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Petroleum Reservoir Uncertainty Mitigation Through the Integration with Production History Matching

This paper presents a new methodology to deal with uncertainty mitigation using observed data, integrating the uncertainty analysis and the history matching processes. The proposed method is robust and easy to use, offering an alternative way to traditional history matching methodologies. The main characteristic of the methodology is the use of observed data as constraints to reduce the uncertainty of the reservoir parameters. The integration of uncertainty analysis with history matching naturally yields prediction under uncertainty. The workflow permits to establish a target range of uncertainty that characterize a confidence interval of the probabilistic distribution curves around the observed data. A complete workflow of the proposed methodology was carried out in a realistic model based on outcrop data and the impact of the uncertainty reduction in the production forecasting was evaluated. It was demonstrated that for complex cases, with a high number of uncertain attributes and several objective-function, the methodology can be applied in steps, beginning with a field analysis followed by regional and local (well level) analyses. The main contribution of this work is to provide an interesting way to quantify and to reduce uncertainties with the objective to generate reliable scenario-based models for consistent production prediction.

Keywords*: reservoir simulation, uncertainty mitigation, history matching, production prediction*

Introduction

The geological, reservoir, economic and technologic uncertainties influence the management decisions of hydrocarbon reserves and of future development plans. Consequently, the quantification of the impact of these uncertainties provides an increased reliability of this process.

The uncertainty term states the degree of knowledge about the properties of the system under analysis. The risk concept indicates the objective-functions (OF) variability of the problem, obtained from the probability analysis of the possible scenario-based models. In the context of this work, the OF indicates the misfit between the observed production and pressure data and the simulated data of the corresponding models. The cumulative distribution of the objective-function probabilities is a density curve, known as uncertainty curve, which allows determining the history matching quality for the analyzed possible models.

The scarcity of quality information makes the construction of a dynamic model difficult, making it necessary its calibration derived from the productive response measured in the field. The history matching is an inverse problem, in which different combinations of the reservoir's parameter values can lead to acceptable responses, especially when the degree of uncertainty of these parameters is high. The problem tends to worsen in the cases when the history period is short. Even though different solutions provide reasonable confidence comparing with observations, any one of them could produce a different prediction, leading to a range of distinct responses.

The methodology used in this paper leads to the detection of calibrated models within the range of defined acceptability. The integration is made gradually, proceeding through stages (global, regional and local), for the different attributes and the identified objective-functions (OF). The objective is seeking to reduce the occurrence probabilities of those scenarios that do not present a good matching and, consequently, increase the probabilities of the models which have performed close to the history. This paper presents methods that make possible a redefinition of the values of the studied uncertain attributes, allowing a reduction of the uncertainty in the history matching stage as well as in the prediction period.

The uncertainty inherent to dynamic modeling of a reservoir depends on several factors. One of them is a consequence of the model's own error in trying to represent a reality. Other factors are caused by random nature and insufficient static and dynamic data. The uncertainties are analyzed taking into account that knowledge of the reservoir is only partial, using, in the initial phases of exploration and discovery of a field, indirect information, having few, sparse direct data. From the field development up to its abandonment, new information about the reservoir is added, but the knowledge is always partial and incomplete. Thus, it is necessary to incorporate a probabilistic approach in the history matching and predictions of production with uncertainty.

Traditionally, the uncertainty analysis is applied in the initial stages or in the prediction phase; however, the advance was small in the use of this analysis in history matching studies. Obtaining the best deterministic matching is not the target of the proposed methodology, but rather reflecting on how the history data makes possible the mitigation of uncertainties.

The objective of this paper is to apply and improve, in more complex reservoir model, the methodology proposed by Maschio et al. (2005) and Moura Filho (2006), originally developed in a simple model. The static and dynamic data, detected in the uncertainties analysis workflow, are included through a consistent methodology that permits integration of probabilistic analyses of the uncertain attributes with the history matching process.

Nomenclature

A	= *reservoir uncertainty attribute*
$A0$	= *probable level attribute*
$A1$	= *pessimistic level attribute*
$A2$	= *optimistic level attribute*
$A0N$	= *new probable level attribute*
di^{obs}	= *observed data (history)*
di^{sim}	= *simulated data (calculation)*
D	= *sum of misfit*
Ds	= *sum of square misfit*
Dn	= *sum of misfit of all models of the level n*
OF	= *objective-function*
Li	= *attribute inferior limit*
Ls	= *attribute superior limit*

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LiN	= *new attribute inferior limit*
LsN	= *new attribute superior limit*
k	= *total number of uncertainty levels*
Mn	= *number of models of the level n*
NS	= *simulations number*
NTG	= *net-to-gross ratio*
Np	= *standard cumulative oil* (m^3)
Pn	= *probability of the level n*
P[A0]	= *probability of the level A0*
P[A1]	= *probability of the level A1*
P[A2]	= *probability of the level A2*
p	= *reservoir pressure (kPa)*
pwf	= *bottom hole pressure (kPa)*
Q	= *standard oil production rate* (m^3/d)
Qo	= *standard oil production rate* (m^3/d)
Qw	= *standard water production rate* (m^3/d)
Sn	= *symmetry of the level n*
S0	= *symmetry of the level A0*
S1	= *symmetry of the level A1*
S2	= *symmetry of the level A2*
t	= *time (days)*
w_{Qw}	= *weight for water production rate in well's OF*
w_{pwf}	= *weight for bottom hole pressure in well's OF*
Wp	= *standard cumulative water (m3)*

Literature

The first papers presented in the technical literature combining probability analysis procedures of static and dynamic data with a variety of scenarios date from the 1990's. The multi-disciplinary approach to history matching combined with uncertainty analysis is rather recent (approximately 8 to 10 years) and there is a variety of treatments in the literature. Roggero (1997); Christie et al. (2002) and Kashib and Srinivasan (2006) proposed methods based on conditional probabilities, following the Bayesian formalism, to update the distribution of geologic attributes taking into consideration the additional information contained in the dynamic responses of the observed variables.

The combination of geostatistical modeling and the recorded history values is discussed by Bissel (1997); Bennett and Graf (2000) and Jenni et al. (2004). The uncertainties of fields in production are estimated by means of generating multiple reservoir models and evaluating the history matching through the respective gradient information, demanding a large computation effort. The practical use can be limited depending on the complexity of the models. Zabalza-Mezghani et al. (2004) present several options for the uncertainties management based on techniques of experimental design, construction of proxy-models and the combined use of geostatistics. The method consists in obtaining multiple history matching considered probabilistically equivalent by the stochastic proximity, and then extrapolated for the prediction under uncertainty analysis.

Lépine et al. (1999) propose a practical method, although restrictive, to calculate the effects of the uncertainties during the prediction period. From a single history matched simulation model, using gradient minimization techniques, the base values of attributes that permit the solution are slightly disturbed. Then, the modification of the selected gradients allows a range of possible future production profiles to be obtained. Landa and Guyaguler (2003) proposed the use of the gradient information of uncertainty attributes to determine the influence of the uncertainties and the subsequent construction of response surface at the end of the history period. Proxy-models are also used to reduce the computational effort required by the combination of a large quantity of uncertainty attributes to reach the representative models. Along the same line are the works of Manceau et al. (2001).

The joined matching of production data with seismic attributes is the line of study begun by Guérillot and Pianelo (2000). Litvak et al. (2005) presented an article for the estimation of the degree of prediction variation by means of production and seismic data. The neighborhood algorithm was applied to select the matching parameters in each simulation. Varela et al. (2006) used the seismic amplitude data and analyzed its influence on production performance to reduce the prediction uncertainties. When the authors evaluated the range of production predictions, it was observed that the seismic amplitude data do not improve uniformly the variability of predictions for water breakthrough time in production wells.

The use of statistical methods is another analytical line. Gu and Oliver (2004) applied the Kalman filter method to obtain automatic multiple history matching for subsequent estimation of the predictions uncertainty. Alvarado et al. (2005) pointed out the importance of quantification of uncertainty in production predictions. A procedure that considers probability distribution of the prediction period based on the quality and weight attributed to the matching of a defined objective-function for the history period was proposed. Other papers along the same research topic are from Williams et al. (2004) and Ma et al. (2006). Queipo et al. (2002) present a methodology based on the use of artificial neural networks on efficient global optimization, for the calculation of the spatial distribution of permeability and porosity in heterogeneous reservoirs with multiple fluids through the calibration of available static and dynamic data. Reis (2006) also uses artificial neural networks to combine risk analysis with history matching.

Based on the use of optimization algorithms, Nicotra et al. (2005) and Rotondi et al. (2006) showed methods of production prediction and uncertainty quantification using neighborhood algorithms, consisting of stochastic sampling algorithms, in search of an acceptable matching of the observed data. Also, using the neighborhood algorithm in conjunction with a geostatistical multiple-point process was the suggestion of Suzuki and Caers (2006), in whose paper each scenario was quantitatively described by a training image and a geological model execution, both stochastically generated.

From the bibliographic review, it can be deduced that the combined analysis of uncertainty and risk with history matching is a subject that has various, recent approaches. In the methodology showed in this paper, improved by Becerra (2007), the main differences in relation to the discussed methods are centered on the techniques of uncertainty quantification, on the OF used and on the way the degree of knowledge in certain areas of the reservoir is conditioned through the observed data.

Methodology

The main idea is to reduce the uncertainties as much as possible within boundaries set by the quantity and quality of the observed data. Consequently, the conditioned probabilistic analysis allows a quantitative integration approach. Three methods are presented, based on probability redistribution. In Method 1, there is a change in the initial probabilities assigned to the levels of uncertainty of the attributes. In Method 2, those uncertainty levels that produce great mismatch are discarded, reducing the number of possible scenarios. Method 3 implies the use of acceptance and evaluation criteria that conduct a reduction of the uncertain attributes variation range considered. The proposed methodology is more appropriate for petroleum fields in intermediate stages of production, in which a reasonable quantity of information is available, but, even so, a high degree of uncertainty exists in the description of the reservoir.

Original methods

Several scenarios of the reservoir are obtained from the combinations of the most important uncertain attributes. Fig. 1(a) shows a general view of the procedure. The upper left frame illustrates an example of an uncertain attribute represented by a probability density function with three discrete levels. The graph also illustrates the probability redefinition of the discrete levels. The extreme values of the levels represent the initial variation range associated with a probability distribution. The lower left frame shows examples of the obtained cumulative probability curves, being that the central vertical line represents the history data. The frames to the right present the redefinition of the distributions and the effect on the production profile during the history and prediction period.

The uncertainty quantification was carried out through derivative tree technique using reservoir simulation (Maschio et al., 2005); however, other techniques could be used (neural networks, experimental design combined with surface response, Monte Carlo simulation, etc). The levels of the uncertain attributes are combined, such that each branch of the tree results in a different simulation model. Thus, b^a models are generated, where 'b' is the number of levels and 'a' the number of attributes (Schiozer et al., 2005). For example, for four attributes each with 3 levels of uncertainty, the total number of simulations will be $3^4 = 81$. The inclusion of one more variable, also with three levels, elevates the number to $3^5 = 243$. This makes evident the importance of sensitivity analysis, in order to identify the more critical uncertain attributes and to limit the total number of simulations.

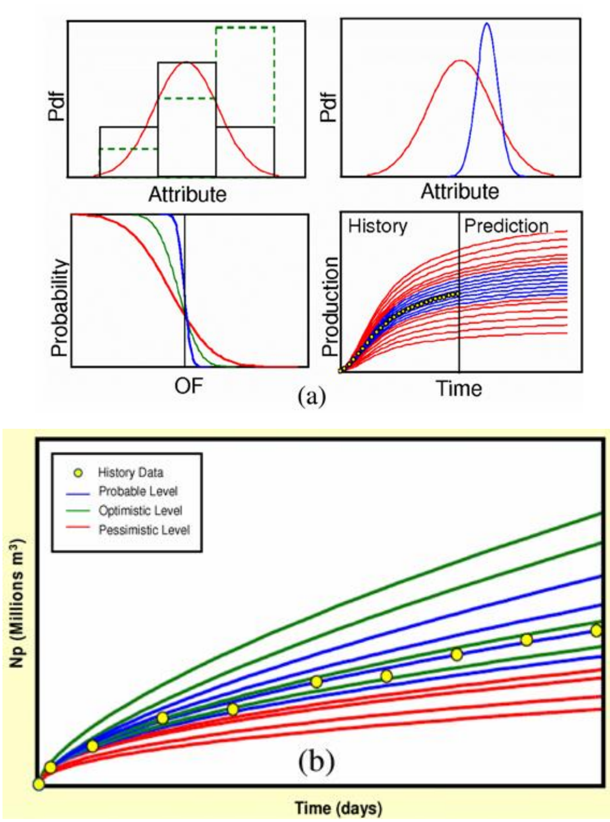


Figure 1. General aspect of the methodology (a) and examples production profiles (b).

The OF is defined according to the following equations:

$$OF = \frac{D}{|D|} D_s \tag{1}$$

where:

$$D = \sum_{i=1}^{N} (d_i^{obs} - d_i^{sim}) \tag{2}$$

and

$$D_S = \sum_{i=1}^{N} (d_i^{obs} - d_i^{sim})^2 \tag{3}$$

In the above equations, N is the number of observed data. The quotient D/|D| in Eq. (1) defines the sign of mismatching, indicating the position of the simulated data in relation to the observed data, an important concept for the next steps.

Method 1 uses the deviation distances calculated between the simulation models and the observed data for redistributing the probabilities of the attribute levels. The new probability for each level is calculated in accordance with the following equation:

$$P_n = \frac{(1/|S_n|)|D_n^{-1}|}{\sum_{L=1}^{k} (1/|S_n|)|D_n^{-1}|} \tag{4}$$

The subscript n identifies one of the discrete levels considered (0, 1 or 2 in the case of 3 levels, k = 3), while D_n and S_n are calculated by means of:

$$D_n = \left(\sum_{j=1}^{Mn} D_S \right) \tag{5}$$

and

$$S_n = \frac{D_n}{|D_n|} \tag{6}$$

In Eq. (4), Eq. (5) and Eq. (6), k is the number of discrete levels of the analyzed attribute, M_n is the number of models referred to the level n and the term D_n is the sum of deviation distances squared (D_s) of the M_n models during the history period considered. S_n factor represents a concept introduced as a measure of symmetry. It provides a greater probability value for those models better distributed around the production history curve. The sum (from j = 1 to M_n), in Eq. (5) is a global indicator of deviation above or below the values observed in the scenarios corresponding to the level n.

Consequently, the value of S_n varies between –1 and +1, zero being the value that indicates a curve distribution centered with respect to the history data. The value –1 indicates that all the curves are above the history data, and +1 that the curves are below the same. From the previous affirmation, it can be deduced that values close to zero have greater influence on the calculation of the respective value of P_n. In Eq. (4), the factor (1/ S_n) represents the degree of relative importance or weight of the group of curves for a given level. In the original work, a limitation for this factor is considered, with a maximum value of five, to avoid attributing very high weights and, consequently, to avoid excessive influence of the same:

$$1 \leq 1/|S_n| \leq 5 \tag{7}$$

From Eq. (7), the value of module $|S_n|$ varies in the interval from 0.2 to 1. Figure 1(b) exemplifies the distribution of the observed data with respect to the curves of possible reservoir models classified according to an uncertain attribute. The yellow points represent the production history. The curves in red are all located on the same side (below) of the history data, thus they present an S value equal to +1. The curves in green and in blue, however, are distributed around the production history and, for this reason, present S values that vary from –1 to +1. Even so, because the group of curves in blue presents greater symmetry around the history, their respective factor S value is closer to zero.

Figure 2 illustrates the aim of Method 1. The example schematizes the theoretic curves obtained from 9 scenarios derived from the combinations of two defined attributes with three defined levels. The three groups of curves represent the combination of the three levels of attribute A (A0, A1 and A2) with each level of attribute B. Level A2 receives the greatest probability because of the proximity of the corresponding models to the observed data. In the opposite direction, level A1 has a lower probability.

Method 2 consists of the elimination of one or more uncertainty levels of the attribute being considered and a redistribution of the probabilities resulting from this elimination. For a discrete level to be eliminated, it must satisfy the conditions expressed in Eq. (8) and Eq. (9).

$$\left|S_n\right| = 1 \tag{8}$$

and

$$P_n \leq 10\% \tag{9}$$

If the simulated curves are entirely asymmetric with respect to the history and if the occurrence probability of the level is less than 10%, this level is eliminated and the probabilities are redistributed to the remaining levels of that parameter. Considering the example of Fig. 2, level A1 is discarded and the values of the occurrence probabilities of the remaining levels are recalculated.

Finally, Method 3 consists in the redefinition of the uncertainty levels, in conformity with the curve distribution of the models relative to each attribute level. Following the example of Fig. 3(a), the new levels are calculated by Eq. (10) and Eq. (11).

$$Ls^N = Ls \tag{10}$$

and

$$Li^N = A_2 \tag{11}$$

The new probable level is calculated as:

$$A_0^N = (Ls^N + Li^N)/2 \tag{12}$$

Considering the example shown in Fig. 3(b), the new probable level is calculated as follow:

$$A_0^N = \frac{A_0 \times P[A_0] \times \left(1/\left|S_0\right|\right) + A_1 \times P[A_1] \times \left(1/\left|S_1\right|\right)}{P[A_0] \times \left(1/\left|S_0\right|\right) + P[A_1] \times \left(1/\left|S_1\right|\right)} \tag{13}$$

and the new upper and lower limits are given by:

$$Ls^N = A_1 + (A_0 - A_1) \times P[A_1] \tag{14}$$

$$Li^N = Li + (A_1 - Li) \times (1 - P[A_1]) \tag{15}$$

With the calculation of the new limits and most probable level, according to the triangular distribution, the new pessimistic and optimistic levels (A_1^N and A_2^N) are obtained. There are several possible conditions for obtaining the new values of the uncertainty attributes of the reservoir with triangular distribution. The same considerations are valid in the case of adoption of other types of probability distributions (normal, lognormal, and uniform, among others).

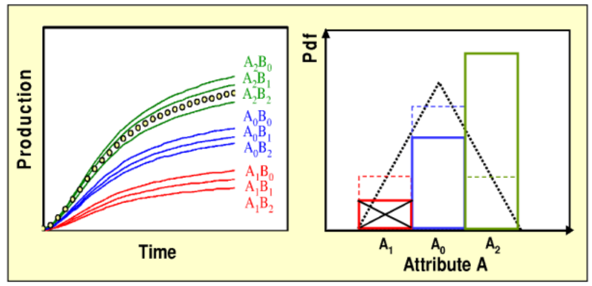
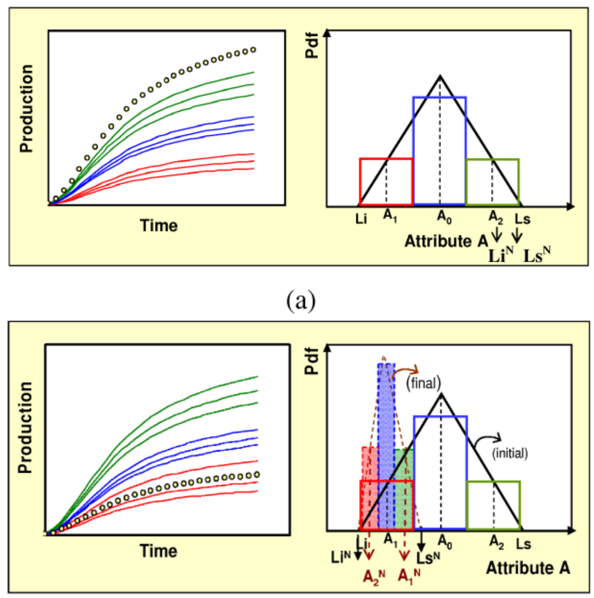


Figure 2. Schematic representation of Methods 1 and 2.



(a)

(b)

Figure 3. Method 3: redefinition of attribute limits.

The attempt is made to modify the uncertainty curve of the OF being studied, by the application of these methods, in the direction presented by Fig. 1(a) (left down picture), or in other words, bring it closer to the vertical axis representative of the history. Several attempts were made for the calibration and practical application of the methods for a complex model.

Proposed changes

The following items are improvements proposed to the methodology presented initially by Moura Filho (2006):

a) Choice of local objective-function: It is suggested, for local-level analysis, the combination of variables Q_w (water rate) and P_{wf} (bottom-hole pressure) measured in the wells (Moura Filho used only Q_w). Equation (16) presents the OF used for wells history matching. It contains different factor of relative weight for each variable, as a function of its validity and degree of importance.

$$OF = \sum_{i=1}^{n}\left[wi_{Qw}\left(Qw^{obsv} - Qw^{calc}\right)^2 + wi_{Pwf}\left(Pwf^{\,obsv} - Pwf^{\,calc}\right)^2\right] \quad (16)$$

where wi_{Qw} and wi_{Pwf} are weight for water rate and bottom-hole pressure, respectively.

b) Probabilistic scenario treatment: modifications are made of the original formulation.

c) Definition of the target uncertainty range: This allows for evaluation as to whether the uncertainty reduction process should be refined.

d) Case analysis before and after uncertainty reduction: an evaluation of the integration consistency at this point permits restarting the process at the well or regional level. This indicates the interactive character of the methodology.

e) New sensitivity analysis: other variables having been discarded originally could influence the OF at this stage. This analysis is made to reinstate the convenience of including additional attributes in the process and re-start a new step.

f) Uncertainty reduction analysis of the predictions: calculation of the uncertainty range reduction after application of the proposed methods on the predictions of main variables of the model.

Method modifications

After applying the original equations, several alterations attempts were made on weights and calculations of new associated probabilities to apply the methodology to a complex case. The weights act on the alteration of probabilities of the uncertainty levels and the variation of attribute values. At the stage of OF global evaluation, the effects of attribute uncertainty reduction act together, cumulating the dislocations on the newly generated uncertainty curve. Figure 4(a) schematizes a situation in which the uncertainty curve obtained after application of Method 1 manifests an undesirable effect caused by an increase in relative uncertainty for positive values of the OF between 0 and 40% approximately. Positive OF values mean that the values calculated are smaller than the observed values.

Thus, it is necessary some revision or variation on the weights assigned to these models, in which calculated curves are below the history values. The selected variation criterion is related to the standard deviation of misfit distances calculated for all the analyzed models, in relation to the chosen OF variable during the history period. Additionally, the models should be arranged according to the pessimistic, optimistic and most probable levels, beginning with the attribute of greatest sensitivity and continuing with the remaining attributes. Thus, for each analyzed attribute, the standard deviation is calculated as:

$$\sigma_n = \sqrt{\frac{\sum\left(x - \bar{x}\right)^2}{Mn}} \quad (17)$$

where

$$x = K = \sum_{i=1}^{N}\left(d_i^{obsv} - d_i^{sim}\right) \quad (18)$$

and

$$\bar{x} = \frac{\sum x}{Mn} \quad (19)$$

The smallest standard deviation value also corresponds to the attribute with the greatest 1/S value. Next, an F_n factor based on the inverse of standard deviation of each uncertain level permits the modification of initially calculated probabilities P_n. In this manner, a smaller weight is given to the levels originally of greater importance in the combined models with positive OF values.

$$F_n = \frac{\left(1/\sigma\right)_n}{\sum_{i=1}^{n_A}\left(1/\sigma_i\right)} \quad (20)$$

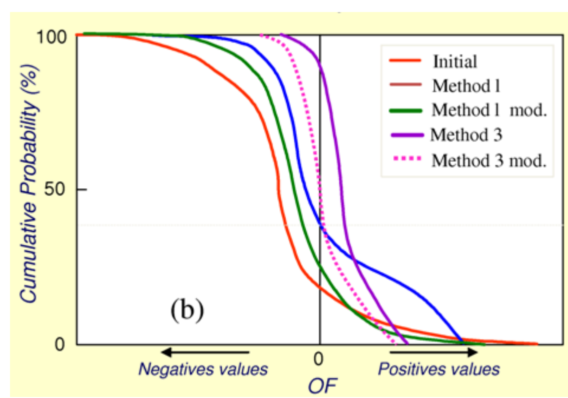
where n_A is the number of chosen attributes.

The new probabilities are calculated according to Eq. (21), in which the factor F_n is the proposed change in the original manner of calculating P_n shown in Eq. (4).

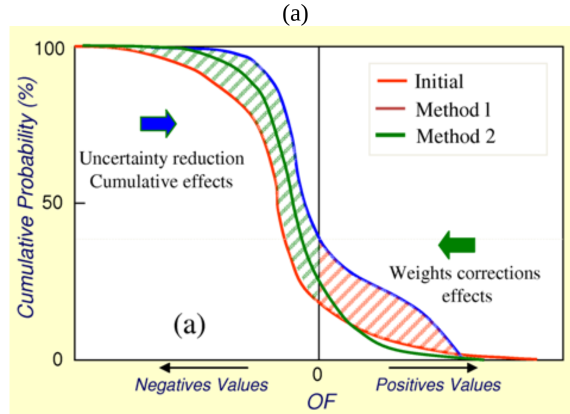
$$P_n^{\,mod} = P_n \times 1/F_n \quad (21)$$

In Figure 4(a), the effects of the applied correction on the uncertainty curve are also shown. At the global evaluation stage of OF, the effects of attribute uncertainty reduction act in conjunction on the newly generated uncertainty curve.

The improvement of this method also produces a similar effect on the subsequent methods. Thus, Methods 2 and 3 are modified beginning from the use of $P_n^{\,mod}$ and the new weights are calculated. Modified Method 3 is defined from the parameters obtained in Method 1 corrected, following the explained procedure. The variation of limits is only applied on those attributes having great weight variation, being that it is readily possible to obtain an uncertainty curve that is centered in relation to the OF value of zero, however, slightly more inclined. Figure 4(b) exemplifies the shift of the uncertainty curve from Method 3.



(a)

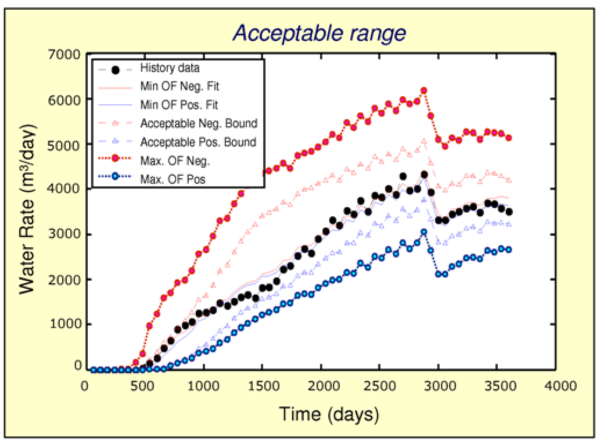


(b)

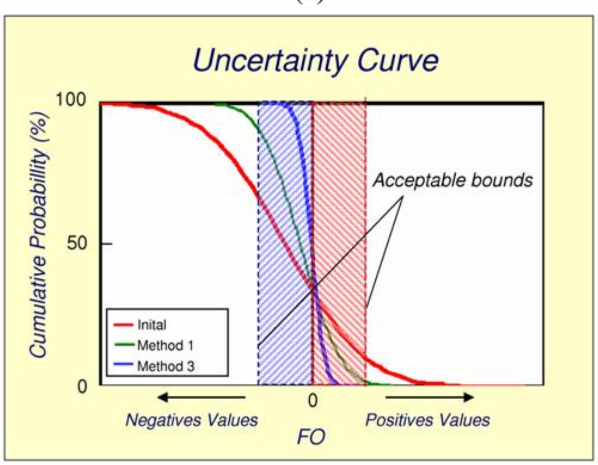
Figure 4. Theoretic uncertainty curves: correction of cumulative effects (a) and comparison of the methods (b).

Definition of an uncertainty range target

This range should be based on the value of the objective-function of the curves considered as acceptable limits, selected according to the value of a percentage of the total range between the extreme cases considered. In the example of Fig. 5(a), the maximum negative dispersion is calculated from the difference between the history matching corresponding to the smallest value of the OF with a negative sign (*Min. OF Neg. Matching red curve*) and the history matching that corresponds to the maximum negative OF value (*Maximum OF Neg.*). Thus, the maximum positive range is calculated from the difference between the matching corresponding to the smallest OF value with a positive sign (*Min. OF Pos. OF Matching blue curve*) and the matching corresponding to the maximum negative value acceptance (*Maximum OF Positive*). From the calculation of these extreme ranges and by means of the choice of an acceptance percentage of each total range for each sign, it is possible to identify the acceptable limits. These limits have OF values of the closest models within an acceptable tolerance limit (*Negative Acceptable Limit and Positive Acceptable Limit*). Figure 5(a) shows an example for the case of a specific percentage choice of the total range. Thus, after the identification of the aforementioned cases, the calculated limits can be plotted on the uncertainty curve graph, permitting the qualitative and quantitative measurement of the degree of uncertainty reduction reached through the application of the methods (Fig. 5(b)).



(a)



(b)

Figure 5. Definition of an uncertainty range target: selection of bound models (a), target range and uncertainty curves (b).

Integration of global, regional and local stages

An interactive five phase's process is proposed, in the scope of the reduction uncertainty and evaluation, from this procedure.

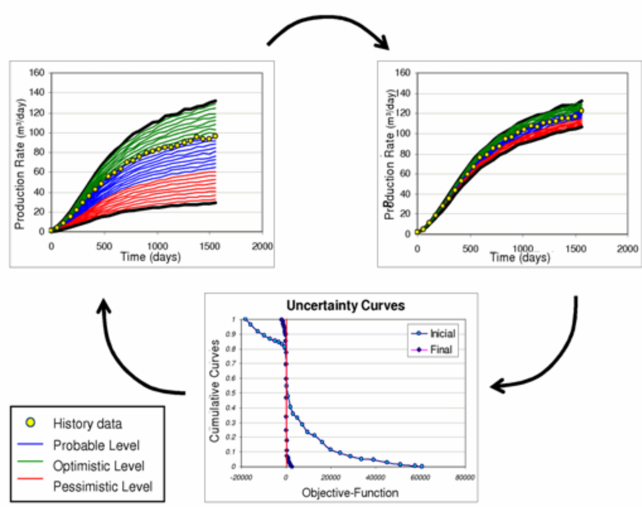
Phase 1: Application of the described methods, over the chosen OF with global scope, until obtaining acceptable results (Fig. 6(a)). In this way, through an interactive process, new simulations are performed directed by Method 3 until an acceptable reduction is reached. As a result, a range of curves of global production smaller than the initial dispersion is obtained, and this range is positioned around the observed data.

Phase 2: In this phase, the local stages of history matching integration at the regional and well levels begin. In Fig. 6(b) the process is schematized. Matching by zones is performed, proceeding from the choice of the best global matching from the previous phase. In this phase, manual or automated history matching methodologies can be used.

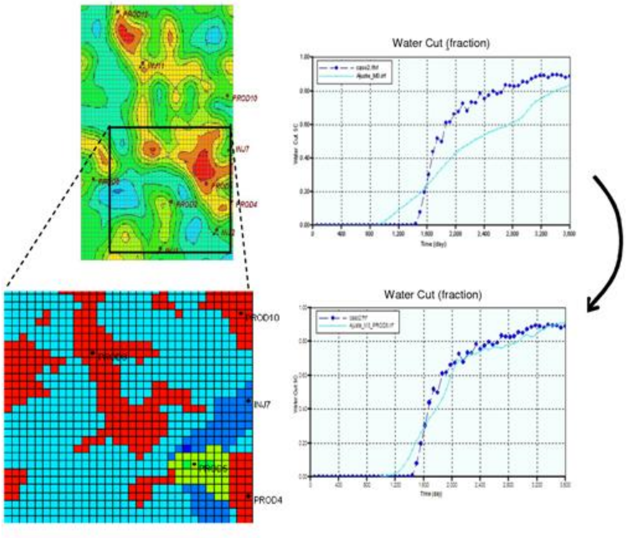
Phase 3: All the modifications at the regional and well levels, explored at the previous stage, are considered. Obtaining new combinations of models, considering the uncertainty still present in the zones where little information is found, permits evaluation of the degree of uncertainty based on the observed data. Figure 7(a) illustrates the final profiles obtained after the reconstruction of the derivative tree with improved local matching.

Phase 4: It is necessary to keep control of the results obtained to be in accordance with the acceptable limits determined in the beginning of the process. This evaluation phase is critical. If the uncertainty curves obtained in the previous phases are not included in this range, the whole process can be started again, this being the interactive character of the methodology.

Phase 5: A final range of uncertainty of the dynamic performance of the reservoir in the prediction period is reached (Figure 7(b)). The models corresponding to the percentiles 10% and 90% (although other percentiles can be chosen) of the uncertainty curve accepted in the previous phase are appropriate indicators for future performance with uncertainty, after applying the methodology.

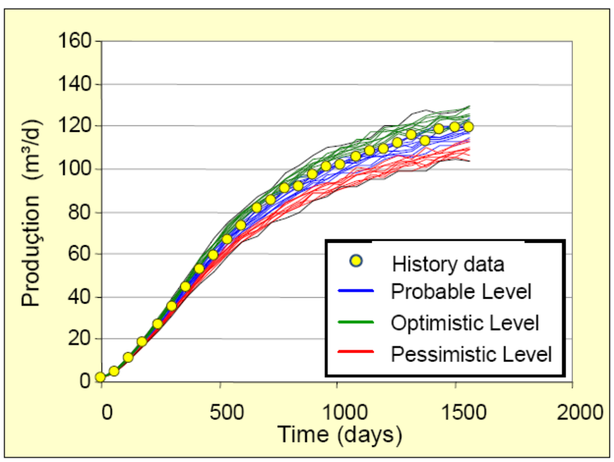


(a)

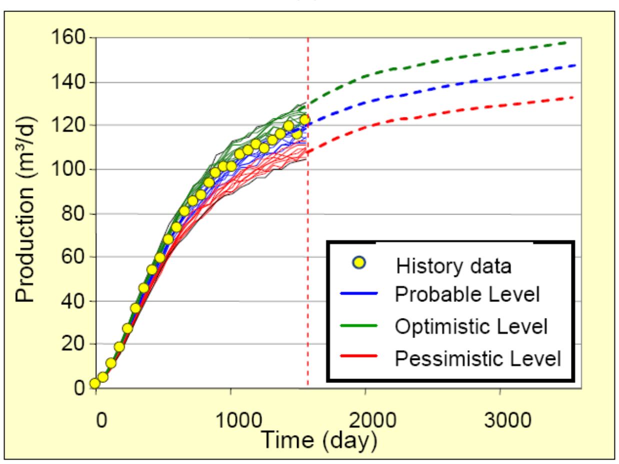


(b)

Figure 6. Integration of global (a) and local analysis (b).



(a)



(b)

Figure 7. Schematic final dispersion in history period (a) and in prediction period (b).

Summarizing, the main changes and improvements in the methodology presented originally by Maschio et al. (2005) and Moura Filho (2006) are: 1) Equation (4) was changed (see Eq. (21)); 2) the use of local objective function; 3) the definition of a target uncertainty range; 4) the integration of global and local analysis and 5) the application to a more complex case.

Application

The methodology was applied in a reservoir model based on outcrop data from Brazil, including well information and seismic interpretations of analog fields in turbidity systems deposited in deep water. The data were treated, qualitatively and quantitatively, for the parameterization of the reservoir. The chosen objective-function is based on monthly water production for the evaluation at global level; however, special attention was given to the well bottom-hole pressures in the phase of local application.

The modeled depositional elements are channels, lateral deposits and hemi-pelagic shales, which represent pauses in the dominant sedimentation process of a turbidite system in deep water. The petrophysical parameters (porosity and permeability) were attributed from correlations with the net-to-gross ratio (NTG), the values being representative of the typical range of existing reservoirs of the Brazilian continental platform (Silva et al., 2005). The refined static model obtained has a grid with 217 x 275 x 6 blocks, with 12 vertical wells, 7 producers and 5 injectors. This model permitted the generation of the synthetic production data taken as reference, for a period of 10 years. This data was subjected to a random noise to represent the common production measurement errors.

Finally, to reproduce the typical conditions of model building in real conditions a second model was constructed from the refined geologic model, to represent the dynamic behavior of the reservoir. The size of the coarse grid model is 43 x 55 x 6 blocks, and with the purpose of changing the original geological conditions, the parameters of the considered elements in each layer were modified following other depositional patterns typical of this environment. Figure 8 shows a three-dimensional view of the corner-point grid used with the spatial distribution of porosity.

After the choice of the uncertain static and dynamic attributes, their global and local influence on the model is evaluated. Each uncertain attribute is discretized into three levels with a probability of 20%-60%-20% considering a triangular probability distribution function. Table 1 lists the most probable values and the pessimistic and optimistic levels of the considered attributes. The listed extreme values were used in the sensitivity analysis.

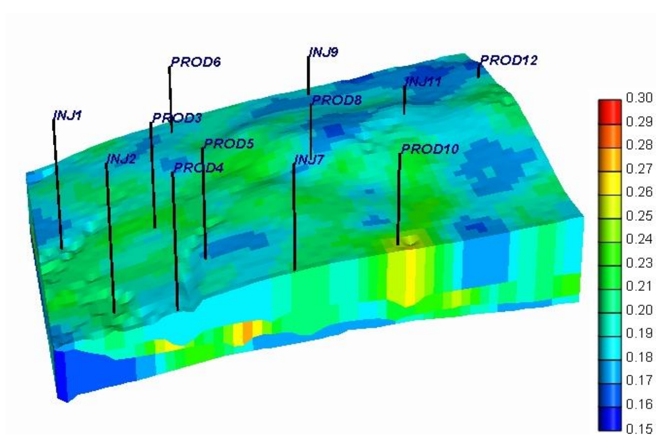


Figure 8. Three-dimensional view of the model studied (porosity).

Table 1. Description of the uncertain attributes.

Attribute	*Representative Values*	*Description*
$NTGf_0$	(0.6)	Net to Gross ratio (poor reservoir zone)
$NTGf_1$	(0.2)	
$NTGf_2$	(1.0)	
Ka_0	(2.0)	Absolute permeability multiplier sandstone zone
Ka_1	(1.0)	
Ka_2	(3.4)	
Kf_0	(0.65)	Absolute permeability multiplier (poor reservoir zone)
Kf_1	(0.30)	
Kf_2	(1.00)	
KK_0	(0.12)	Vertical vs. horizontal permeability ratio
KK_1	(0.05)	
KK_2	(0.35)	
Vma_0	(1.20)	Porous volume multiplier of sandstone zone
Vma_1	(0.85)	
Vma_2	(1.55)	
VMf_0	(0.85)	Porous volume multiplier (poor reservoir zone)
VMf_1	(0.61)	
VMf_2	(1.10)	
Kra_0	(0.40)	Relative permeability of the sandstone
Kra_1	(0.26)	
Kra_2	(0.54)	
Krf_0	(0.60)	Relative permeability (poor reservoir zone)
Krf_1	(0.40)	
Krf_2	(0.90)	
BAR_0	(0.50)	Horizontal barriers
BAR_1	(0.00)	
BAR_2	(1.00)	
RIJ_0	(1.25)	Horizontal permeability anisotropy
RIJ_1	(1.00)	
RIJ_2	(1.75)	
$BARK_0$	(0.65)	Vertical seals
$BARK_1$	(0.40)	
$BARK_2$	(0.88)	
PVT_0	(790)	Oil density
PVT_1	(725)	
PVT_2	(855)	

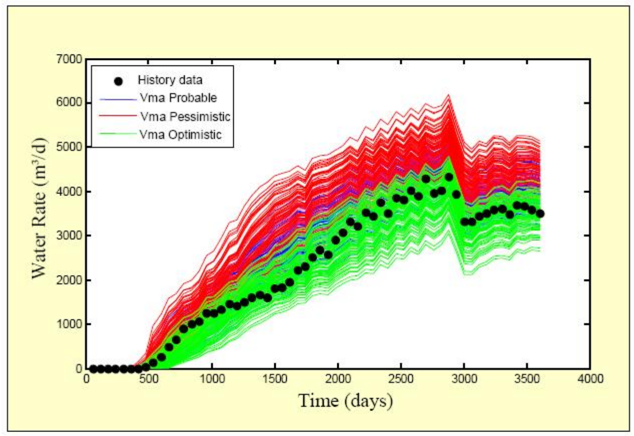
Results

The analysis of the history matching quality is performed in two ways: 1) from the production curves, by observing the reduction of dispersion and comparing it with the observed data and 2) by obtaining the OF's cumulative probabilities curve (uncertainty curve). In this case, the reduction of the uncertainty degree, after application of the methodology, can be evaluated in function of the dispersion around the zero axis, taking into account the target uncertainty range.

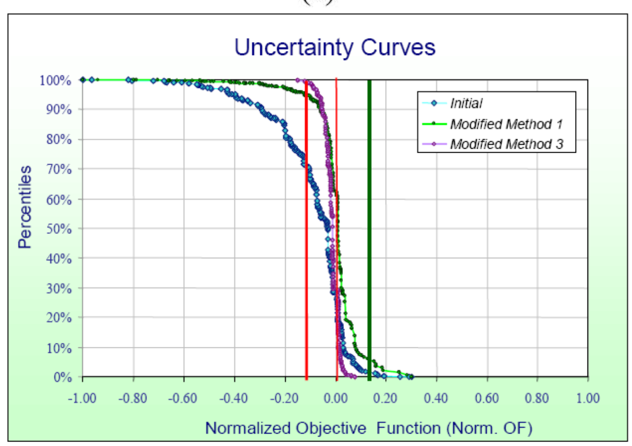
Initially, a comparison among the methods presented by Maschio et al. (2005) and Moura Filho (2006) and the modified methods proposed in this paper is depicted in Fig. 10. This figure shows the improvements in the uncertainty curves obtained.

Additionally, it was also done an analysis of production predictions. From the five critical attributes selected from the sensitivity analysis, discrete in three levels of uncertainty, 35 = 243 simulations were necessary. In Fig. 9(a) the water production curves, grouped following the Vma levels (porous volume in the reservoir zone), are presented as an example. Similar curves are made for all the attributes and, to make the process automatic, the curve differences are quantified and used for the probability changes of the attributes.

The new probability value calculated by Method 1 for Vma1 (pessimistic) is 5.4%, for Vma0 (probable) is 11.7% and for Vma2 (optimistic) is 82.9%. It can be seen that the green curves corresponding to the optimistic level of Vma are closer to the recorded data. Figure 9(b) shows the uncertainty curves that indicated the degree of quality of the history matching (the OF shows normalized deviation from the history). The uncertainty curves obtained by the proposed methods demonstrate a significant uncertainty reduction, Method 3 being the most effective. In this figure, an acceptance range of 25% with respect to the interval of initial variation was considered.



(a)



(b)

Figure 9. Probabilistic profiles of total field water production grouped according to Vma (a) and target uncertainty range in the case of 25% of the total range (b).

Figure 11(a) shows the new disposition of productive profiles obtained from the models constructed after using Method 3 at the global level. The deviation reduction with respect to the history data is expressive, in addition to being well distributed around the observed data for all uncertainty levels.

Results were also generated for an additional local history matching step integrating the global and local matching processes. Figure 11(b) shows the profiles obtained after Method 3, at a local level, for one well of the model. Great uncertainty reductions in all the wells were obtained with the application over an OF with global scope; nevertheless, as it is evident in the case of well PROD5, the global uncertainty reduction is insufficient to improve the local well matching. This situation shows the necessity of a second stage to correct local matching. Including these data in the analysis permits obtaining probabilistic profiles more centered on the history data of each well, although there continues to exist uncertainty in the model because of the lack of data in the regions between wells or in underdeveloped regions, where sampling is not direct.

Two different approaches were taken. In the first approach, the identification, at the regional level, of the wells with more influential overlapping attributes was proposed, in order to subsequently reinitiate the application of the methodology over this region, permitting the reduction of uncertainty around each well. Finally, in each well's influence area, it is selected a combination of uncertain attributes having lower OF values derived from the application of this method. In the second approach, more traditional, the zones close to the wells are modified locally and individual local matching is made without modifying the zones of the remaining wells. This approach is not covered in this paper.

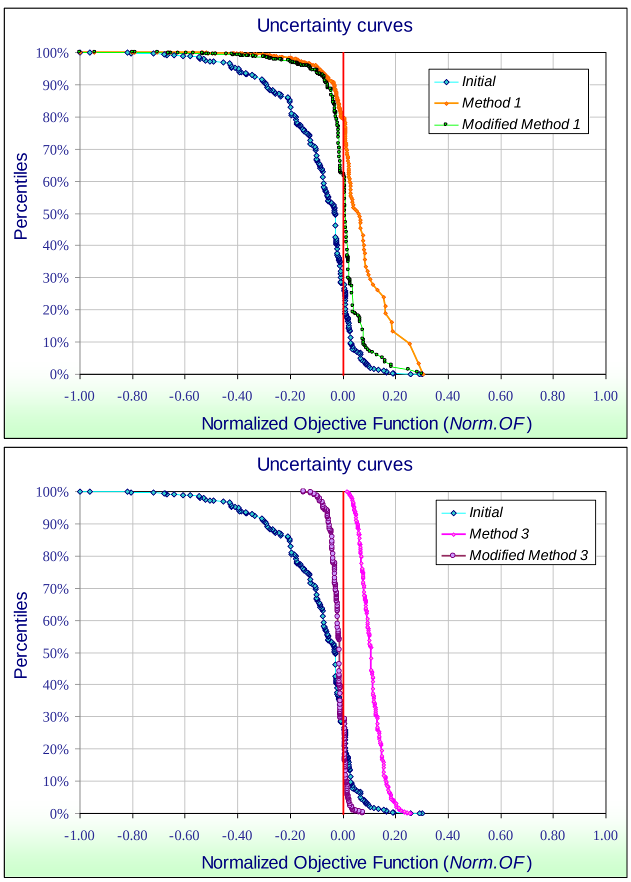


Figure 10. Comparison of Method 1 and 3 proposed by Maschio et al. (2005) and Moura Filho (2006), and Modified Method 1 and 3 (present work).

Different regions were selected by identification of zones with high coincidence of attributes that are more influential over the OF, based on water production and dynamic pressure of the target wells. Then, over each region, the methodology is applied for each well, now with the OF defined in Eq. (16), with weight factors wi_{Qw} and wi_{Pwf} with values of 0.75 and 0.25 respectively. The initial uncertain attributes chosen are Kv (vertical vs. horizontal permeability ratio), Krw (relative sand permeability), Ka (absolute sand permeability multiplier), Kf (multiplier of permeability in the non-reservoir zone) and VMf (porous volume non-reservoir zone).

The variation range of some of these attributes was already reduced in the global treatment of the previous phase. In the case of well PROD3, Fig. 12(a) shows the initial spread of the curves for water rate in reference to the 243 simulation models. In Fig. 12(b), the curve distribution shown refers to the models matched after application of Method 3 modified for the well under analysis. An important narrowing of the range of history matching is verified as expected.

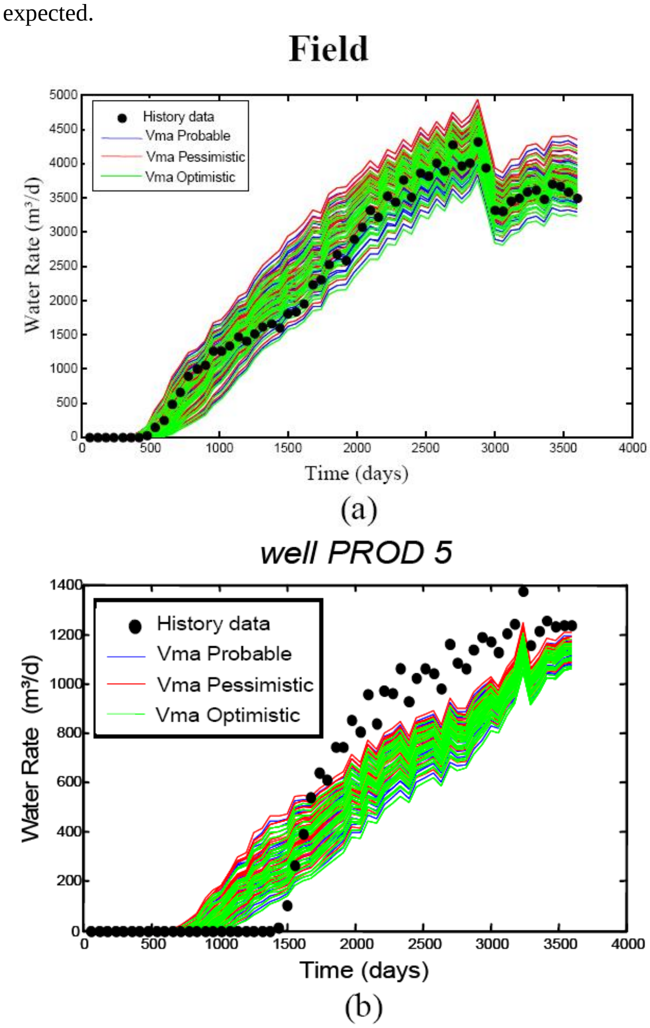
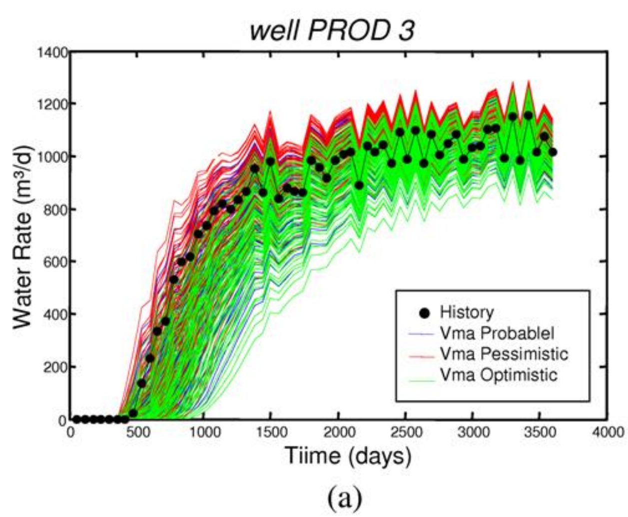
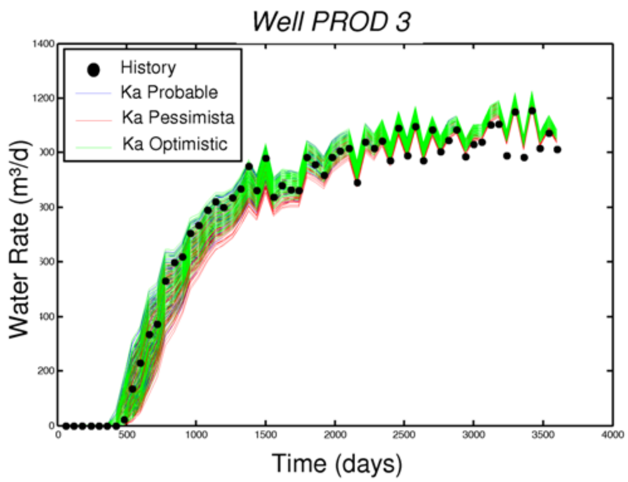


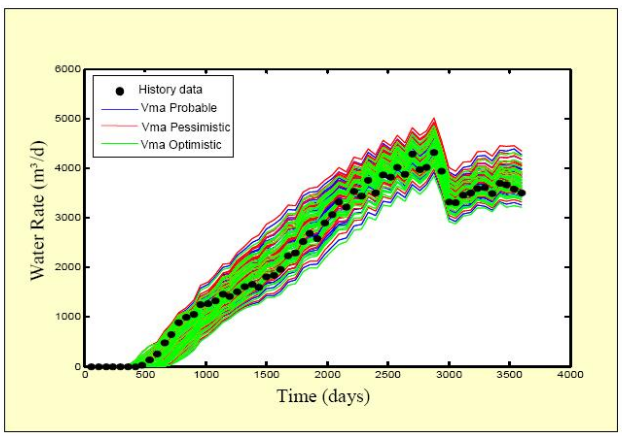
Figure 11. Probabilistic profiles of total field (a) and well PROD5 (b) water production after the application of the methodology at global scale.



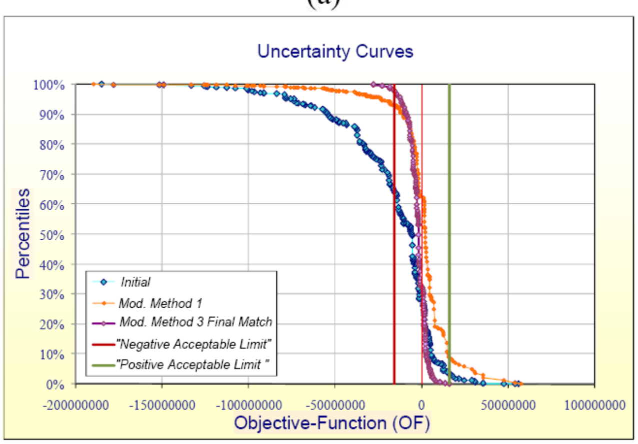


(b)

Figure 12. Initial probabilistic profiles of water rate (a) and after the application of the methodology at local scale (b).



(a)

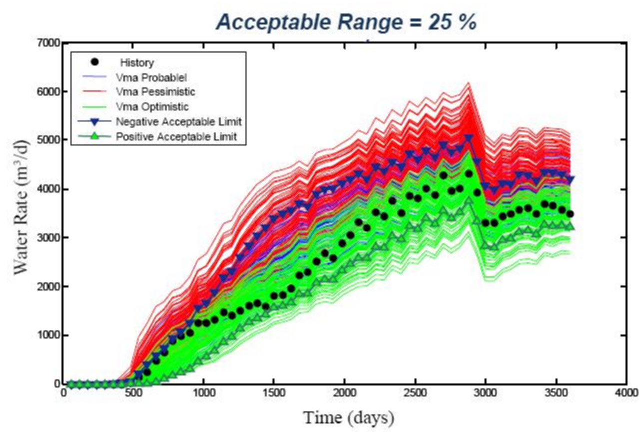


(b)

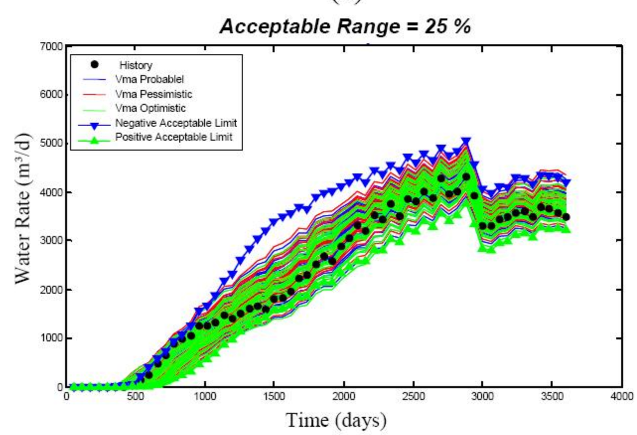
Figure 13. Final probabilistic profiles (a) and uncertainty curves (b).

The local history matching obtained in the previous phase for all selected regions were combined together in the base case considering the reduced uncertainty ranges in Phase 1 for the rest of the reservoir. Finally, with the same limits identified with modified Method 3, the possible combined models are obtained. Figure 13(a) presents the final distribution of the probabilistic profiles of total water production. The obtained set of curves, with less dispersion and well centered in relation to the observed values, represents the final solution. The next phase is the result control through the definition of target ranges (or acceptable limits) for the process of uncertainty reduction. The demarcation limits of the target range are shown in Fig. 13(b). The chosen acceptance range, in this case, is 25% of the total spread. In Fig. 14(a), there are plotted the corresponding curves for acceptable limits.

The uncertainty curve constructed at the end of Phase 3 (Fig. 13(b)) fits, almost entirely, within acceptable limits, demonstrating that the process reached its objectives. This can be confirmed in Fig. 14(b), by contrasting the chosen limits to the final dispersion of the probabilistic profiles after Method 3.



(a)

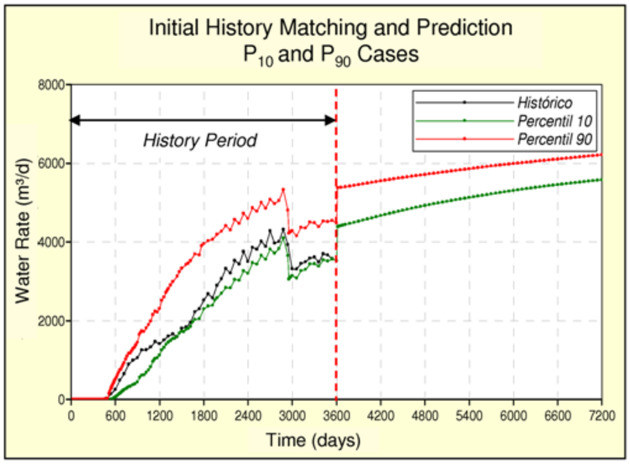


(b)

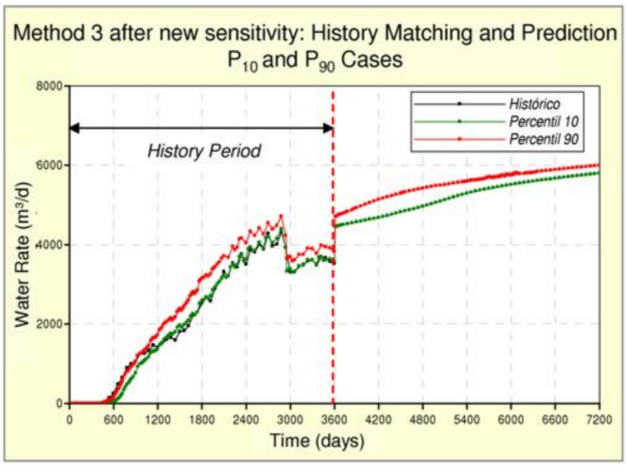
Figure 14. Acceptable limits versus initial dispersion of probabilistic profiles (a) and acceptable limits versus final dispersion of probabilistic profiles (b).

The reduced ranges of the critical attributes allow to a consequent reduction of production prediction spread. The prediction of the water rate of the models representing the percentiles P10 and P90 is reported in Fig. 15. These models were chosen from the uncertainty curve before (Fig. 15(a)) and after (Fig. 15(b)) the application of the methodology presented in this work.

Finally, Figs. 16(a) and 16(b) present the values obtained from accumulated oil production (millions of m3) and water production (millions of m3) for each percentile and according to the applied phase. It can be clearly seen a gradual reduction of the difference between P10 and P90.

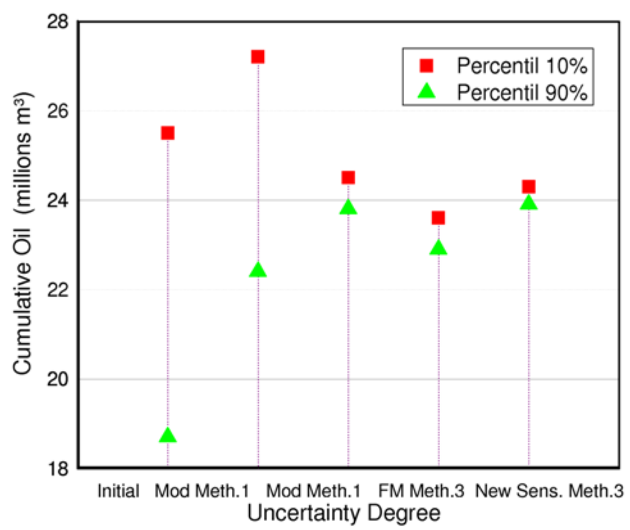


(a)

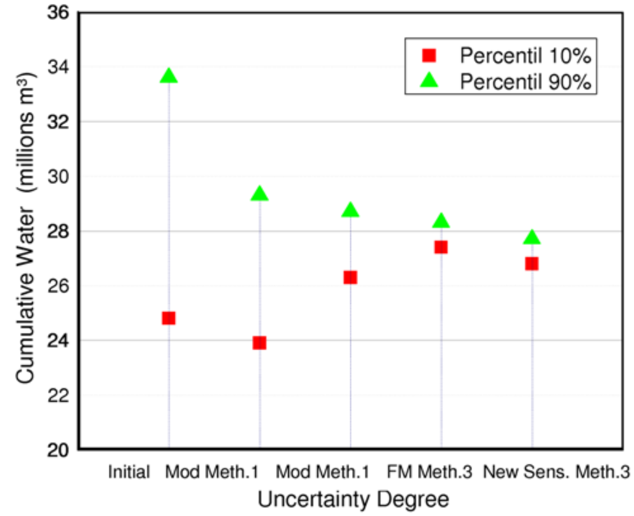


(b)

Figure 15. Prediction of the models P10 and P90 after (a) and before (b) the application of the methodology.



(a)



(b)

Figure 16. Cumulative oil (a) and water (b) as a function of degree of uncertainty.

Conclusions

A consistent and flexible methodology to integrate history matching with uncertainty analysis at global, regional and local levels in a complex model was presented in this paper. The application allows obtaining the following additional conclusions:

- The used methods permitted: 1) reduction of the range of possible history matching; 2) identification and conditioning of the uncertainty present as function of the observed data; 3) reduction of the uncertainty intervals of the identified critical attributes; and 4) demarcation of confident limits for the reservoir's future performance.
- The focus on how to approach the history matching, when there is a set of highly variable attributes and restricted knowledge, was changed, obtaining a defined group of models that comprise the possible matching with their associated probabilities.
- The sensitivity analyses permitted the detection of uncertain attributes critical to the evaluation of the degree of subsequent uncertainty, thus simplifying the problem as well as reducing significantly the number of attributes and, consequently, the run time.
- Methods 1 and 2 were faster, as they did not require new simulations. A new calibration of Method 1 was necessary. Method 3 provided greater uncertainty reduction, yet required greater computational effort, compared to Methods 1 and 2.
- The reduction of global uncertainty did not guarantee a local uncertainty reduction. Consequently, it was necessary to take into account the interaction between regions. The applied methodology permitted analysis by stages, which gives great flexibility to application in practical cases.
- Obtaining representative prediction curves for the reservoir (percentiles P10 and P90, for example) permitted an estimation of the risk reduction of the considered project performance.
- The probabilistic approach of the history matching made available a broader vision, as it points to several possible scenarios in the search for the reservoir's real behavior. Nevertheless, the final choice of representative scenarios depends on the criteria adopted by the analyst.
- When new data are added to the study, the history matching and the predictions can be improved reducing the attribute range by the application of the complete proposed flow chart.

Considering all the above listed items, the consequence is increased confidence in the use of the simulation as an auxiliary tool in the decision process. One advantage is flexibility as to the use of different uncertainty analysis tools and the definition of distinct types of probability distribution in order to mark the levels of the uncertain attributes. Another advantage, compared to automated processes of model calibration, is to make unnecessary the use of sophisticated optimization methods. Equipment with parallel processing and software integration makes it possible its application to real cases.

Other methodologies have analogous conclusions or are similar in some points covered. In this paper, a general procedure attempts a progressive mitigation of uncertainty in all phases of a project, incorporating history matching of the model.

The choice of uncertain attributes levels and their variation limits is a crucial step in the process and has to reflect the real uncertainties of the problem. The experience of a multi-disciplinary team is critical at the beginning of the process, as long as in search for representative attributes levels, processed data from analogical basins and fields can be very useful.

Acknowledgements

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