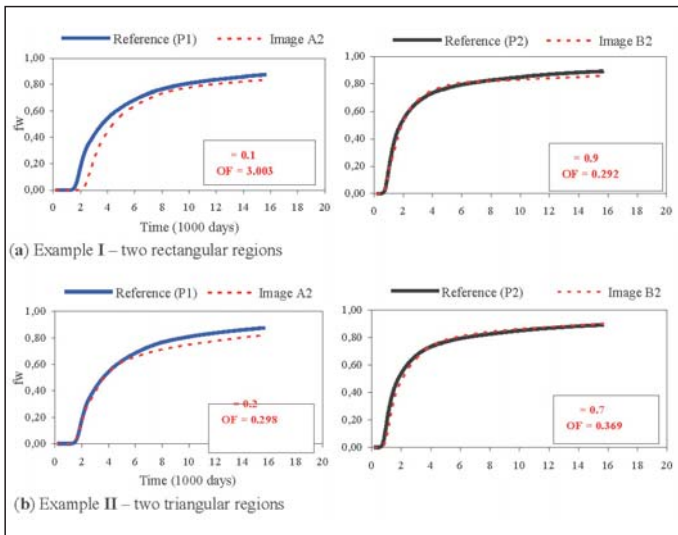


Fig. 9 Watercut curve obtained for iteration 1

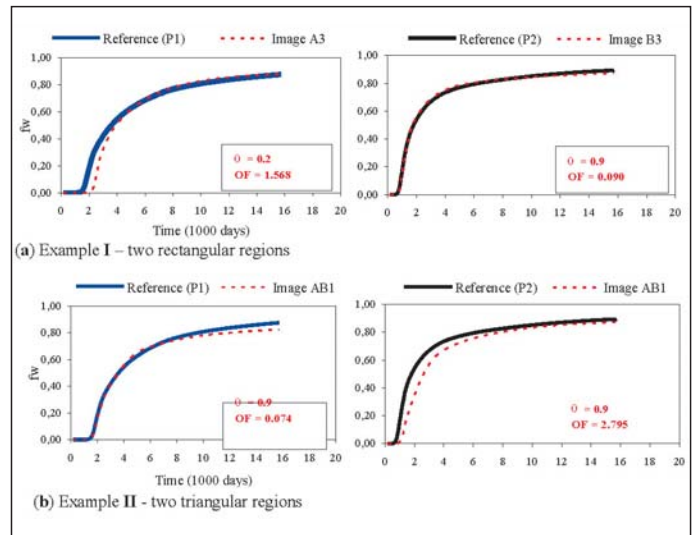


Fig. 11 Watercut curve obtained for iteration 2

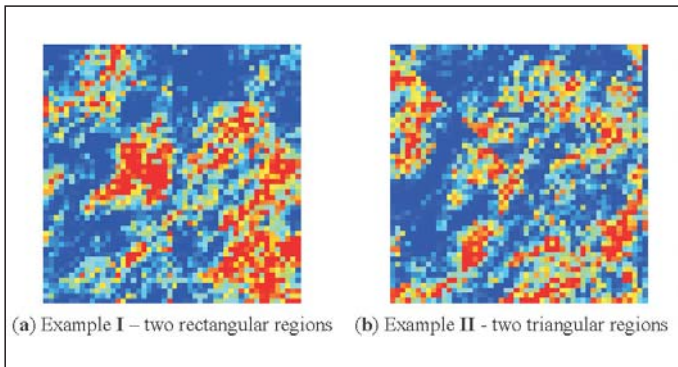


Fig. 10 Composition of secondary information to use in iteration 2

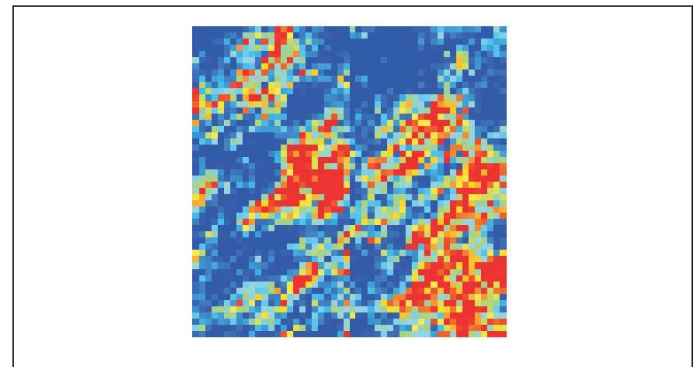


Fig. 12 Composition of secondary information (for example I) to use in iteration 3 (see the rules in Fig. 3 and 6a)

that the lag time (i. e. the time to breakthrough) is also matched besides achieving a good fit for all watercut curves.

Figure 11b shows that it was possible to obtain a single permeability realization (image), termed AB1, that minimizes the objective function (OF) for example II. In other words, at this stage it is not necessary to compose an image to use as secondary information since one already found a single image whose dynamic data matches both producer wells. This however is not the case for example I. Therefore, in the next stage (iteration 3) a secondary image (secondary information) will be composed for example I, whilst for example II the image AB1 is used as secondary information to generate new realizations. The reader should refer to Figure 3 to understand how the secondary image is composed.

According to the algorithm (Fig. 4), nine correlation coefficients (0.1, 0.2, ... 0.9) are used in each iteration step to generate new realizations, and from these new realizations one only draws on the best (best realization is the one that leads to a dynamic response closer to well data) to use as secondary information in the next co-simulation. In this work, both examples I and II lead to better results for co-simulations with low ($\rho = 0.1$ and 0.2) and high ($\rho = 0.7$ to 0.9) correlation

coefficients (Figs. 9, 11, 13, and 14). This information can reduce the number of iterations (and simulations) of the algorithm. The following recommendations can be made based on the extensive tests carried out in this case study [16]: i) for each correlation coefficient carry out co-simulations to generate at least five stochastic images (10 realizations seem an optimum number); and ii) after selecting the realization that globally minimizes the objective function, the number of realizations in each iteration should be increased and the correlation coefficients used in co-simulations should be equal or higher than 0.7.

Table 1 synthesises the comparative evolution of the objective function against the number of forward fluid flow simulations for both regional perturbation examples.

In Table 1 one can see that at the beginning the objective function (OF) decreases suddenly and the following iteration exhibits a slowly decreasing level until the final results presented in Figure 14, which depicts the quality of the match obtained for both examples considered.

4 Concluding Remarks

The algorithm proposed deals directly with original data without any prior transforma-

tion to Gaussian or indicator variable as required by Sequential Gaussian Simulation and Sequential Indicator Simulation, respectively (see, e. g., [31, 32]). In fact Direct Sequential Simulation and Co-simulation (*Co-DSS*) work with original data and allow the integration of production data, via secondary information, to constrain the next stochastic realizations obtained by co-simulations. Perturbation of permeability field preserves the variogram (spatial variability) and histogram of permeability since [25] the co-simulation uses a Markov approach in which only the variogram of the original variable and correlation coefficient (?) between primary and secondary variables are necessary to produce new stochastic realizations.

Previous works, with respect to history matching, generally did not consider explicitly the lag time (Lag) within the optimization criteria. The introduction of Lag as a complementary criterion to use with the sum of square residuals facilitated the decision making during the history matching procedure.

The regional perturbation algorithm shows a good convergence with few iterations (it comprises of only four iterations, see Figs. 9, 11, 13, 14, and Table 1) for both examples tested which make it equivalent, in terms of CPU-time, to other algorithms recently pro-

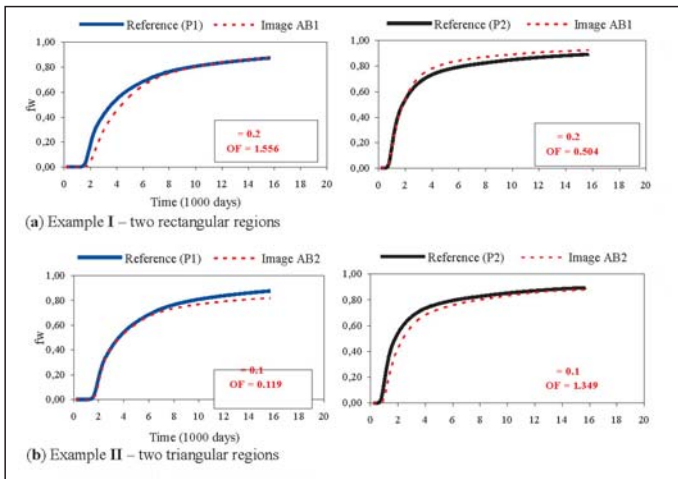


Fig. 13 Watercut curve obtained for iteration 3

Table 1 Evolution of the objective function (OF) during history matching

Cumulative number of simulations	Example I and II			
	Two rectangular regions (see Figs. 6a and 14a)		Two triangular regions (see Figs. 6b and 14b)	
	Producer 1 (P1)	Producer 1 (P2)	Producer 1 (P1)	Producer 1 (P2)
10	42.487	11.089	42.487	11.089
60	3.003	0.292	0.298	0.369
110	1.556	0.090	0.074	2.795
160	1.568	0.504	0.119	1.349
210	0.544	0.416	0.090	0.754
	0.272	0.208	0.045	0.377

Legend:
 □ $OF = \min \sum_{t=i}^n (R_{t,obs} - R_{t,min})^2$ ■ $OF = \min \frac{1}{2} \sum_{t=i}^n (R_{t,obs} - R_{t,min})^2$

posed (e. g., see [11 (p 716), 13, 23, 30 (p. 79)] and acceptable in many practical reservoir simulations (see also [13 (p. 63)]). It would seem interesting in future work to develop and apply these algorithms in a reservoir with the 4D seismic data available. The 4D seismic data is also useful as dynamic data since it permits constraining the stochastic model to respect the space-time evolution of the water saturation in the field. This is important since it would be possible to evaluate the ability of an algorithm to match both local data (e. g. watercut, cumulative production, well pressure) and non-point data corresponding to water saturation evolution in inter-well regions where uncertainty is highly significant.

Nomenclature

- ρ correlation coefficient
- Co-dss direct sequential simulation and co-simulation
- dss direct sequential simulation
- f_w watercut (fractional water flow)
- I injector well
- k absolute permeability
- k_r relative permeability
- Lag lag time (i.e. water breakthrough time)

- OF objective function
- p pressure
- P_i producer well i
- q flux
- S saturation
- ϕ porosity
- μ viscosity

- Subscripts
- obs observed or measured values
 - sim simulated values
 - g gas
 - o oil
 - w water

This article benefited from financial support from the Portuguese Science Foundation (Fundação para Ciência e Tecnologia, FCT) and an explanation on the assumption of direct sequential simulation and co-simulation by Prof. Amílcar Soares of the Technical University of Lisbon (IST).

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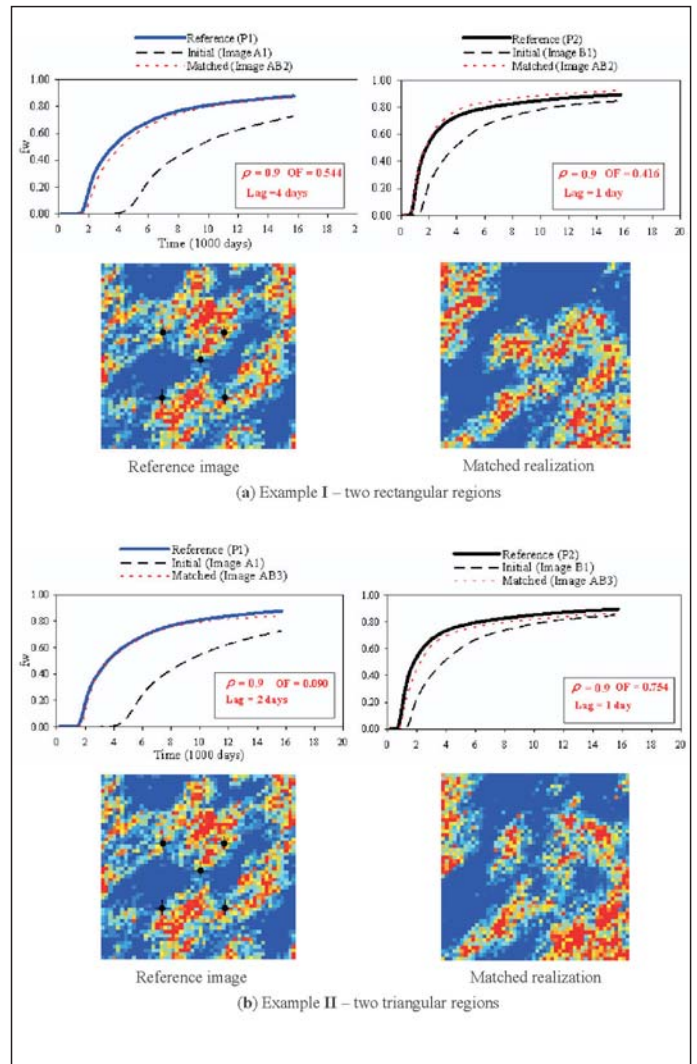


Fig. 14 Final results for regional perturbation considering two regions (iteration 4)

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