COBEM 99
XV Congresso Brasileiro de Engenharia Mecânica
15th Brazilian Congress of Mechanical Engineering
22 - 26 de Novembro de 1999 / November 22 - 26, 1999 Águas de Lindóia, São Paulo,

COMBINING AUTOMATIC HISTORY MATCHING AND GEOSTATISTICAL TECHNIQUES TO IMPROVE OIL PRODUCTION FORECAST

Ricardo Cunha Mattos Portella
Fábio Prais
PETROBRAS/CENPES - Centro de Pesquisas e Desenvolvimento Leopoldo A. Miguez de Mello
Cidade Universitária – Quadra 7 – Prédio 20
Rio de Janeiro, RJ 21949-900, Brasil

Abstract. *The development of automatic history matching techniques is receiving much attention recently. The methods are becoming increasingly faster making practical applications possible. In general, these methods provide a single solution that matches the observed data, but as the solution of inverse problems is not unique, there is no guarantee that production forecasts made with the adjusted model will produce good results. Thus, it would be desirable to know the confidence interval of the adjusted model. The methodology presented in this paper combines a history matching technique with geostatistical modeling to provide equiprobable reservoir images that take into consideration production data. The method uses the reservoir image generated by the optimization algorithm to generate several geostatistical images of the reservoir to provide a measure of uncertainty.*

Although the computational cost of the methodology is high, the information about the uncertainty of the production forecast that it generates compensates the additional time necessary to obtain the results. The paper shows a complete example where the adjusted parameter is the permeability field of the reservoir. This methodology could be applied with any optimization method, and it provides an excellent way to access production uncertainty.

Keywords: *Automatic history matching, Optimization, Reservoir characterization.*

1. INTRODUCTION

Incorporation of dynamic data (production and well test data) in reservoir models for flow simulation is essential to generate more realistic models to be used in production forecast and economic analysis. The process of incorporating dynamic data in the generation of reservoir models is commonly known as automatic history matching.

Automatic history matching techniques fall into two categories: deterministic and stochastic methods. Deterministic methods are based in the inverse problem theory (Tarantola, 1987), while the stochastic methods, in few words, mimic the trial and error approach of the manual history matching procedure.

The most efficient deterministic methods are the gradient methods, so called because they need to compute the gradients of the mathematical model with respect to the parameters (permeability, porosity, or any other property that can be parameterized) in order to minimize the objective function. These methods have a very fast convergence rate to a optimal set of parameters, and for this reason several papers (Landa & Horne, 1997; He et al., 1997; Rahon, 1997) have been published using algorithms of this kind to solve optimization problems in the petroleum industry. As a disadvantage, in some situations these algorithms may not converge or converge to a local minimum of the mathematical model.

In the category of stochastic methods (Ouenes et al.,1994; Bittencourt & Horne, 1997), the most common methods are the ones based on simulated annealing and genetic algorithms. These methods do not need to compute gradients, but their convergence rate is much slower than that of the gradient methods. On other hand, their computational implementation is much easier than the implementation of a deterministic algorithm. Simulated annealing and genetic algorithms are classified as global optimization algorithms because theoretically they always reach the global minimum of the objective function. In practice, the number of iterations is limited, and so, the global minimum may not be reached.

If the optimization algorithm converges, the solution presented by these algorithms guarantees a match with the observed data, but as inverse problems do not have a unique solution, it is not guaranteed that extrapolations done with the adjusted model will reflect the reality. Therefore, a single solution provided by the optimization algorithms is not satisfactory; also, it is necessary to assess the uncertainty of the model. A recent work by He et al. (1997) proposes a methodology that combines geostatistical methods with gradient algorithms to generate realizations that honors the dynamic data and takes into consideration uncertainties in the prior geostatistical model. Although He et al. methodology is mathematically rigorous, its implementation is very complex and very time consuming.

Geostatistical simulation provides a way to assess model uncertainty, but as it does not take into account dynamic data, the flow simulations results obtained using the equiprobable images of the reservoir show a broad range between the optimistic and the pessimistic cases. In this paper, we propose a simple methodology that uses an optimization algorithm to account for the dynamic data (production and injection flow rates, reservoir pressure, etc.), and geostatistical simulation to account for the model uncertainty. The results of flow simulations of these images have a much smaller dispersion than results over geostatiscal images that only take into account static data. The next sections will describe in more details the methodology, the optimization algorithm used, and a sample application case with results will be discussed.

2. SIMULATED ANNEALING ALGORITHM

The simulated annealing optimization algorithm was chosen because it is extremely simple to implement and to adapt to existing flow simulator codes, it is a global optimization algorithm, it can be easily adapted to optimize a large variety of parameters (block properties, relative permeability curve parameters, well locations, etc.), and discontinuities in the objective function. The convergence of simulated annealing methods is very slow if compared with the convergence of gradient methods, and it only makes sense to compare its convergence speed with the tedious manual history matching procedure. More detailed information about the simulated annealing procedure can be found in Ouenes et al (1994).

The simulated annealing algorithm will stop either because the objective function felt below a predetermined value or because an iteration limit was reached. The objective function used in this implementation is as follow:

$$E = \left(\vec{d}_{obs} - \vec{d}_{sim}\right)^T \mathbf{W}\left(\vec{d}_{obs} - \vec{d}_{sim}\right)$$

Where $\vec{d}_{obs}$ and $\vec{d}_{sim}$ are respectively the vectors of observed and simulated data and $\mathbf{W}$ is a diagonal matrix which provides a way of assigning different weights to the observed variables.

The simulated annealing algorithm was coupled with an in-house flow simulator. In this implementation it is possible to do the match for the main production data observed in wells, like oil production, water production, gas production, and bottom hole well pressure. The parameters that can be modified to fit the observed data are end-points and exponents of power law type curves for relative permeabilities, transmissibilities between blocks, porosity and absolute permeability of blocks. In the latter case, it is possible to modify the properties for each block of the model or to work with regions. In addition, in the case of porosity and permeabilities, it is possible to modify only a few values and then use these values as conditioning points for a kriging (Deutsch & Journel, 1998) to determine the values of the other blocks. In this way, we not only save time in the fitting procedure by having less parameters to modify, but also introduce geological features by using a variographic model of the variable in question. This technique is also known as pilot points method and several other authors (Fasanino et al., 1986; Wen et al., 1996; Rama et al, 1995; Roggero, 1997) also used it.

3. PROPOSED METHODOLOGY

As previously mentioned, inverse problems do not have a single solution, and therefore, production forecast made with models generated by optimization algorithms do not guarantee a good result. So, it would be desirable to assess the uncertainty of such model to have a better idea of the risks involved in an economical analysis that uses the generated model. The proposed methodology generates several equiprobable images of the reservoir conditioned not only to the available static data from the wells, but also to data derived from the adjusted image. The images generated this way do not fit exactly the observed data, but they will present a much smaller dispersion around the real data than images generated using only static information from the wells.

3.1 Application Example

A generated example will be used to present the proposed sampling methodology. A 3-D reservoir (50 x 50 x 2 grid with cell size of 20 m x 20 m x 20 m) was set up with one injector in the middle and four producers at the corners, with constant porosity equal to 0.2, and a heterogeneous permeability field generated by a sequential gaussian algorithm (SGSIM, Deutsch & Journel, 1998). An anisotropic spherical variogram was used with no nugget effect, and ranges in the main directions equal to 500 m x 200m x 20m. The permeability distribution was lognormal with $\mu = 448.4$ mD and $\sigma = 406.5$ mD. Figure 1 shows the permeability field for layers 1 and 2.

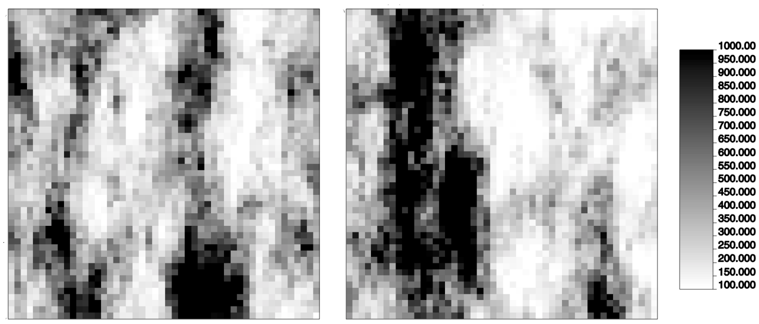

Figure 1 – Reference Permeability Field – Layers 1 and 2

The wells in this model were completed in both layers and either the production and the injection rate was controlled by a specified bottom hole pressure. A waterflood, with end-point mobility ratio of 2.3, was conducted in the reference reservoir during 1000 days. The water and oil production history of the wells was the data to be fitted.

Using the same variogram that generated the reference reservoir and considering the permeability of the well blocks of this reservoir as conditioning points, 10 realizations were generated using the same sequential gaussian simulation program (SGSIM). Figure 2 shows the permeability field for realization number 1. A waterflood was conducted in these 10 realizations whose results can be seen in the graph Cumulative Produced Oil (Np) versus Time (Figure 3). For each of these simulations, the value of the objective function was calculated (see Table 1). As can be observed in Figure 3, the dispersion of the results around the reference answer was large. Notice that in the construction of these images we did not make use of the production data.

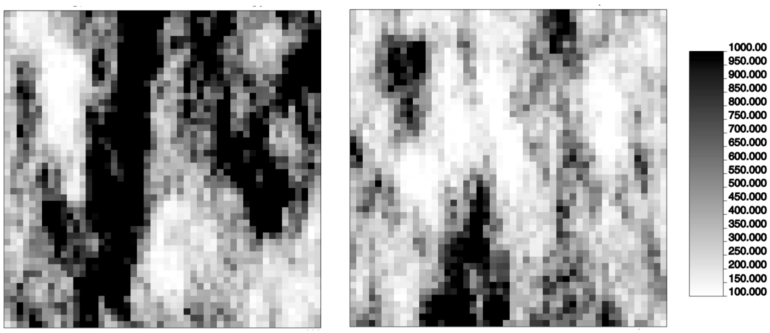

Figure 2 – Realization 1 generated only with static points – Layers 1 and 2

Table 1 – Average objective function values points – historic period.

Method	Average	Standard Deviation
Geostatiscal Static Points	**550823.01**	**326796.79**
Proposed Methodology	**207111.17**	**89049.56**

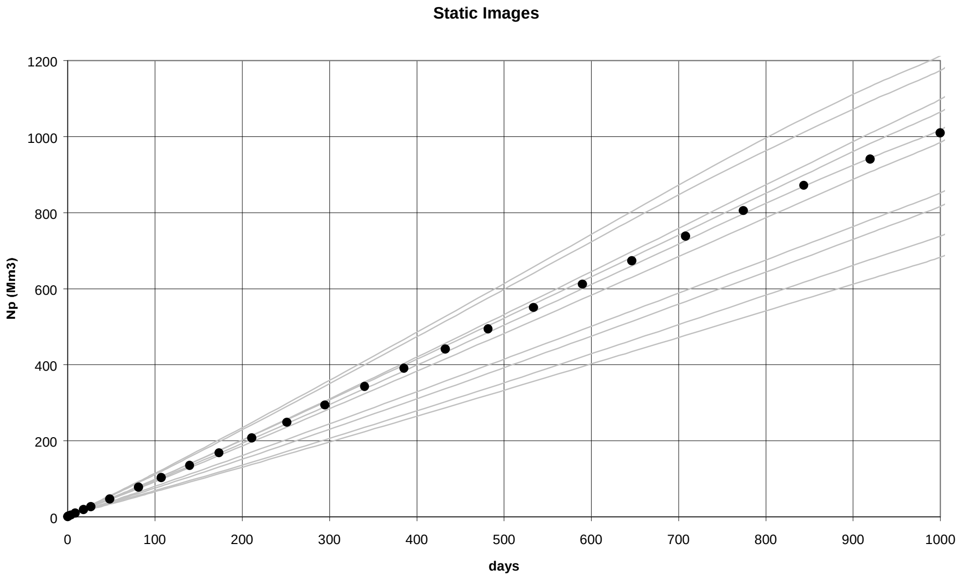

Figure 3 – Simulation Results for the Static Images (solid lines) and Reference Field (black dots)

A history matching was done using the simulated annealing method with 200 random pilot points. The permeability in the well blocks was considered known and these values remained constant throughout the process, and were used in the kriging procedure of the pilot points technique. The maximum number of iterations of the simulated annealing was set into 2000, and the target objective function was set into 0.9. The initial guess consisted of a homogeneous reservoir with 100 mD except at the well locations were the right permeability value was used. The fitting procedure stopped at the maximum number of iterations and the value of the objective function at that time was of 1926.67. The match with the observed data was almost perfect as can be seen in Figure 4. The fitted permeability field (Figure 5) did not give a good match with the reference permeability field (Figure 1). This was expected since inverse problems admit an infinite set of solutions for a given data set. The similarity between the two images would increase if there were more information available to do the match (seismic information, bottom hole pressures, etc.). The differences between the images will have a big impact in the production forecast, as it will be seen later in this paper.

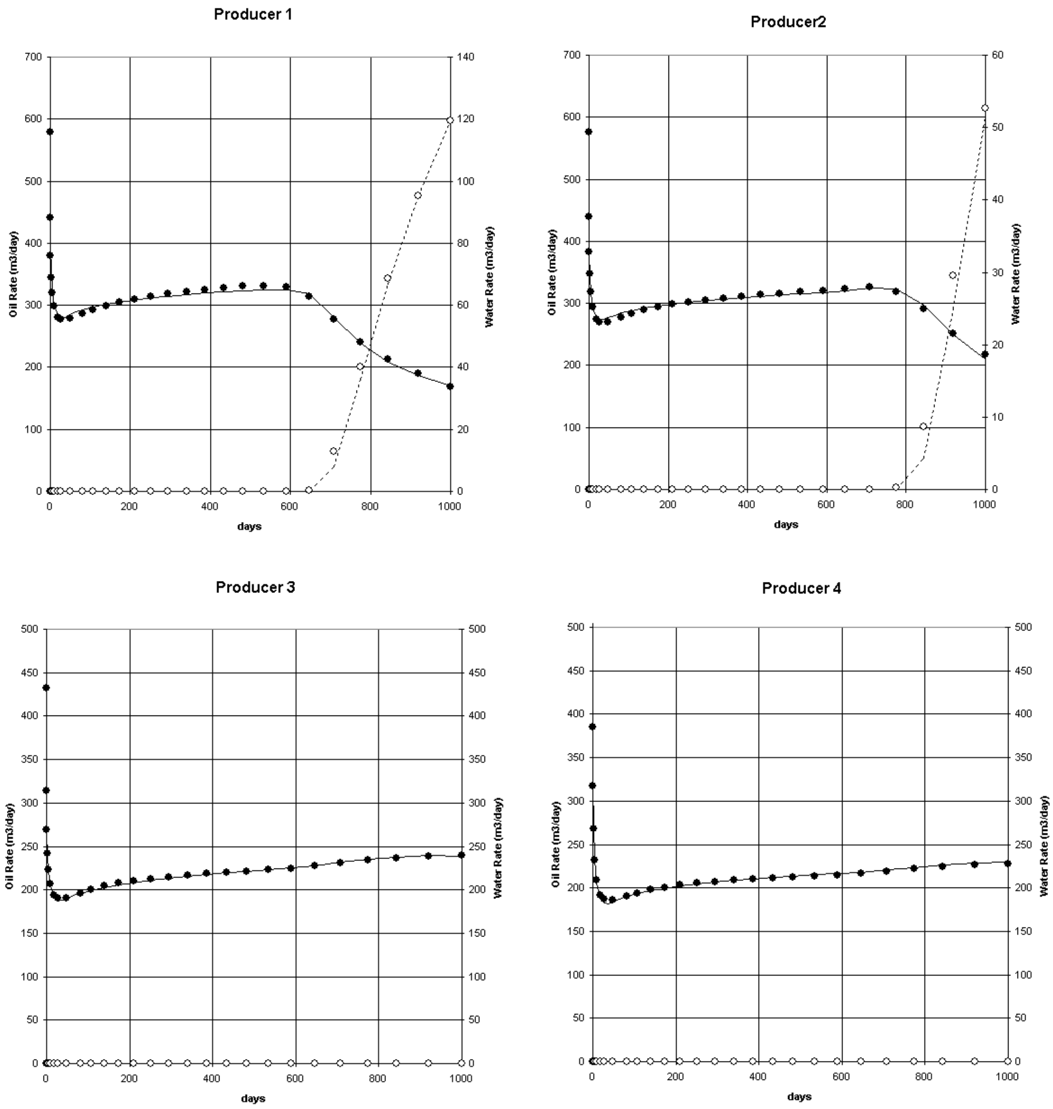

Figure 4 – Automatic History Match Results – dots are results from the reference field – lines are results from the adjusted image

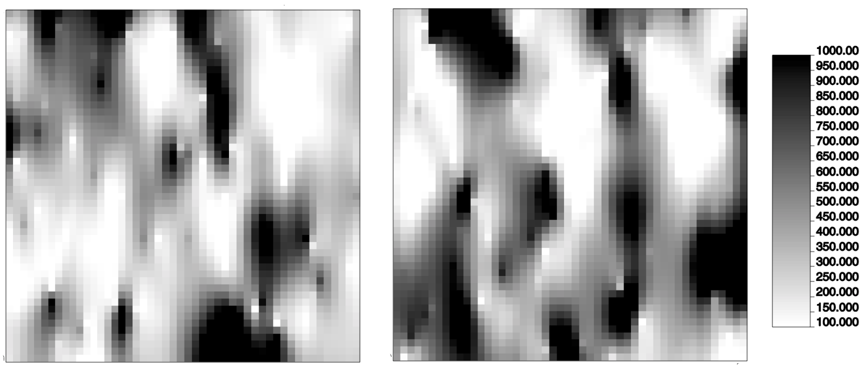

Figure 5 – Adjusted permeability field

Using the 200 pilot points of the fitted permeability field plus the original 10 values of permeability at the well locations as conditioning values, additional 10 realizations of the reservoir were generated using the SGSIM program. The number of tem realizations was a compromise between CPU time and a number enough to represent the variability of the permeability field. Figure 6 shows realization number 1. Using these realizations a waterflood was conducted and the results can be shown in Figure 7. In this figure, the black dots correspond to the results of the reference field, the thick solid line corresponds to the results of the fitted permeability field, and the thin solid lines corresponds to the results of the new realizations. Table 1 shows the average values of the objective functions for these simulations. Figure 7 and Table 1 indicates a great improvement over the results of the simulations that used the images generated considering only the information in the well blocks. The average value of the objective function decreased in 64% and the standard deviation also decreased substantially.

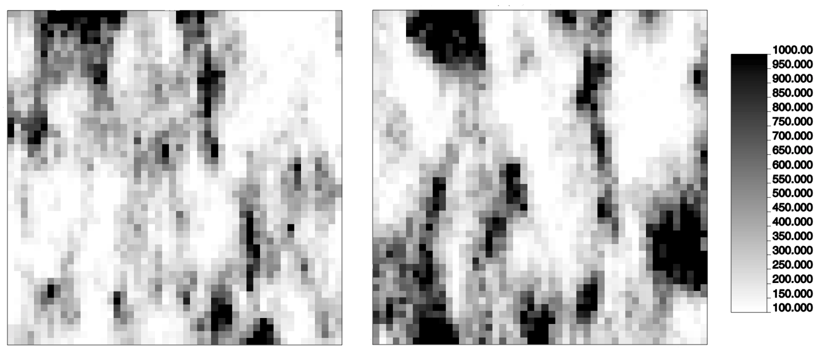

Figure 6 – Realization 1 generated with static and pilot points from the adjusted image

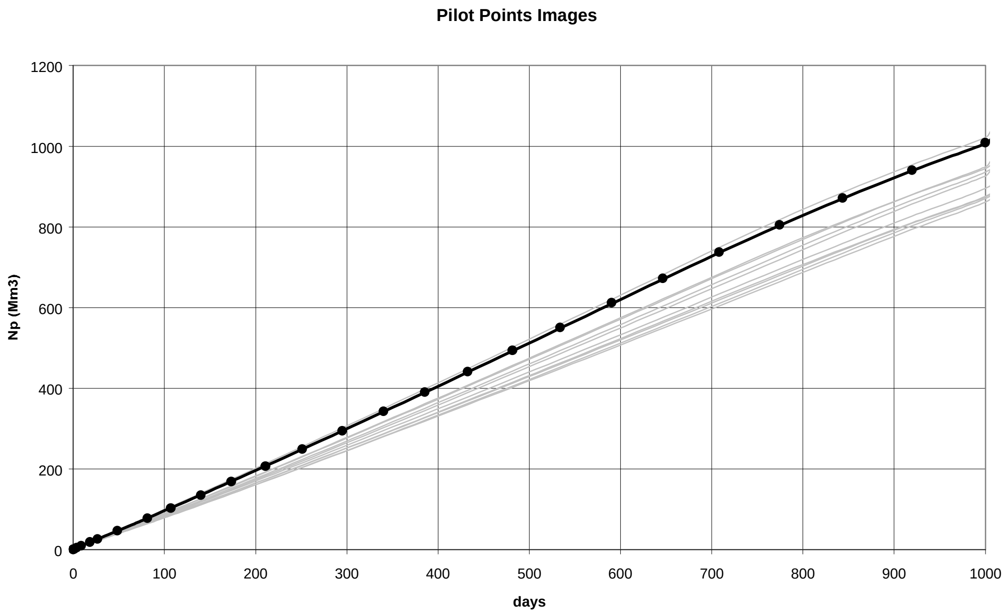

Figure 7 – Simulation Results for the Pilot Points Images (thin solid lines), Adjusted Image (thick solid line), and Reference Field (black dots)

3.2 Production Forecast

The next step in this study was to investigate the behavior of this methodology in the extrapolation period. To do this, four new production wells were drilled in a way to form a 9-spot pattern. The waterflood was continued for more 1000 days. This was done for the reference field, the fitted field, and for all images generated. Figure 8 shows the results for the images generated with static data, and Figure 9 shows the results for the images generated with data from the fitted permeability field. Table 2 shows the average value of the objective function for both methods for the extrapolation period.

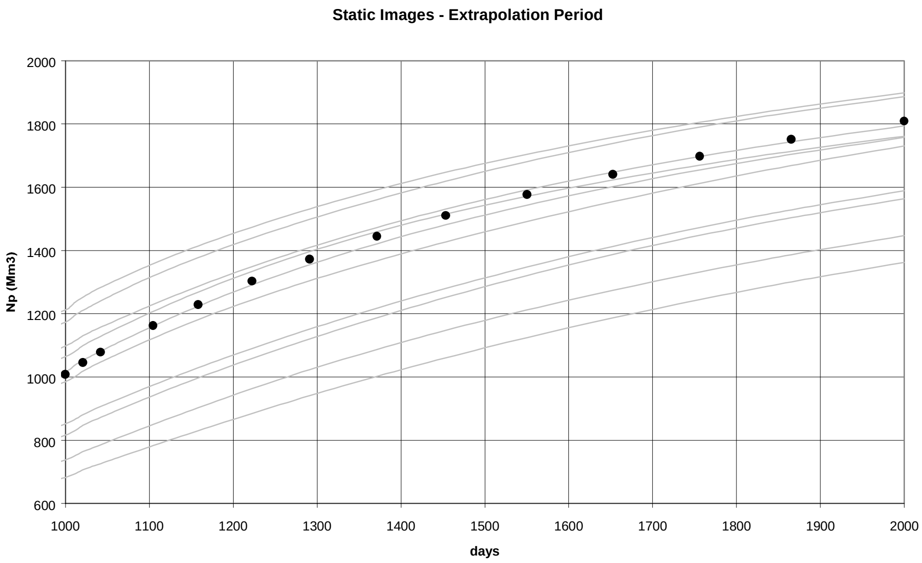

Figure 8 – Simulation Results for the Static Images (solid lines) and Reference Field (black dots) during the extrapolation period

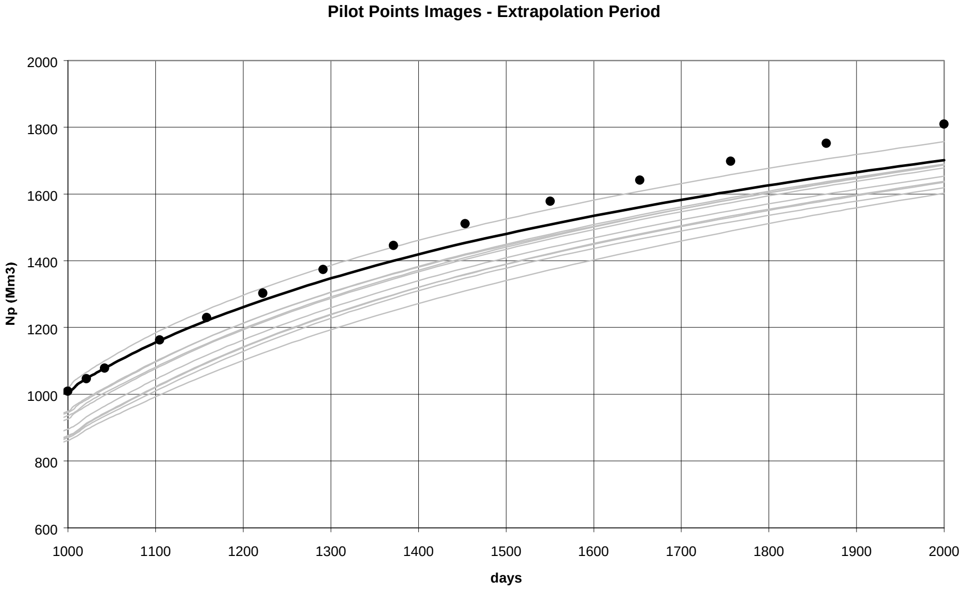

Figure 9 – Simulation Results for the Pilot Points Images (thin solid lines), Adjusted Image (thick solid line), and Reference Field (black dots) during the extrapolation period

Table 2 – Average objective function values points – extrapolation period.

Realization No.	Average	Standard Deviation
Geostatiscal Static Points	1954312.69	2836817.87
Proposed Methodology	1016033.37	946134.22

The results from the fitted image, that had a perfect match with the observed data in the production history period, diverged substantially from the results of the reference field in the extrapolation period. No matter which algorithm we used to obtain the history match this problem could occur anyway, because of the nature of the inverse problem. Therefore, this reinforces the necessity of a sampling algorithm to determine the uncertainty of the fitted permeability field.

Although there was an improvement in the results, Figure 9 puts into evidence a bias in the results that had already showed up in Figure 7. The bias in the results is also present in the results of the static images (Figures 3 and 8). That suggests that the problem is in the data shared by both sets of images, that is, the permeability values at the well blocks. In fact, the average and the standard deviation of the well block permeabilities, 281.4 mD and 260.4 mD respectively, have values that are much lower than the correspondents values of the reference field, 448.4 mD and 406.5 mD respectively. Table 3 shows the average and the standard deviation of the absolute permeabilities for all realizations. The table shows that both sets of images did not have a good estimate of true average permeability. The worse result in the estimation of the average by the images obtained with our method is consequence of the kriging that is used with pilot points technique. As a smoothing algorithm, kriging trims the upper and lower limits of the data set.

Definitely, the average and the standard deviation of the variable to be adjusted must be a matching parameter to enter in the history matching procedure. Doing this, certainly the results would improve even more.

Table 3 – Average field permeabilities for the realizations generated only with static points (Static Images) and those generated with static and pilot points from the adjusted model (Pilot Points Images).

	μ	σ
Static Images	**406.9**	**417.8**
Pilot Points Images	**383.13**	**362.2**

4. CONCLUSIONS

History matching procedures are inverse problems that normally admit several solutions. During the production history period the match between the observed data and model data is usually very good, but this is not necessarily true during the extrapolation period (production forecast). In this paper we used a realization provided by a history matching algorithm (simulated annealing) to serve as basis to generate several realizations of the reservoir. These images are used to assess the production uncertainty of the reservoir. The results of these images have much less dispersion around the observed data than results of images that were generated using only static data.

The bias observed in the results of the images, especially from the images generated with our technique, was due the wrong average provided by the static data (absolute permeabilities in well blocks). To eliminate this bias, the average and standard deviation of the permeability must be a matching parameter. We believe that this action will eliminate the bias while still keeping the good features of the method shown here.

The simulated annealing procedure proved to be easy to implement and very reliable but it has a slow convergence. The introduction of pilot points techniques in the simulated annealing algorithm allowed the reduction of the number of matching variables and the introduction of geological features in the matching procedure.

REFERENCES

Tarantola, A.: Inverse Problem Theory, Methods for Data Fitting and Model Parameters Estimation, Elsevier Science Publishers (1987) Amsterdam.

Landa, J. L. and Horne, R. N.: “A Procedure to Integrate Well Test Data, Reservoir Performance History and 4-D Seismic Information into a Reservoir Description,” paper SPE 38653 presented at the 1997 SPE Annual Technical Conference and Exhibition, San Antonio, TX, Oct 5-8.

He, N., Oliver, D. S., and Reynolds, A. C.: “Conditioning Stochastic Reservoir Models to Well-Test Data,” paper SPE 38655 presented at the 1997 SPE Annual Technical Conference and Exhibition, San Antonio, TX, Oct 5-8.

Rahon, D., Edoa, P. F., and Masmoudi, M.: “Inversion of Geological Shapes in Reservoir Engineering Using Well-Tests and History Matching of Production Data,” paper SPE 38656 presented at the 1997 SPE Annual Technical Conference and Exhibition, San Antonio, TX, Oct 5-8.

Ouenes, A., Bhagavan, S., Bunge, P. H., and Travis, B. J.: “Application of Simulated Annealing and Other Global Optimization Methods to Reservoir Description: Myths and Realities,” paper SPE 28415 presented at the 1994 SPE Annual Technical Conference and Exhibition, New Orleans, LA, Sep 25-28.

Bittencourt, A. C. and Horne, R. N.: “Reservoir Development and Design Optimization,” paper SPE 38895 presented at the 1997 SPE Annual Technical Conference and Exhibition, San Antonio, TX, Oct 5-8.

Deutsch, C. V. and Journel, A. G.: GSLIB Geostatistical Software Library and User´s Guide, 2n Edition, Oxford University Press, (1998) New York.

Fasanino, G., Molinard, J., and de Marsily, G.: “Inverse Modeling in Gas Reservoirs,” paper SPE 15592 presented at the 1986 SPE Annual Technical Conference and Exhibition, New Orleans, LA, Oct 5-8.

Wen, X., Gomez, J., Capilla, J., and Sahuquillo, A.: “Significance of Conditioning to Pieozometric Head Data for Predictions of Mass Transport in Groundwater Modeling,” Mathematical Geology (1996), Vol. 28, No. 7, 951-968.

Rama Rao, B. S., Venue, A. M. L., de Marsily, G., and Marietta, M. G.: “Pilot Point Methodology for Automated Calibration of an Ensemble of Conditionally Simulated Transmissivity Fields. 1. Theory and Computational Experiments,” Water Resources Research (1995), Vol. 31, No. 3, 475-493.

Roggero, F.: “Direct Selection of Stochastic Model Realizations Constrained to Historical Data,” paper SPE 38731 presented at the 1997 SPE Annual Technical Conference and Exhibition, San Antonio, TX, Oct 5-8.