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Integration of dynamic data in a mature oil field reservoir model to reduce the uncertainty on production forecasting

MATHIEU FERAILLE[1]; EMMANUEL MANCEAU[1]; ISABELLE ZABALZA-MEZGHANI[1]; FREDERIC ROGGERO[1]; LIN-YING HU[1]; and LEANDRO COSTA REIS[2]
[1]Institut Français du Pétrole, Rueil-Malmaison, France
[2]Petrobras, Rio, Brazil

Introduction

In current practice history matching is often performed with a unique model realization. However, it is well known that history matching problems have non-unique solutions and that several equiprobable reservoir models may match the production data. Therefore, uncertainty on production forecasts is highly underestimated when considering only one matched model.

The Response Surface Methodology (RSM) and experimental design theory [1, 2, 3] can be used to model production forecast uncertainties as a function of deterministic/continuous uncertain parameters, such as petrophysical and production parameters. The Joint Modeling (JM) method [4, 5, 6, 7] extends these methods to allow as well to take into account stochastic uncertainties such as equiprobable matched models. In this approach, the dispersion due to the stochastic uncertainties is modeled in a rigorous statistical framework by modeling the variance of production forecasts. Thus, this method enables the quantification of the impact on production forecasts of not only the continuous uncertainties but also of the stochastic uncertainties, such as uncertainties on history matching.

The JM method was successfully applied to a real field located offshore Brazil (PBR field) [8, 9]. The objective was to maximize the total production of the reservoir while taking into account the uncertainty on history matching induced by the existence of equiprobable matched models. The study was performed in the following steps:
- History matching: The geostatistical and flow models were constrained to the production data. Several equiprobable matches were obtained.
- Production scheme optimization: The JM method was applied to optimize the locations and production rates of two new wells while taking into account the uncertainty on history matching. The goal was to maximize the total oil production and to quantify the uncertainty on production forecasts.

Finally, some posterior validations were performed to check the proposed method and its ability to manage equiprobable matched models:
- Validation of the production forecast prediction interval with new constrained realizations not used for the JM method.
- Comparison between the JM method results and the optimization results obtained using one particular matched model.
- Quantification of the added value of history matching in terms of uncertainty reduction on production forecast.

Response Surface Methodology, Experimental Design and Joint Modeling Method

The general purpose of the RSM is to approximate a complex process with respect to several parameters varying within a given uncertainty domain. Thus, after defining the uncertain parameters and the observed variable of the process, called response, the RSM allows to build an approximated regression model (response surface model) which links the response to the uncertain parameters. This approximated model can be used to predict the process response for any parameter values within the uncertainty domain. Moreover, a Monte Carlo sampling technique can be used with the approximated model to generate a probabilistic distribution of the response with a negligible cost compared to the CPU-time required to run the reservoir simulations.

The approximated model is calibrated using a set of simulated responses obtained with different parameter values. The experimental design technique provides the right set of reservoir simulations to perform in order to model properly the response behavior in the uncertainty domain. Tabulated experimental designs may be selected and are a compromise between the accuracy of the approximated model and the maximum number of simulations accepted for the study.

The experimental design technique has been widely used in petroleum applications to quantify the impact of uncertainty on deterministic parameters such as petrophysical parameters, PVT data, well locations,… The Joint Modeling method allows to quantify also the impact of stochastic uncertainties corresponding to several reservoir model realizations.

In such a case, the JM method allows to model the production response with two regression models:
(a) A mean model which describes the production response as a function of the deterministic parameters,
(b) A variance model which quantifies the dispersion of the production response due to the consideration of several reservoir model realizations.

PBR field modeling workflow
The PBR reservoir is a real oil field located offshore Brazil. It is developed with 34 oil production wells and 13 water injection wells (Figure 1). The production began in June 1979. During the 5 first years the field was produced by depletion. Water injection started in April 1984 for pressure maintenance (Figure 2 & Figure 3).

Four facies have been identified in the reservoir. Facies LT-1 and LT-2 are composed of sandstone and have good reservoir properties. Facies LT-3 and LT-4 include clays and marls and correspond to non-reservoir zones.

The PBR field is composed of three genetic units. The geostatistical simulation of the lithofacies model is performed separately in each unit.

The workflow of the PBR reservoir model has been fully integrated in the same simulation process, from the construction of the geostatistical lithofacies model to the fluid flow simulation:
- The non-stationary truncated gaussian approach is used for the geostatistical simulation. The facies proportions are obtained by kriging the indicators of the facies well data.
- This model is filled in with the facies petrophysical properties given in Table 1.
- The geostatistical model is upscaled using the renormalization method to obtain the coarse fluid flow simulation model.

Table 1: Summary of the petrophisical properties per facies.

Facies	Phi - %	Kh - mD	Kv - mD
1	30	1100	100
2	24	550	80
3	10	10	0.1
4	6	5	0.1

History matching process
An objective function was defined to measure the differences between the observed data (d_i^{obs}) and the simulated data (d_i^{sim}) using the weighted least square formulation:

$$OF = \frac{1}{2}\sum_{i=1}^{n} w_i (d_i^{obs} - d_i^{sim})^2$$

where w_i are weighting factors.

The production data available for the PBR field are the oil flow rates at surface conditions, the water cuts and the static pressures for all the production wells.

The objective function is minimized using an optimization algorithm. It is based on an approximated computation of the gradients of the simulation results with respect to the inversion parameters. The integration of the entire simulation workflow in the same inversion process allows to select history matching parameters everywhere in this workflow, either in the geostatistical simulation or in the fluid flow simulation data.
- A preliminary sensitivity study was performed, using experimental design technique and RSM, to select the most influential inversion parameters among the deterministic uncertain parameters of the simulation workflow. Finally, the following 8 deterministic history matching parameters were selected (cf. range on Table 2):
- The correlation lengths of the geostatistical facies model in the horizontal and vertical anisotropy directions;
- The horizontal permeability of the facies LT-1, LT-3 and LT-4;
- The Kv/Kh ratio of the facies LT-3 and LT-4;
- The relative permeability end point Krowm.

Table 2: Range of the deterministic parameters.

Name	Min	Max	Default
Colh	500	1500	900
Colv	5	15	10
Kh1	558	1622	1081
Kh3	7	135	11
Kh4	3	64	5
Kv3/Kh3	0.001	0.025	0.0125
Kv4/Kh4	0.001	0.106	0.025
Krowm	0.74	1	0.74

- In addition to these 8 deterministic inversion parameters, the geostatistical realization itself was considered unknown in the inversion process. The spatial distribution of the facies model was parameterized using the Gradual Deformation Method [10, 11, 12] (GDM). The GDM enables continuous transformations of the initial model realization while respecting the overall model properties. The inversion process is controlled by a user defined number of parameters and allows global or local transformations. For the PBR field 3 global deformation parameters were used for each of the 3 genetic units.

The history matching process was performed 5 times with different sets of initial deterministic parameters and with different initial geostatistical realizations. The initial sets have been chosen within the predefined uncertainty domain, as shown in Table 3.

Table 3: Initial optimization of the 5 optimizations (-1,1 and 0 are the min max and mean of the parameter range)

	kh1	kh3	kh4	kv3/kh3	kv4/kh4	colh	colv	Krowm
M1	Default							
M2	0	0	0	0	0	0	0	0
M3	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
M4	-0.5	-0.5	-0.5	-0.5	0.5	0.5	0.5	0.5
M5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5

Figure 4 shows the evolution of the OF during the history match process for the 5 inversions. Despite a satisfactory convergence rate, the OF remains at a high value because the reservoir model cannot reproduce the water breakthrough observed in the south part of the reservoir. However, as shown on Figure 5, a satisfactory match of the global reservoir oil production is obtained for the 5 cases.

Production scheme optimization
The objective was to maximize the reservoir cumulated oil production after an additional period of production of 10 years (COS_10y) and to quantify the remaining uncertainty after history matching. The history matching uncertainty was assumed to be represented by the five matched models obtained previously. The JM method was applied to model the COS_10y response as a function of four production parameters while considering the history matching uncertainty. The deterministic production parameters to optimize were the positions and production rates of the two infill wells (NW1, NW2). A preliminary sensitivity study has shown that the Y locations of the wells were not significantly influential on the production forecasts. Thus, they were fixed (Figure 6) and only the X locations were considered. Finally, the JM was performed with respect to the following production parameters: the X locations (X1, X2) and the oil production rates (Q1, Q2) of the two infill wells (NW1, NW2). The production parameters (X1, X2, Q1 and Q2) had to be optimized within the investigation domain shown in Table 4.

Table 4: Range assigned to each production parameter.

Name	Min	Max	Unit
X1	34	40	cell #
X2	41	47	cell #
Q1	500	1500	m3/d
Q2	500	1500	m3/d

The JM method requires first to run the same experimental design for each of the matched models to catch the mean behavior of the response. A central composite design with 25 simulations was selected to investigate the 4 production parameter domain. The combination of this experimental design with the 5 matched models led to a total number of 125 numerical simulations.

The 125 COS_10y response values, corresponding to the 25 simulations performed for each of the 5 matched models, are shown on Figure 7. We remark that the response is highly sensitive to the production parameters for a given history matched model, meaning that the 4 production parameters are influential and should be optimized. Moreover, for a given set of these parameters, the effect of considering several matched models can be very significant. Therefore, this history matching uncertainty must be taken into account during the production scheme optimization.

Hence, the COS_10y response was modeled as a function of both the new well parameters and the stochastic uncertainty using the JM method. The JM method provided two second order polynomial models, which describe the mean and the variance of the COS_10y response:

$$\begin{aligned}\text{Mean(COS\_10y)} = {} & 55.137237 + 0.085860\ X1 + 0.089977\ X2 + 0.076521\ Q1 + 0.161005\ Q2 - 0.080553\ X1^2 \\ & - 0.096469\ X2^2 - 0.114991\ Q1^2 - 0.088038\ Q2^2 + 0.005831\ X1{:}X2 + 0.061725\ X1{:}Q1 \\ & + 0.003405\ X1{:}Q2 + 0.014594\ X2{:}Q1 + 0.080306\ X2{:}Q2 - 0.186350\ Q1{:}Q2\end{aligned}$$

$$\begin{aligned}\text{Variance(COS\_10y)} = {} & \exp[-0.609404 + 0.056656\ X1 + 0.032581\ X2 + 0.284077\ Q1 + 0.398920\ Q2 - 0.097387\ X1^2 \\ & + 0.016453\ X2^2 - 0.089107\ Q1^2 - 0.124305\ Q2^2 - 0.014721\ X1{:}X2 - 0.002009\ X1{:}Q1 \\ & - 0.024571\ X1{:}Q2 - 0.025189\ X2{:}Q1 - 0.011311\ X2{:}Q2 - 0.202738\ Q1{:}Q2]\end{aligned}$$

The quality of the joint models, which characterizes the capability of the models to fit the response, is very good: 98.5% for the mean model and 98.8% for the variance model. Thus, the joint models can be safely used for the optimization of the production scheme.

The optimization of the production scheme is done by maximizing the mean model. It gives the optimal values for the X1, X2, Q1 and Q2 parameters and the corresponding mean and variance values of the COS_10y response forecast. The maximum production 55.32 MMm^3 is obtained for X well positions equals to 38 and 47 (grid block indices in X-direction) and for oil production rates equals to 852 and 1500 m^3/d respectively for the two wells NW1 and NW2. The 95% prediction interval of the production forecast is derived from the variance value: the COS_10y prediction varies between 53.7 and 57 MMm^3 when the production parameters are fixed to the optimum values. All these results are summarized in Table 5 and Figure 8. Note that for well NW2 the optimization results are bounded by the maximum values of the uncertainty domain. It could be interesting to further investigate the optimization of well NW2 by increasing the parameter ranges for X2 and Q2.

Table 5: Results of the optimization of the production parameters using the JM method.

	Optimal values	Unit
X1	38	cell #
X2	47	cell #
Q1	852	m3/d
Q2	1500	m3/d
Mean COS_10y	55.32	MMm3
Variance	0.71	$(MMm3)^2$
Standard deviation	0.84	MMm3
Min of the 95% confidence interval	53.68	MMm3
Max of the 95% confidence interval	56.97	MMm3

Validation of the COS_10y 95% prediction interval
The COS_10y 95% prediction interval was validated by comparing it with the predictions obtained with five new matched models. In a first step, the five new model realizations were history matched using the procedure already described. In a second step, fluid flow simulations were performed while fixing the infill well parameters (X locations and rates) to their optimal values. The objective was to validate that the 5 new production values are inside the prediction interval.

The simulated production forecasts of the 5 new models are plotted on Figure 8. Note that the 5 new simulated values of the COS_10y production forecasts satisfy the 95% prediction interval.

In conclusion, the 5 matched models involved in the JM method are sufficient to catch the uncertainty due to several matched models not involved in the JM method. Thus, the JM method allowed to successfully quantify the uncertainty on production forecasts.

Discussion of the Joint Modeling method compared to the use of a particular model realization
As already mentioned, history matching is often performed with a unique model realization. The optimization of a production scheme using a particular matched model does not take into account the history matching uncertainty and can lead to big mistakes on production forecasts. Moreover, the development plan found from a unique model realization is generally sub-optimal in comparison with the one obtained by considering several possibilities.

To emphasize this capability the optimum solution of the JM method was compared to the optimization results obtained separately with each of the 10 previous matched models. For each matched model, a central composite design including 25 simulations was selected for the 4 production parameters (X1, X2, Q1 and Q2) and a response surface model of the field production COS_10y was optimized. From the results shown on Table 6 we can observe that the optimal sets of production parameters as well as the corresponding COS_10y response differ significantly from one matched model to the other. This means that considering a unique matched model for the PBR production scheme optimization is not recommended. On the contrary, the JM method enabled the computation of a global optimal set of production parameters, which takes into account the history matching uncertainty. Moreover, it was checked that even if this global optimal set does not correspond to the best optimization obtained for each matched models separately, it corresponds to the best optimization for all the matched models considered simultaneously.

Quantification of the added information of history matching

The main goal of history matching is to drastically reduce the uncertainties of the simulation results by calibrating uncertain parameters using the production history period. Using history matched models thus results in a better confidence in the production forecasts. Since the JM method enables to quantify the uncertainty on production forecasts while considering several matched models, it is possible to quantify the added information of history matching on production forecasts. A validation was made by comparing the uncertainties on production forecasts obtained before and after history matching with production parameters fixed to the optimal solution of the JM method.

Table 6: Optimal sets and COS_10y values for each of the 10 matched models.

	X1	X2	Q1	Q2	COS_10y value	COS_10y with optimal set #5
Units	cell #		m3/d		MMm3	
Match1	34	46	748.33	1500	53.94	53.78
Match2	38	47	807.93	1500	55.76	55.66
Match3	37	47	970.26	1500	56.29	55.83
Match4	40	47	943.77	1500	55.53	55.28
Match5	40	44	1500.00	691.33	55.10	
Match6	40	47	1057.00	1500	56.30	55.95
Match7	37	47	929.83	1500	55.45	55.25
Match8	37	46	500.00	1500	54.62	54.08
Match9	36	47	739.30	1500	55.00	54.60
Match10	38	47	787.13	1500	55.42	55.16
JM method	38	47	852.00	1500	Mean = 55.32 Std dev = 0.84	

The uncertainty on production forecasts before history matching was quantified using the JM method with 4 new model realizations. The experimental design was a fractional factorial design defined for the 8 deterministic parameters which correspond to the history matching parameters (Table 2). This experimental design requires a set of 16 simulations which must be combined with the 4 model realizations. Therefore, a total number of 74 simulations was performed.

Figure 9 presents the simulated production of the field (COS) for the 74 simulations. The large spread of production forecasts is compared to the 5 previous history matched models and to the 95% prediction interval. As expected, the history matching significantly reduces the uncertainties during the production history period and also on the production forecasts, as shown in Table 7. The uncertainty is decreased by 75% on the production forecasts when using history matched models.

Table 7: Uncertainties on the production results before and after history matching.

	Before history matching	After history matching
At the end of the production history period	30.7 ± 9.5%	33.6 ± 0.14%
COS_10y	50.3 ± 13%	55.3 ± 3%

Conclusions

The Joint Modeling method has been successfully applied and validated on the PBR real oil field case. It was possible to optimize the development of two new wells in a mature field while taking into account the historical data available. Moreover, the uncertainty on production forecasts was quantified by considering several history matched models for the optimization of the production scheme. In addition, we have been able to determine a prediction interval of the production forecasts, which takes into account the uncertainties linked to the history matching process. The main advantage of the JM method is to provide not only an optimal solution which maximize the oil production forecast but also a simplified model of the mean and variance in the entire uncertainty domain.

The dual aspect of JM, namely the modeling of the mean and variance, allows to consider production scheme optimization from several points of view depending on the field development strategy. A first possibility is to look for the production parameters which maximize the mean oil production forecasts, as presented in the PBR study. Another objective could be to find the parameters which minimize the uncertainty due to the existence of several history match solutions (that is, to minimize the variance model). Finally, one could be interested in a compromise, i.e. finding the production parameters which maximize the production forecasts while preserving a small uncertainty value.

Acknowledgments

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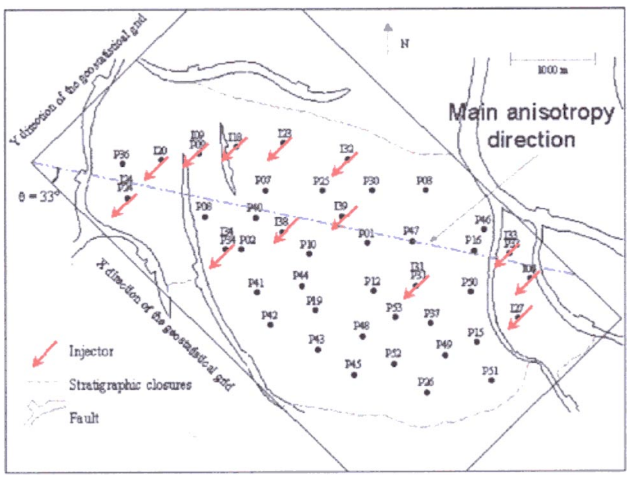

Figure 1: Top view of the PBR reservoir. The lateral limits of the geostatistical model (rectangle) and the main anisotropy direction (dashed line) are represented.

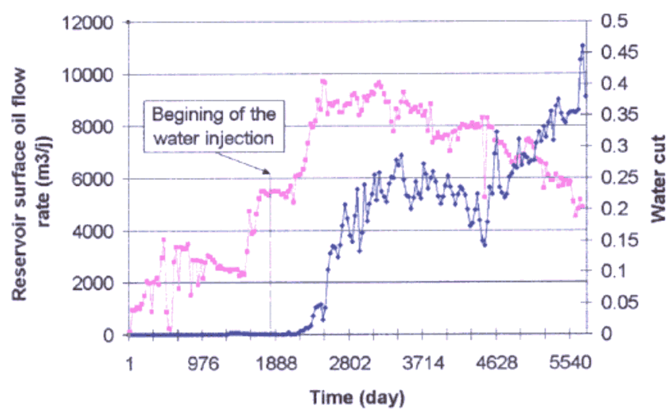

Figure 2: PBR reservoir oil production and water cut data.

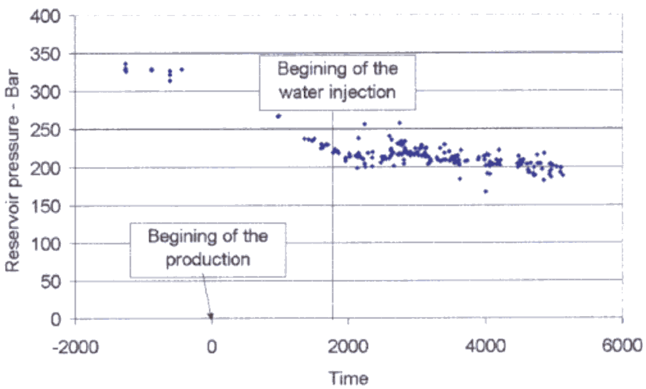

Figure 3: Reservoir pressure data.

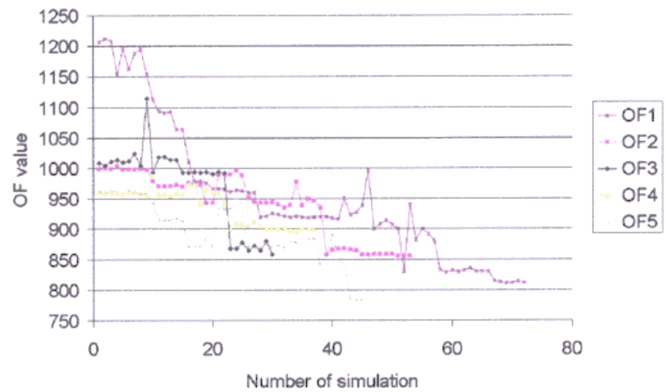

Figure 4: Evolution of the total OF for the 5 optimization processes.

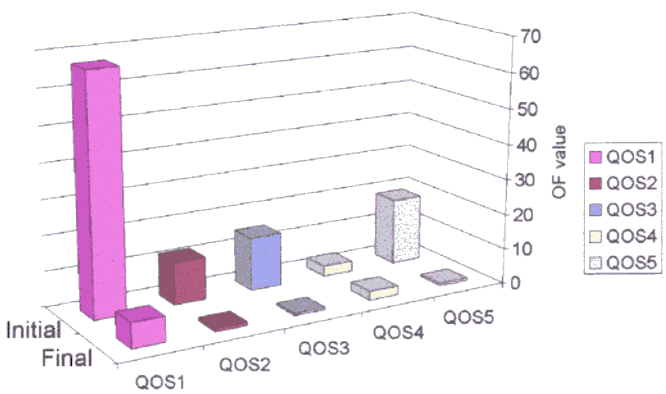

Figure 5: Initial and final QOS OF for the 5 optimizations.

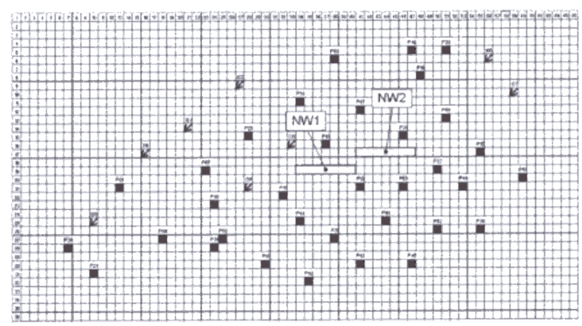

Figure 6: Range of the 2 new wells NW1 and NW2. The Y locations are fixed.

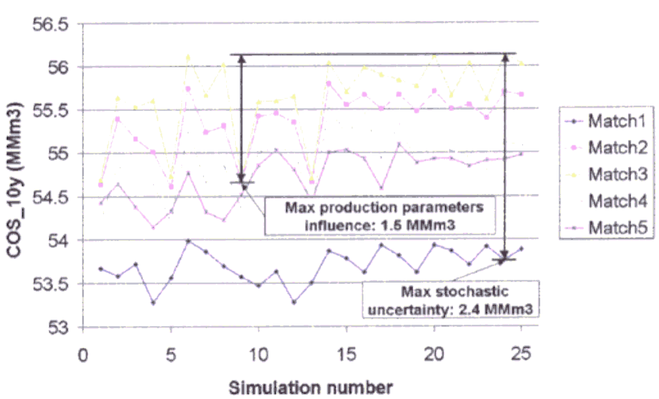

Figure 7: COS_10y response values. The history matching uncertainty and the production parameter influence are highlighted on the graph.

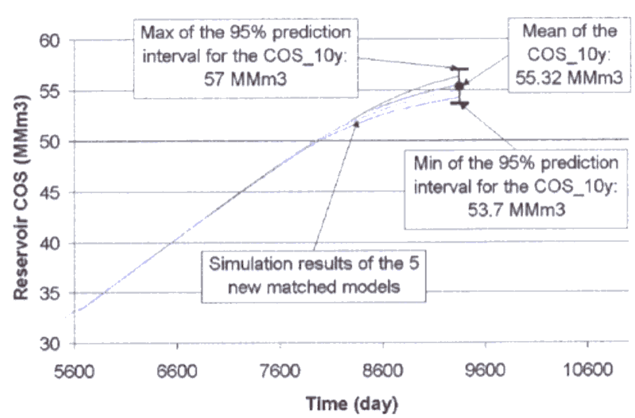

Figure 8: Simulation values of the reservoir COS for the 5 new matched models. The 95% prediction interval for the COS_10y is represented.

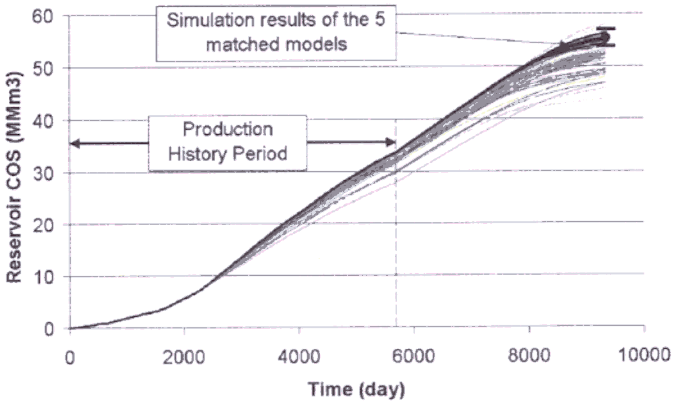

Figure 9: Comparison between the uncertainties before and after history matching.