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RESERVOIR HISTORY MATCHING USING A GEOSTATISTICAL METHODOLOGY: THE INFLUENCE OF DYNAMIC RESPONSE PARAMETERS

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Abstract. *This paper studies the effect of different observed dynamic parameters in a geostatistical history matching methodology. The methodology is based on Direct Sequential Simulation and Cosimulation for generating stochastic realizations of the static model. Direct Sequential Simulation and Cosimulation have the advantage of using continuous variables without any transformation and they are also capable of reproducing the variogram and histogram of sample data in the simulations. After that, flow simulations are performed to obtain the dynamic reservoir responses for each realization and an objective function is calculated to identify which one better fits dynamic data. Finally, an iterative process is done using the previous best realization as secondary information during Direct Sequential Cosimulation in order to obtain a matched realization. In this work, a comparison between the use of production group and production wells data is presented. Moreover, a study using different dynamic parameters in the objective function was done and the different reductions of objective function provided by each one are shown.*

Keywords: *Geostatistics, History matching, Reservoir characterization, Direct sequential simulation and cosimulation, Stochastic simulation*

1. INTRODUCTION

The prediction of an oil reservoir behavior is an extremely important activity performed during different moments of reservoir life cycle. It's necessary to investigate if all investment related to oil production will be valuable and profitable.

In order to achieve a proper characterization of a reservoir model, a complete study not only of the petrophysical parameters (static model) but also the properties related to the fluid flow (dynamic model) is necessary. History Matching techniques are commonly applied for integrating static and dynamic data. However, as mentioned by Caeiro et al. (2015), this integration is not trivial due to the fact that the distribution of petrophysical parameters is often non-stationary and its relation with the fluid flow is highly non-linear.

After oil production begins, history matching techniques are normally applied to exploitation planning: it uses inverse problem theory in order to determine the petrophysical model that generates the observed dynamic response. As Olivier and Chen (2010) said, history matching is an inverse problem that can be seen as finding a vector of reservoir model variables $\boldsymbol{m}$ that is the solution of Eq. (1), where $\boldsymbol{d}_{obs}$ is the observed data and *g( )* is the forward model.

$$g(\boldsymbol{m}) = \boldsymbol{d}_{obs} \tag{1}$$

This paper aims to apply and explore new possibilities of an iterative history matching process proposed by Mata-Lima (2008). The iterative process consists of a sequential perturbation of the permeability field and the analysis of its dynamic response, with the objective of getting as close as possible to the observed oil production data.

The perturbation methodology used by Mata-Lima (2008) is based on Direct Sequential Simulation (DSS) and Cosimulation, a geostatistical simulation method proposed by Soares (2001). A sequential simulation is considered direct if it's not necessary to perform any transformation of the original variable. Direct sequential simulation was initially applied only for simulation of categorical variables, for example, in Soares (1998).

The development of direct sequential simulation for continuous variables started with Journel (1994), he presented a methodology able to reproduce the spatial covariance model of the original variable. However, his method wasn't capable of reproducing the histogram. Some years later, Soares (2001) proposed a new approach of Direct Sequential Simulation (DSS) and Cosimulation, capable of reproducing not only the variogram (and consequently, the covariance) but also the histogram of a continuous variable. His approach also has a great advantage that's the basis for Mata-Lima's (2008) work: it can generate cosimulations without any transformation of the original variables too.

Mata-Lima (2008) algorithm consists in an iterative process of cosimulations of reservoir parameters (permeability field) aiming to minimize the difference between the observed and simulated responses. The algorithm uses Direct Sequential Cosimulation to integrate as secondary information the best permeability field found in the previous iteration and this procedure is repeated until a certain preset decrease in the mismatch between observed and simulated data is reached.

2. ITERATIVE DIRECT SEQUENTIAL COSIMULATION

The methodology applied in this work is strongly based in Mata-Lima (2008) and corresponds to the history matching with global perturbation:

Step 1. Obtain the reference oil production data. In this paper, as a synthetic reservoir is used, this data is obtained by running a deterministic flow simulator with the reference permeability field. The simulator used for all oil reservoir simulations in this paper was IMEX, from CMG (2016).

Step 2. Use DSS (Soares, 2001) to obtain a set of stochastic realizations of reservoir permeability field. During this research, the Geostatistics and Geosciences Modeling Software (GEOMS2) from CERENA (2013) was used as a geostatistical tool to perform Direct Sequential Simulation and Cosimulation.

Step 3. Run the deterministic flow simulator in order to obtain the dynamic reservoir responses for each permeability field.

Step 4. Verify the difference between the responses of simulated permeability fields (obtained in step 3) and reference production data (obtained in step 1). To quantify this difference, an objective function (OF) is calculated and the objective of history matching is to minimize its value. In this work, the sum of squared residuals is used as OF, as shown in Eq. (2):

$$OF = min \sum_t \sum_w (R_w^{ref}(t) - R_w^s(t))^2 \qquad (2)$$

where $R_w^{ref}(t)$ is the reference response in the well w at time *t* and $R_w^s(t)$ is the response of a simulated permeability field in the well w at time *t*. The OF is calculated for all simulations and it is the criterion to select the best realization.

Step 5. The best realization is used as secondary information for generating a new set of stochastic realizations by Direct Sequential Cosimulation (Soares, 2001). In Mata-Lima (2008), three different global perturbation algorithms are presented as possibilities for this integration.

The iterative process consists in repeating steps 3, 4 and 5 until desirable stop criteria be achieved.

2.1 Global perturbation

Direct Sequential Cosimulation using global perturbation implies that the whole permeability field is affected by the same correlation coefficient by secondary information. In this work, all three global perturbation algorithms presented by Mata-Lima (2008) were implemented in order to verify their convergence when dealing with different parameters.

Single cosimulation. The best realization is used as secondary information with one global correlation coefficient by iteration. This coefficient grows in each iteration due to the fact that the simulated permeability field is getting closer to the reference and consequently the influence of secondary information should be bigger. For this case, when the OF doesn't decrease in a new iteration, the iteration is repeated with a higher coefficient.

Multiple cosimulation. The best realization is used as secondary information with multiple global correlation coefficients by iteration. In this case, there are more possibilities to obtain a lower OF value, however the computational effort is clearly higher than using single cosimulation.

Image combination and cosimulation. In this algorithm, two images are linearly combined in order to generate new images that are used as secondary information in cosimulations. For each two images, ten secondary images are created according to Eq. (3):

$$A_{i+1} = rA_0 + (1-r)A_i \text{ , with } r = [0, 0.1, 0.2, \ldots, 0.9] \quad (3)$$

where *r* is a weighting factor and A_i is the image used in iteration *i*. A_0 and A_1 are chosen from the first set of realizations (step 2) and they are combined in iteration *i*=1 to generate 10 different A_2. During all iterations, A_0 does not change and it is combined with the previous best image. Particularly for iteration 1, A_0 and A_1 are defined as the best and worst realizations of DSS (step 2). The cosimulations are performed with a single and high correlation coefficient and each one generates only one realization. In fact, Mata-Lima (2008) proposed the cosimulation only to assure the spatial pattern of secondary images.

3. CASE STUDY

3.1 Egg model

To verify the behavior of the presented algorithm, a synthetic reservoir model called Egg Model is used. The Egg Model parameters used in this work correspond to the standard version proposed by Jansen et al. (2014). The necessary files to run this model in IMEX simulator were provided by Wellano (2016).

The model is composed by 7 layers, each one with 60 x 60 blocks, in a total of 25.200 blocks. However, only 18.553 blocks are active. Grid-blocks have a length of 8m, width of 8m and height of 4m. There's no aquifer and no gas cap in the model, consequently injection wells are necessary to provide oil production and they are distributed all along the reservoir. In this way, the model has a total of 12 wells (8 injection wells and 4 production wells) and all of them are completed in all 7 layers.

The stochastic model has a set of 100 realizations of the permeability field. The reservoir has low permeability, except for some channels of high permeability. In this work, one of the realizations is taken as reference and its dynamic response data is the target of history matching process. The chosen realization is shown in Fig. 1. From the remaining 99 realizations, a new permeability field was created by calculating the average permeability in

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each block. This new permeability field (Fig. 2) was used to extract the samples used as hard data for the geostatistics simulation algorithms.

The samples positions are exactly the same as the 12 wells and as they are completed in the 7 layers, the considered set has 84 samples. The histogram of the set and its statistic information obtained in GEOMS2 (CERENA, 2013) is available in Fig.3.

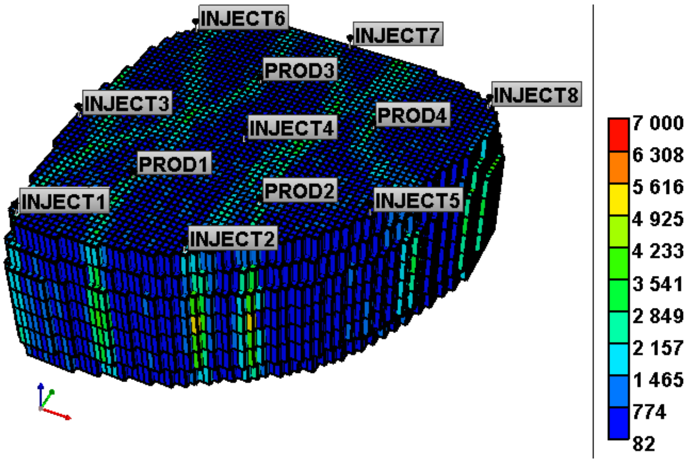


Figure 1. Permeability (md) - Egg Model realization selected as reference

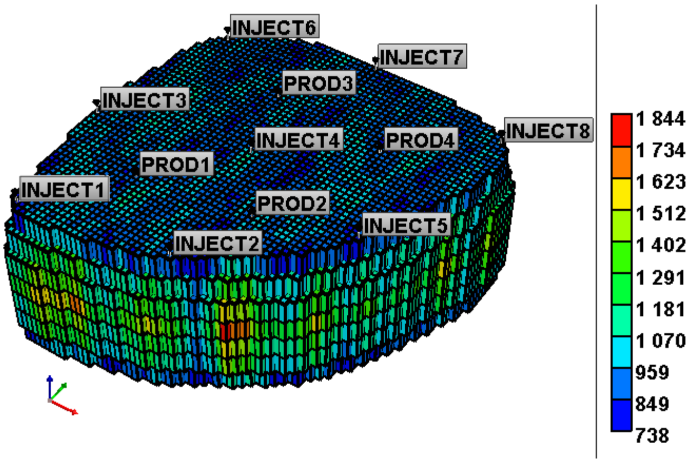


Figure 2. Permeability (md) - Egg Model used to extract samples

3.2 History matching strategies: production group and sum of production wells

An assumption proposed by Mata-Lima (2008) for the application of global perturbation algorithm is that the objective function is calculated for only one producing well.

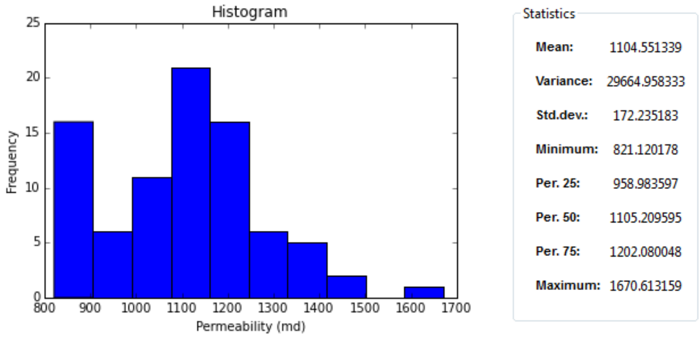


Figure 3. Samples histogram and statistics

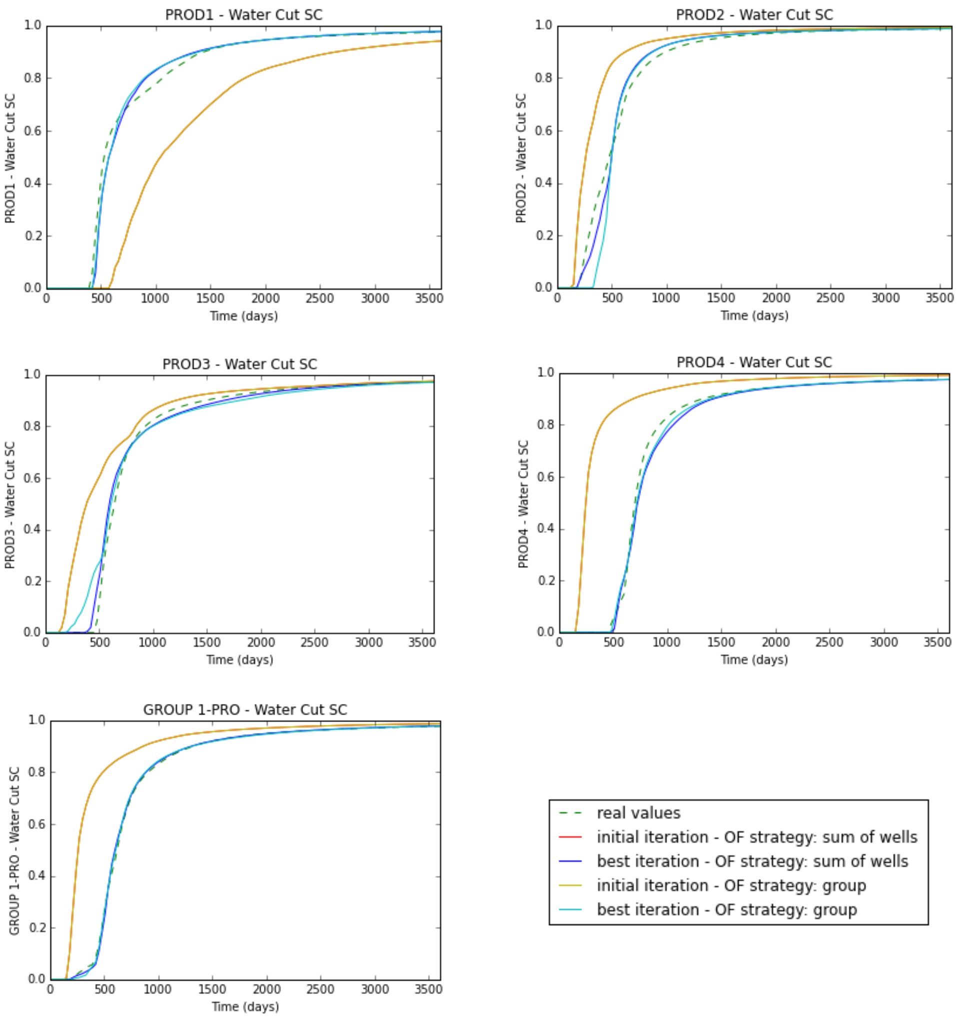


Figure 4. History matching for production wells and production group

In this work, the global algorithm is applied to Egg Model (a reservoir with 4 producing wells) and two alternative approaches are presented and compared. The first one is to treat all producing wells as only one well, it means that production data represents the production group and OF is calculated for the whole group. The second approach is to consider the information of each well separately, calculate individual OF and sum them. In this case, the data used represents production wells.

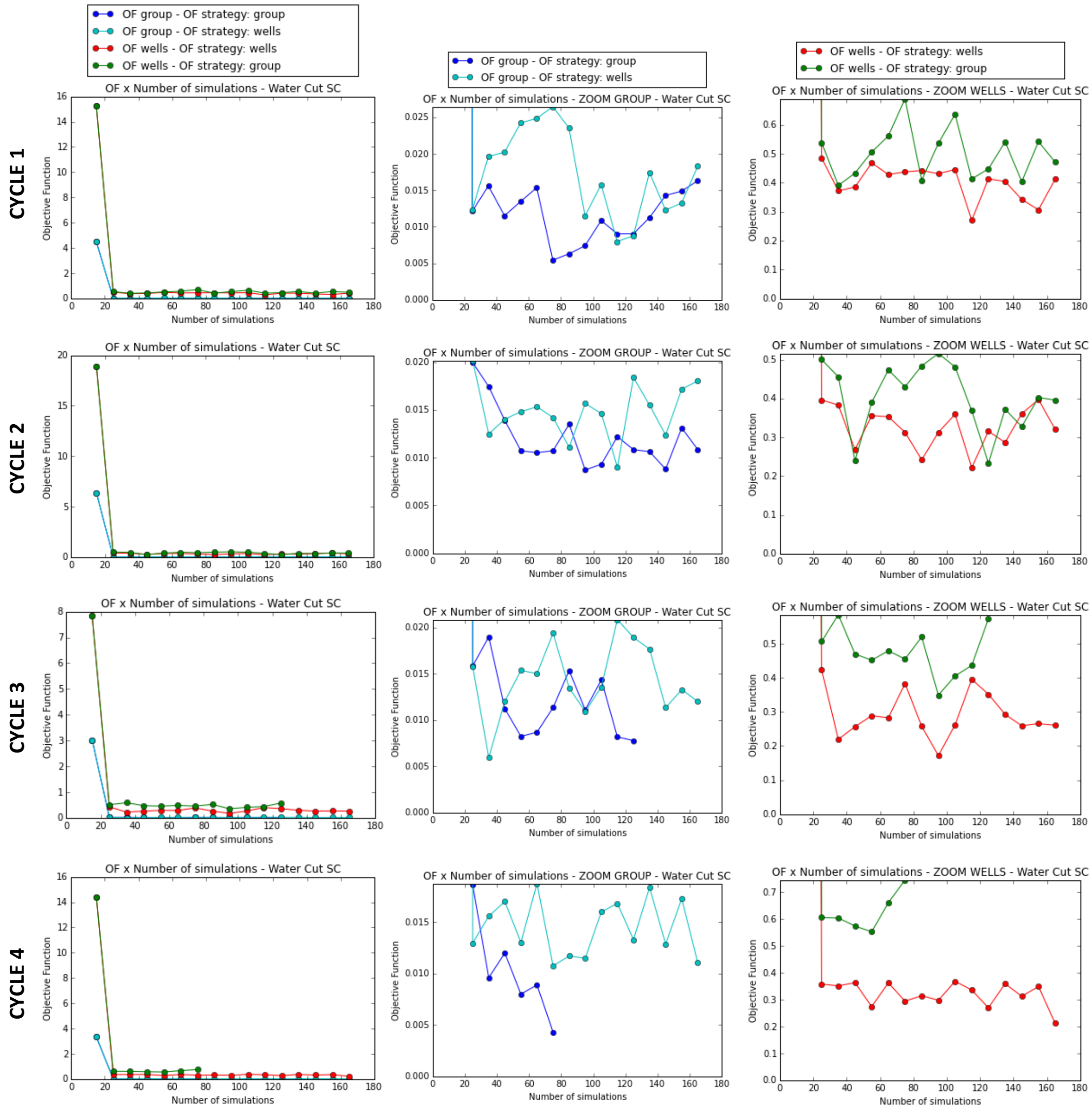


Figure 5. OF evolution x Number of simulations - Independent cycles of History Matching

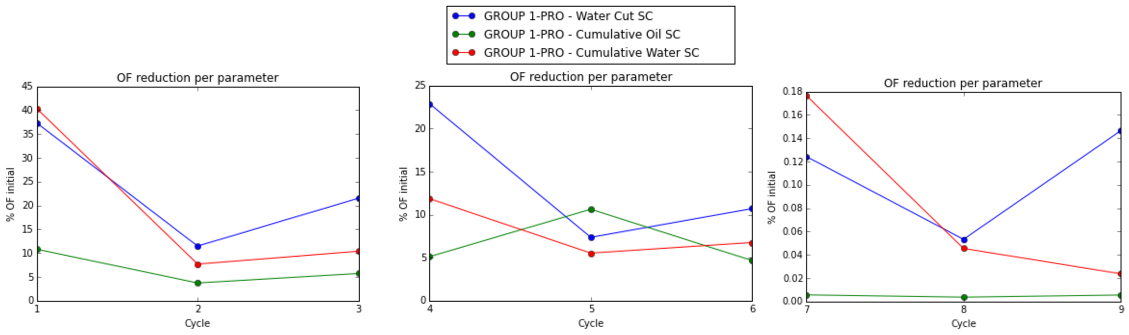
For this study, the perturbation is made by image combination and cosimulation and the production parameter minimized is the Water Cut SC. The history matching was made with the first 750 days of simulation. The initial and matched realizations were later compared for a total of 3600 days. The initial DSS generates 15 realizations and each cosimulation iteration generates 10 realizations. For this comparison, both strategies were applied for the same initial 15 realizations of DSS.

For both approaches, the results were satisfactory: in Fig. 4 the initial and matched realizations achieved by both strategies are shown for production wells and production group. This experiment was made 4 times (4 independent cycles) and the OF values for production group and production wells considering both strategies are in Fig. 5. Using both strategies, the OF values for Water Cut SC of production group (Fig. 5, second column) are lower than Water Cut SC by sum of wells (Fig. 5, third column) – and that was expected because in production group data the wells tend to compensate each other. Figure 5 also shows that most of the time the production group OF is lower when the iterative process strategy is based on production group. The same happens to the wells OF: it’s lower when the iterative process strategy is based on production wells.

3.3 History matching strategies: different dynamic parameters

In order to compare how well different dynamic parameters are matched during history matching, three different parameters were selected to be used in OF: Water Cut SC, Cumulative Oil SC and Cumulative Water SC. All three global perturbation algorithms were tested and the iterative process was made using production group data.

Three independent cycles per algorithm were performed, in a total of 9 cycles. In each cycle, the same initial set (generated by DSS) is used for history matching based on different dynamic parameters. The history matching was made with the first 750 days of simulation. The initial and matched realizations were later compared for a total of 3600 days. The ratios between matched and initial realization OF (calculated for 750 days) are shown in Fig. 6.



(a) Single cosimulation (b) Multiple cosimulation (c) Image combination and cosimulation

Figure 6. Percentual of OF in matched realization over initial realization

In single cosimulation case, initial DSS generates 3 realizations and each cosimulation generates 15 realizations. The history matching process is repeated for a maximum of 8 cosimulation iterations. This algorithm is flexible and allows new cosimulations with higher correlation coefficients when OF increases between two iterations, in this work a maximum of 3 different correlation coefficients per iteration is fixed. The History Matching and OF evolution achieved in cycle 2 are presented in Fig. 7 and Fig. 8.

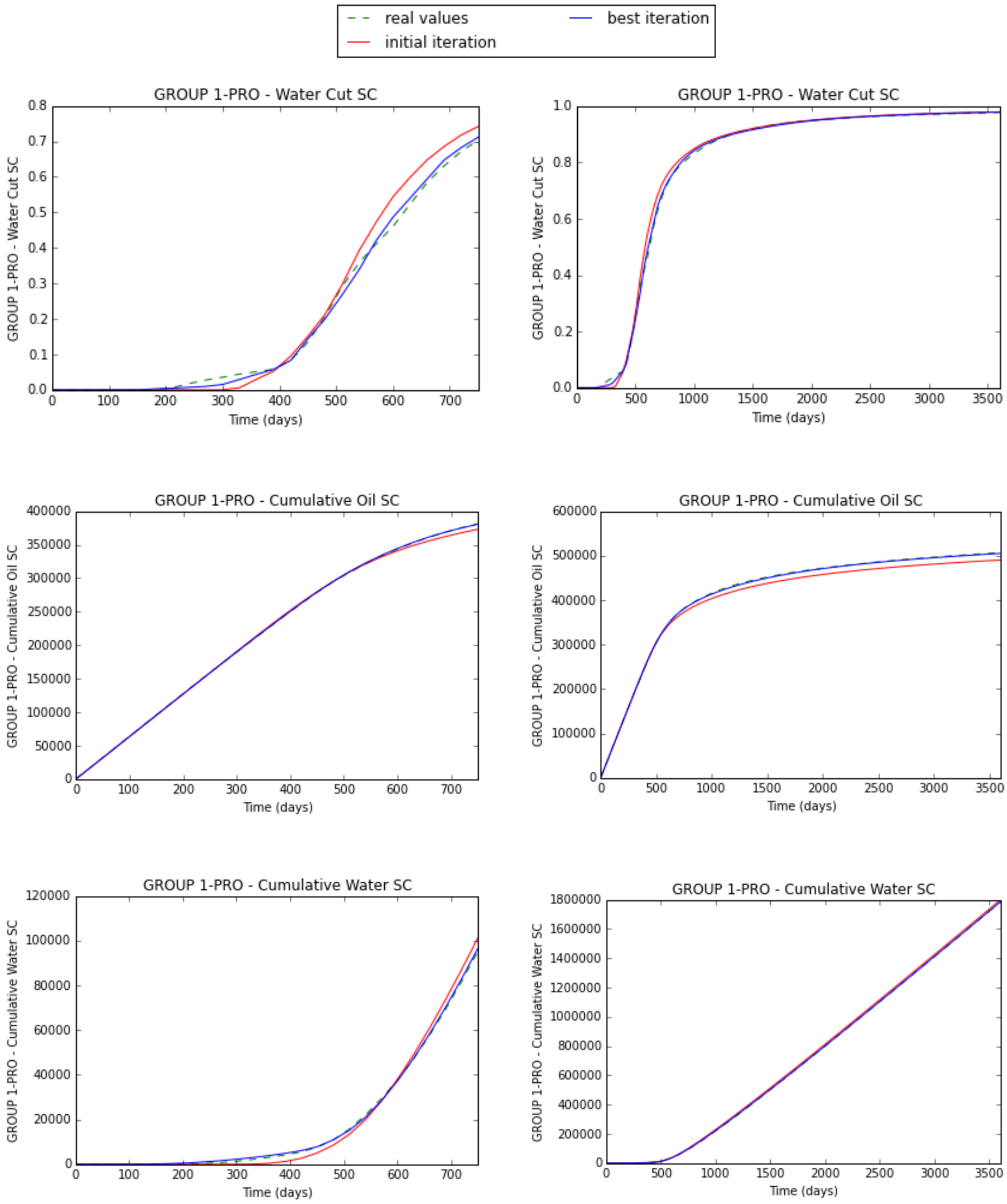


Figure 7. Single cosimulation – History matching: Water Cut SC, Cumulative Oil SC (m^3) and Cumulative Water SC (m^3) – Cycle 2

In multiple cosimulation case, initial DSS generates 3 realizations. Nine correlation coefficients are used to perform cosimulations: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8 and 0.9. For each coefficient, 5 realizations are generated, totalizing 45 realizations. The history matching process is repeated for a maximum of 5 cosimulation iterations or if OF increases more than the specified tolerance (100% over the previous OF). The History Matching and OF evolution achieved in cycle 6 are presented in Fig. 9 and Fig. 10.

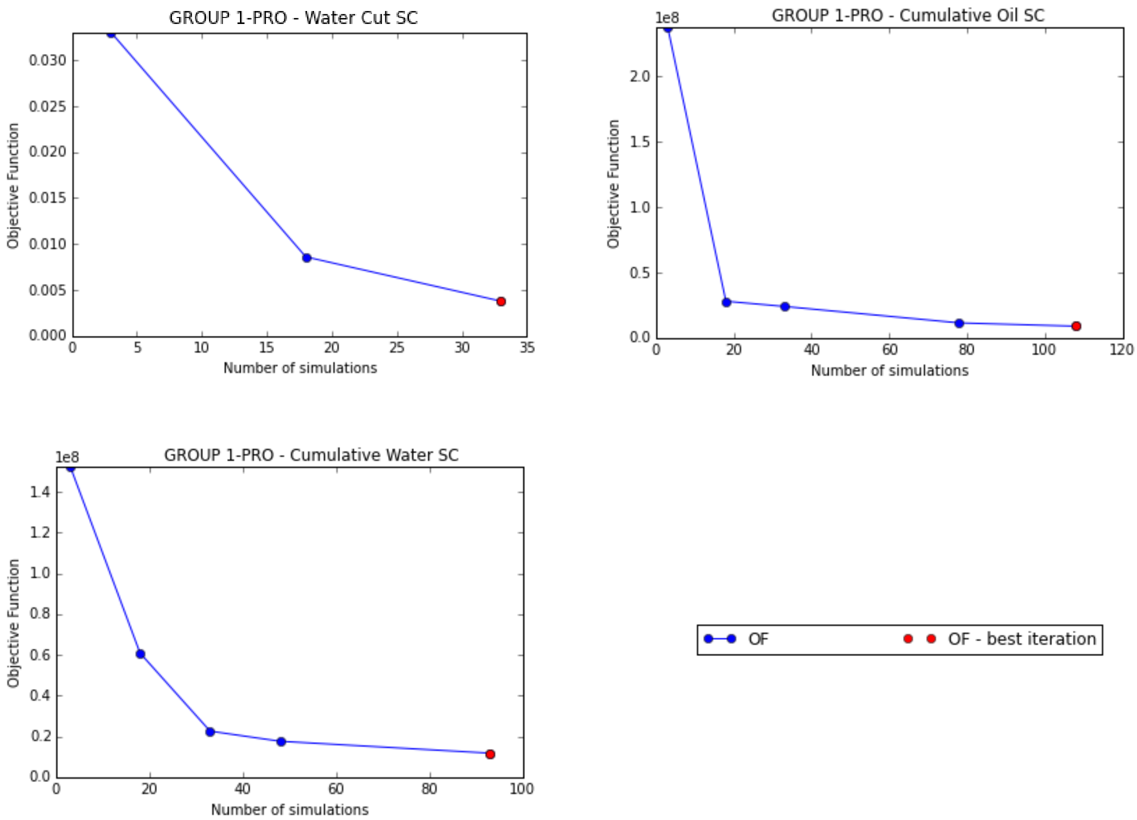


Figure 8. Single cosimulation – OF evolution – Cycle 2

In image combination and cosimulation case, initial DSS generates 15 realizations and each cosimulation generates 10 realizations. The history matching process is repeated for a maximum of 10 cosimulation iterations or if OF increases more than the specified tolerance (100% over the previous OF). The History Matching and OF evolution achieved in cycle 9 are presented in Fig. 11 and Fig. 12.

For each dynamic parameter, the OF evolution x Number of simulations for all 9 cycles are available in Fig. 13.

Figure 6 indicates that for all three algorithms most of the time the parameter that best succeeded in OF minimization process was the Cumulative Oil SC. The second and third best matches were for parameters Cumulative Water SC and Water Cut SC, respectively. As can be seen in Fig. 13, the good reduction obtained by Cumulative Oil SC was achieved after 50 to 115 simulations. Cumulative Water SC parameter needed no more than 100 simulations (except for one cycle) and Water Cut SC no more than 150 simulations to present a considerable OF reduction.

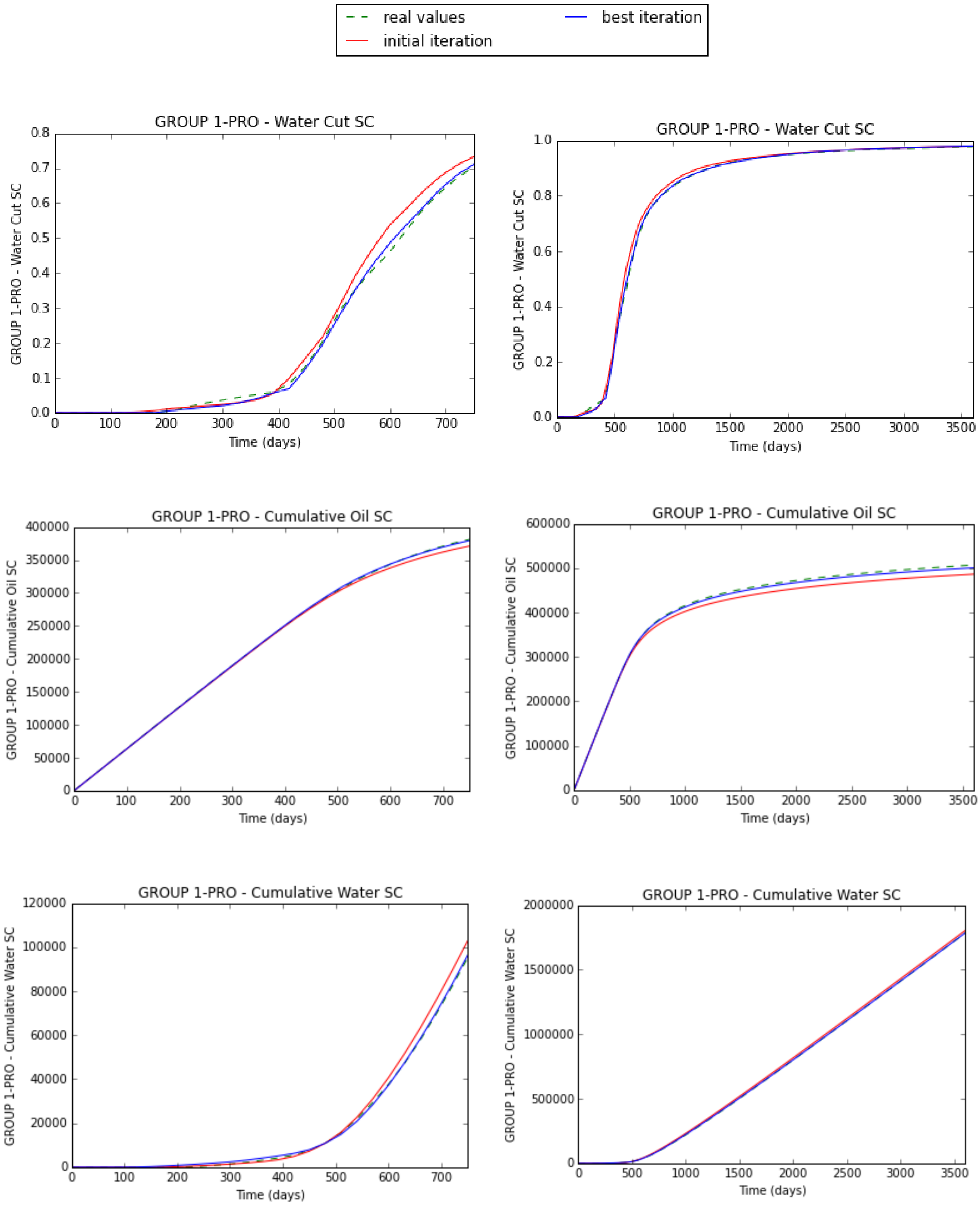


Figure 9. Multiple cosimulation – History matching: Water Cut SC, Cumulative Oil SC (m^3) and Cumulative Water SC (m^3) – Cycle 6

The OF reduction obtained by Image combination and cosimulation (Fig. 6c) is higher than the other algorithms. This is partially explained by the fact that initial realization in this algorithm is not the best DSS realization, according to Mata-Lima (2008) it is the most distant one. According to his analysis, among the global algorithms presented, Image combination and cosimulation is the fastest one. Figures 7, 9 and 10 show how distant from real values the initial realization (provided by DSS) is. In this work, a low number (three) of DSS realizations was used in Single cosimulation and Multiple cosimulation in order to make more visible the cosimulation convergence.

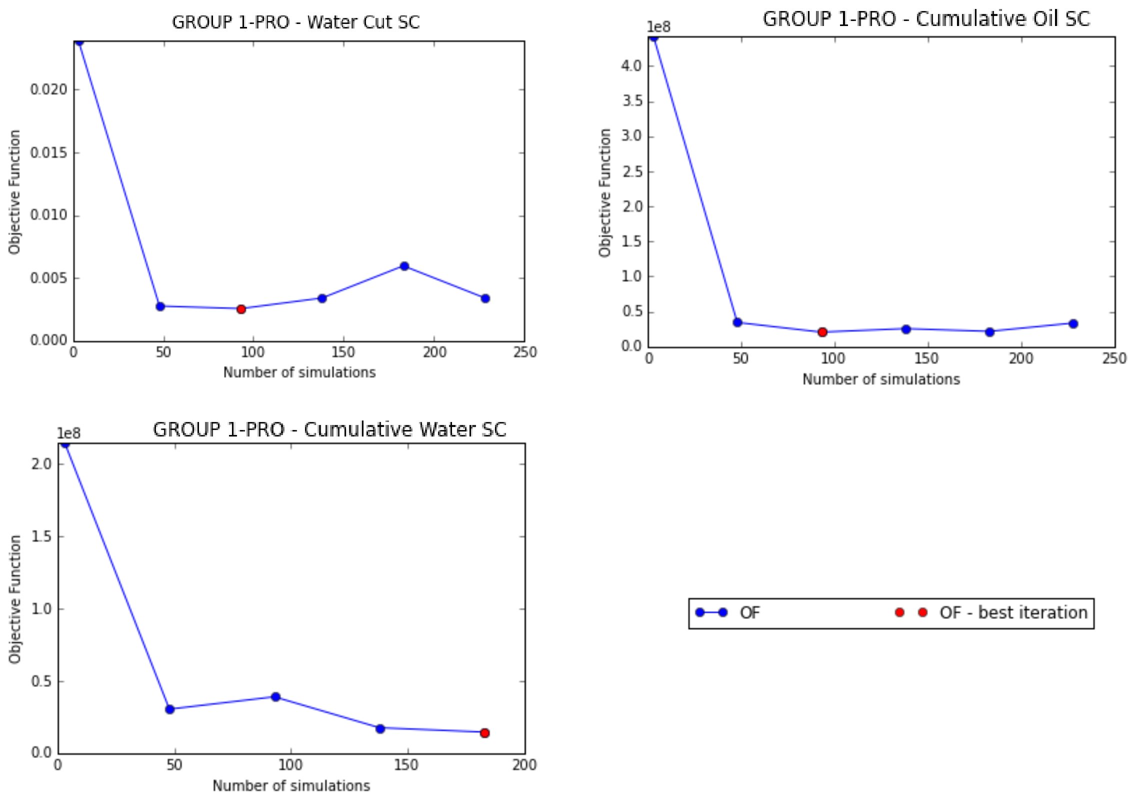


Figure 10. Multiple cosimulation – OF evolution – Cycle 6

4. CONCLUSIONS

The iterative direct sequential cosimulation algorithms proposed by Mata-Lima (2008) using global perturbation were successfully applied to Egg Model and led to satisfactory results.

Two alternative approaches for OF calculation in global algorithms were presented: using production data from production group as if it was only one producing well or use the sum of all production wells. Both were tested in Egg Model and in most cases the strategy used to calculate OF led to lower results of that parameter than the other strategy. It means that production group OF is lower when the iterative process strategy is based on production group and the sum of production wells OF is lower when using production wells information. Therefore, in the studied situation, even with the knowledge of each well production data, if the major interest is the study of the whole reservoir, better history matching results are usually achieved when using global information (production group data).

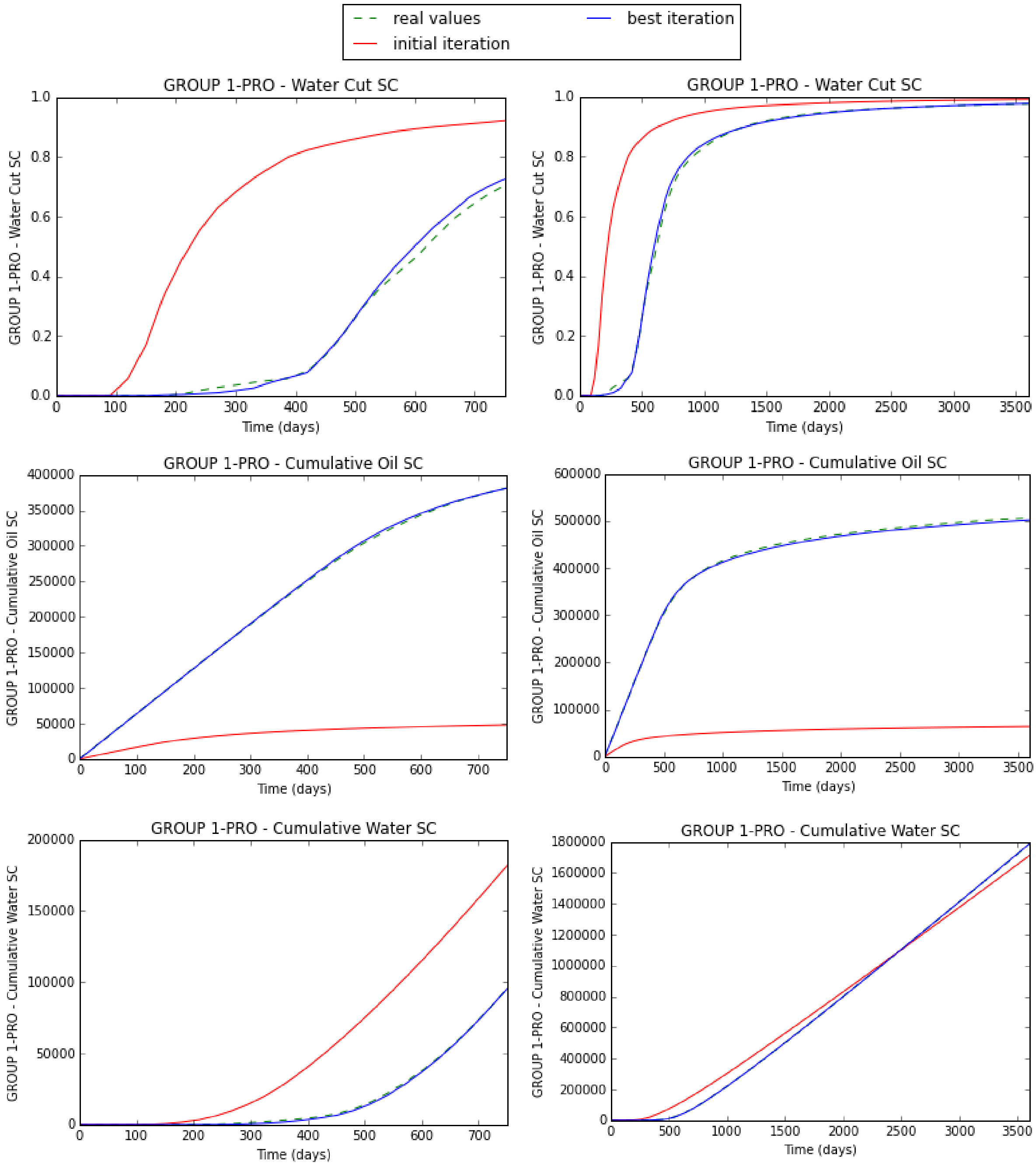


Figure 11. Image combination and cosimulation – History matching: Water Cut SC, Cumulative Oil SC (m^3) and Cumulative Water SC (m^3) – Cycle 9

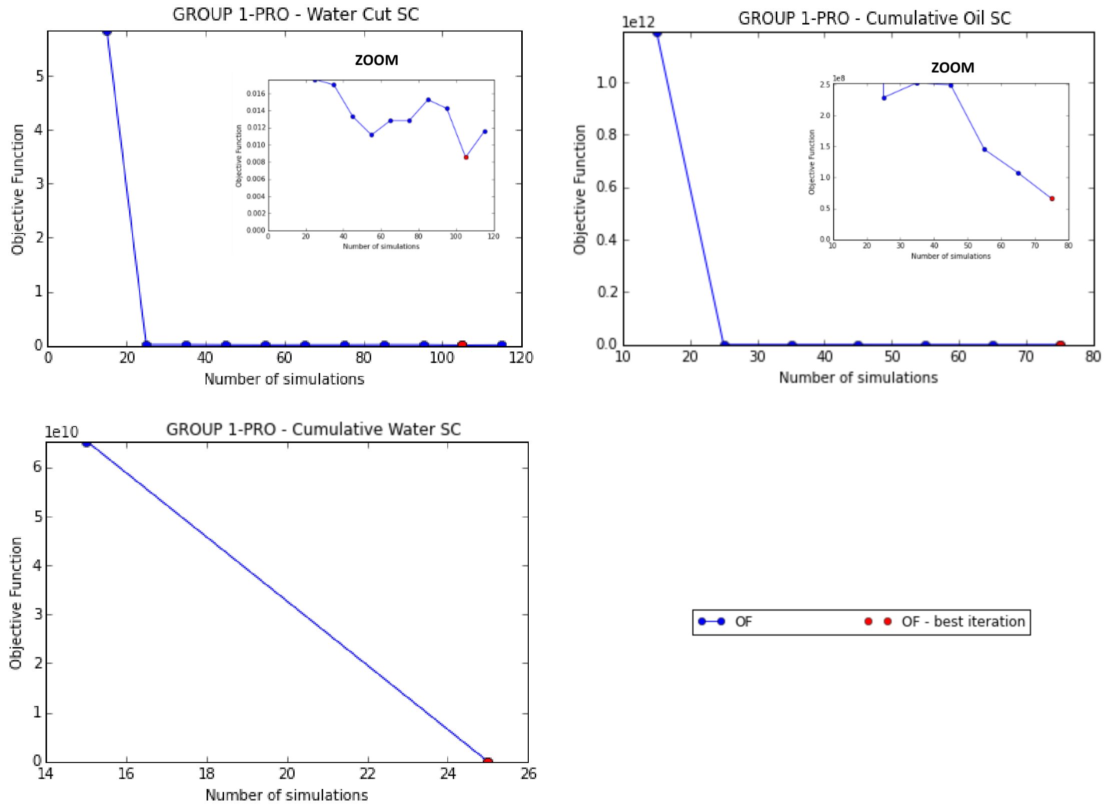


Figure 12. Image combination and cosimulation – OF evolution – Cycle 9

Additionally, a study of different dynamic parameters in OF calculation was done with the following information: Water Cut SC, Cumulative Oil SC and Cumulative Water SC. When the OF was calculated employing Cumulative Oil SC, it presented the highest reduction for all global algorithms in most times.

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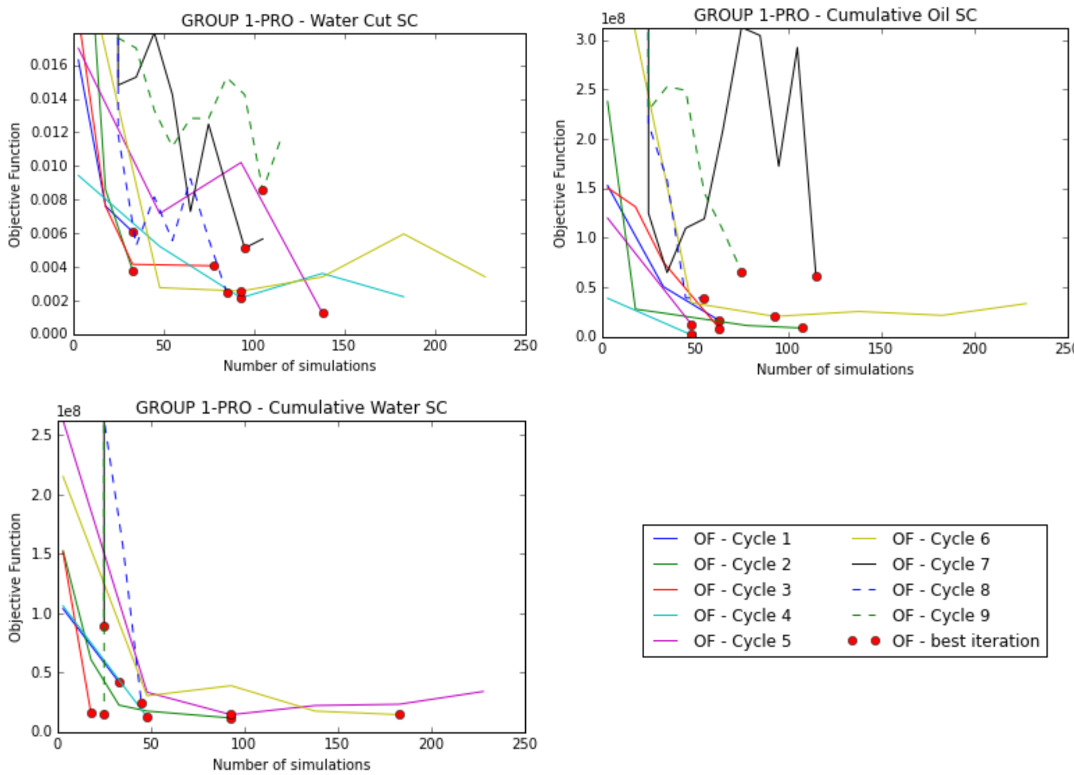

Figure 13. OF evolution x Number of simulations