Assisted History-Matching for Fractured Reservoirs Characterization and Recovery Optimization using Connectivity Analysis*

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Abstract

It is estimated that 60% of the world's proven reserves reside in carbonate reservoirs for conventional oil, and that 90% of these reservoirs are fractured (Pabian-Goyheneche, 2010). Fractures usually affect the production behavior and final recovery. The increasing number of mature fields where fractures caused unexpected production features gave rise to extensive efforts in better characterizing and integrating fracture properties in field-scale flow simulation models, for a correct production assessment and optimization (Cosentino, 2001). Specific workflow and tools have been developed for fractured reservoir characterization in the past years (Bourbiaux et al., 2002). In this workflow, (a) geologically-realistic models of the fault and fracture network are constructed from seismic, well and outcrop data (Cacas et al., 2001), (b) the flow properties of these models are then characterized from dynamic field information (e.g. well tests, production data...) (Sarda et al., 2001), (c) an equivalent simulation model applicable at reservoir scale is constructed thanks to appropriate flow up-scaling procedures (Bourbiaux et al., 1998; Sarda, et al., 1997), and (d) multiphase field production is simulated at reservoir scale with this equivalent model (Sabathier, 1998). Using this workflow, reservoir-scale flow simulation models remain interpretable in geological terms, thus facilitating the understanding of the possible reservoir behaviors.

However the characterization of the flow properties of the geological fault/fracture network model, occurring in step (b), remains critical (Lange, 2009). Indeed it requires inferring highly uncertain properties such as fracture length and/or fracture conductivity

distribution from dynamic tests data, thus requiring accurate flow models directly applicable on geologically-realistic, e.g. multiscale fracture models. The associated computational cost limits the characterization to be performed through the calibration of local dynamic tests (flowmeters, well tests…), thus imposing a characterization strategy depending on fracture scale: (i) first the flow properties of multi-scale fracture networks are estimated from accurate flow models, but from local dynamic tests, then (ii) large-scale fractures, i.e. that cannot be homogenized at reservoir-cell scale, are characterized from reservoir-scale production history simulations, that involve appropriate upscaled flow models with an explicit fault representation. Various inversion methodologies have been proposed for the local characterization of multiscale fracture networks from local flow data (Lange, 2009; Bruyelle and Lange, 2009; Lange and Bruyelle, 2011). This article presents an inversion methodology adapted to large-scale fault networks, i.e. seismic and sub-seismic faults, via production history matching.

Model from History-Matching

The characterization via history-matching of sub-seismic fault networks, i.e. faults below the seismic resolution, is a particularly challenging task because: (i) large uncertainties have to be accounted for in their properties (spatial distribution, geometry and permeability), requiring stochastic modeling, (ii) the reservoir flow dynamics are usually very sensitive to each fault network realization, and (iii) the history-matching requires many costly reservoir simulations to be performed. A specific fault model and optimization workflow were developed to characterize seismic and sub-seismic fault networks from history-matching (Verscheure et al., 2010). This model and the workflow are presented, then connectivity analysis applications on a synthetic fractured reservoir model illustrate how this connectivity information provides a mean to characterize and classify fault network realizations. Other applications illustrate that correlations may be found between the water breakthrough time and the injector-producer connectivity, thus allowing one to identify the most probable fault network realizations to match the observed water breakthrough time. Finally, for a given fault network realization, it is shown how the oil recovery can be optimized by correlating injectors rates with the injector-producer connectivity.

Since sub-seismic fractures cannot be observed from the seismic data, some assumptions are usually made regarding their properties. The fractal concept provides a convenient tool for modeling realistic fault network distribution via a few number of parameters. Although the validity of this concept for describing natural fracture systems is still investigated, it has been proven very useful for describing some complex natural fault systems (Aviles et al., 1987; Cacas et al., 2001). Fractal behavior has been observed on many field outcrops, and can be proved using geomechanical theories under simplifying assumptions, even if such behaviour is not universal (Verscheure et al., 2010). The fractal fault model considered in this paper has been developed by Verscheure et al., 2010. It has been designed specifically to facilitate the fault characterization via history-matching, using the gradual deformation approach (Hu, 2000; Hu and Jenni, 2005).

However, two major difficulties remain to be overcome. First, the optimization workflow is an iterative process that requires starting from an initial fault model. This initial estimate has a strong impact on the effectiveness of the optimization, i.e. the convergence rate of the iterative process. For instance, if the initial estimate is too far from a satisfactory solution, the optimization algorithm may converge very slowly towards the targeted solution, thus requiring a lot of costly reservoir simulations. Moreover, the iterative deformation of the fault network realizations usually result in noisy objective functions to optimize, thus strongly impacting the optimizer convergence rate. It is proposed to facilitate the history-matching process by analyzing the connectivity properties of the fault network. The connectivity properties analysis aimed at: (1) classifying the fault network realizations according to their connectivity properties, so that the objective function noise may be reduced by considering specific classes of interest, and (2) correlating the connectivity properties with production data to identify the most probable realizations that match the production data, thus facilitating the history-matching.

Example

Considering a five-spot well configuration involving one injector and four producers, as depicted on Figure 1, the graph distances from the injector are computed for different fault network realizations. An example of graph distance distribution is plotted on Figure 1. The gradual deformation of the sub-seismic fault model was performed at the level of the fault positions and fault length distribution, thus disturbing the connectivity properties between the wells. Reservoir fluid flow simulations were performed for each step of the gradual deformation. The water breakthrough times for all producers were recorded and plotted as a function of the injector-producer graph distance on Figure 3. The breakthrough times distribution for all producers show a clear correlation with the graph distance. As expected, the breakthrough time increases as the injector-producer distance increases. Given measured breakthrough times, this correlation can be used to identify fault network realizations such that the computed injector-producer graph distances reproduce the measured breakthrough times according to the correlation trend. This allows one to estimate the fault network realizations that are the most probable to match the measured breakthrough times.

Considering a five-spot well configuration involving four injectors and one producer, the graph distances from the producer are computed for a given fault network realization, as depicted on Figure 4. The simulated water saturation map at breakthrough time is also depicted on Figure 4, to illustrate the strong similarity between the graph distance and the water saturation distributions. This indicates that the sweepage efficiency of the injectors may be estimated from the graph distance distribution for this case. Note that all injection rates are identical, equal to 6000 sm^3/day, and the production rate has been set to 24,000 sm^3/day. It is proposed to investigate whether modifying the injection rates according to the producer-injector graph distance could improve the sweepage efficiency, i.e. the oil recovery. The oil rate is depicted in Figure 5, for the initial case where all injection rates are identical (sim 1), and for the controlled case where the injection rates were modified (sim 2) as a function of the injector-producer graph distance. It is observed that the oil production increased considerably, with a total gain of 3.25 million cubic meters of oil at the end of the simulation time. Note that the water breakthrough time has been delayed by about 16 years. Therefore the oil recovery could be increased by improving the sweepage efficiency based on the analysis of the graph distances between the wells.

Conclusion

The proposed methodology and tools facilitate the history-matching of fractured reservoir, such that consistent reservoir models with production data can be found, and used for production forecast and optimization.

References

Aviles, C.A., C.H. Scholz, and J. Boatwright, 1987, Fractal analysis applied to characteristic segments of the San Andreas fault: Journal of Geophysical Research, v. 92, p.331-344.

Beicip-Franlab, 2008, FracaFlow Training Guide: Member Case, February.

Bourbiaux, B., M.C. Cacas, S. Sarda, and J.C. Sabathier, 1998, A Rapid and Efficient Methodology to Convert Fractured Reservoir Images into a Dual-Porosity Model: Revue de l'Institut Français du Pétrole, v. 53/6, p. 785-799.

Bourbiaux, B., R. Basquet, M.C. Cacas, J.M. Daniel, and S. Sarda, 2002, An Integrated Workflow to Account for Multi-Scale Fractures in Reservoir Simulation Models: Implementation and Benefits: SPE 78489, 14 p.

Bruyelle, J., and A. Lange, 2009, Automated Characterization of Fracture Conductivities from Well Tests Inversion: SPE 121172, 15 p.

Cacas, M.C., J.M. Daniel, and J. Letouzey, 2001, Nested Geological Modeling of Naturally Fractured Reservoirs: Petroleum Geoscience, v. 7, p. 43-52.

Cosentino, L., Y. Coury, J.M. Daniel, E. Manceau, C. Ravenne, P. Van Lingen, J. Cole, and M. Sengul, 2001, Integrated Study of a Fractured Middle East Reservoir with Stratiform Super-K Intervals – Part 2: Upscaling and Dual Media Simulation: SPE 68184, 13 p

Diestel, R., 2000, Graph Theory: Graduate Texts in Mathematics, v. 173, Springer, Berlin.

Dijkstra, E.W., 1959, A Note on Two Problems in Connection with Graphs: Numerische Mathematik, v. 1, p. 269-271.

Hu, L.Y., 2000, Gradual deformation and iterative calibration of Gaussian-related stochastic models: Mathematical Geology, v. 32/1, p. 87-108.

Hu, L.Y., and S. Jenni, 2005, History matching of object-based stochastic reservoir models: SPE Journal, v. 10/3, p. 312-323.

Lange, A., R. Basquet, and B. Bourbiaux, 2004, Hydraulic Characterization of Faults and Fractures Using a Dual Medium Discrete Fracture Network Simulator: SPE 88675, 10 p.

Lange, A., 2009, Assisted History-Matching for the Characterization of Fractured Reservoirs: AAPG Bulletin, v. 93/11, p. 1609-1620.

Lange, A., and J. Bruyelle, 2011, A Multimode Inversion Methodology for the Characterization of Fractured Reservoirs from Well Test Data: SPE 143518, 14 p.

Lantuejoul, C., 2002, Geostatistical Simulation - Models and Algorithms: Springer-Verlag, Berlin, Heidelberg, New York, 256 p.

Pabian-Goyheneche, C., 2010, Réservoirs Carbonatés: Caractérisation, Production et Grands Enjeux: presented at the Journées Annuelles des Hydrocarbures, Paris, France, 13-14 October. Web accessed 05 December 2012.

Sabathier, J.C., B. Bourbiaux, M.C. Cacas, and S. Sarda, 1998, A New Approach of Fractured Reservoirs: SPE 39825, 11 p.

Sarda, S., B. Bourbiaux, M.C. Cacas, and J.C. Sabathier, 1997, An Innovative Procedure to Compute Equivalent Block Size in a Dual-Porosity Model: presented at the 9th European Improved Oil Recovery Symposium, The Hague, The Netherlands, Oct. 20-22.

Sarda, S., L. Jeannin, R. Basquet, and B. Bourbiaux, 2001, Hydraulic Characterization of Fractured Reservoirs: Simulation on Discrete Fracture Models: SPE 66398, 12 p.

Verscheure, M., 2010, Inversion Conjointe des Propriétés Géométriques et Hydrodynamiques d'un Réservoir Fracturé: PhD Thesis, Ecole des Mines de Paris – IFP Energies nouvelles.

Verscheure, M., A. Fourno, and J.P. Chilès, 2010, History Matching of a Realistic Stochastic Fault Model: SPE 129759, 10 p.

Verscheure, M., A. Fourno, and J.P. Chilès, 2010, History Matching of a Realistic Stochastic Sub-Seismic Fault Model: SPE 129759, 10 p.

Warren, J.E., and P.J. Root, 1963, The Behavior of Naturally Fractured Reservoirs: SPE Journal, v. J3, p. 245-255.

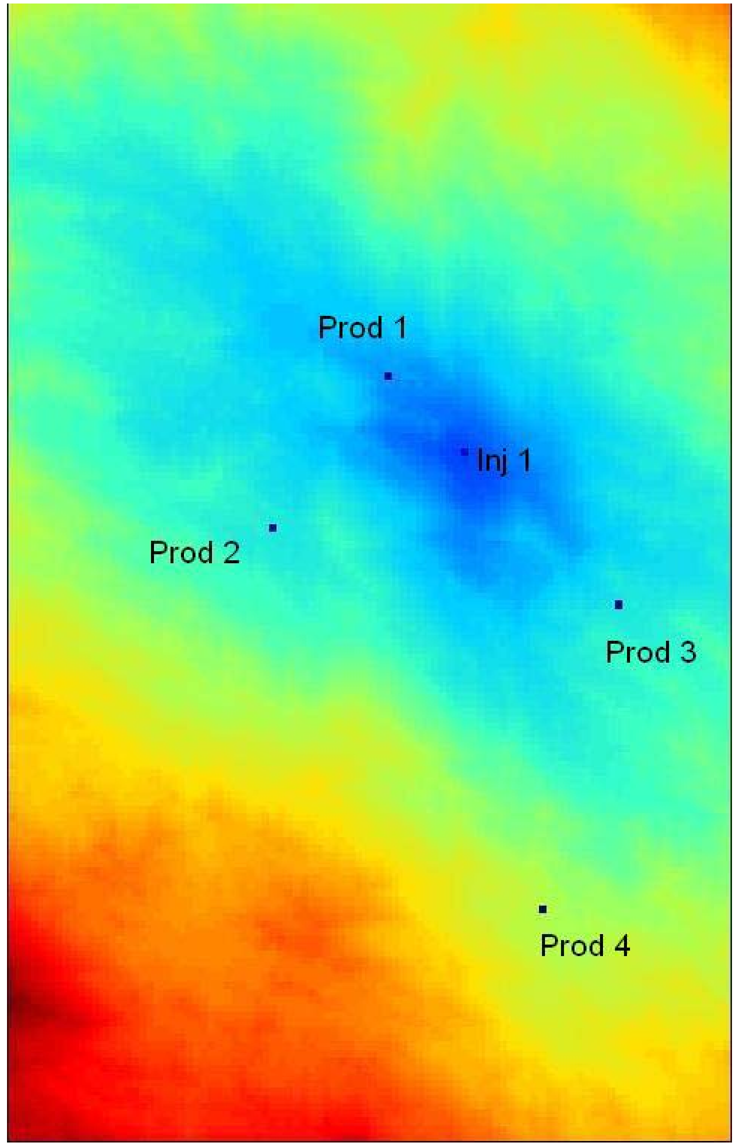

Figure 1. Case 1 - Graph distance distribution from injector 1, five-spot without fault barrier.

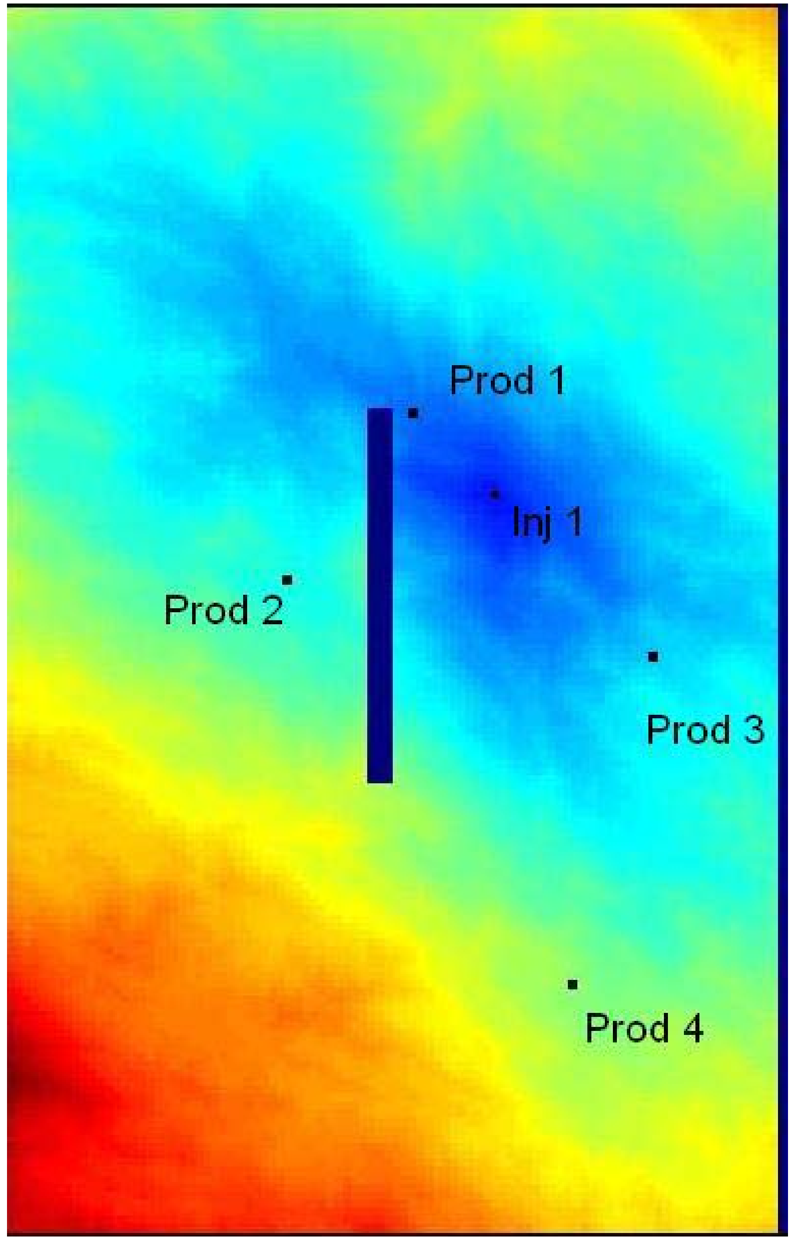

Figure 2. Case 2 - Graph distance distribution from injector 1, five-spot with fault barrier.

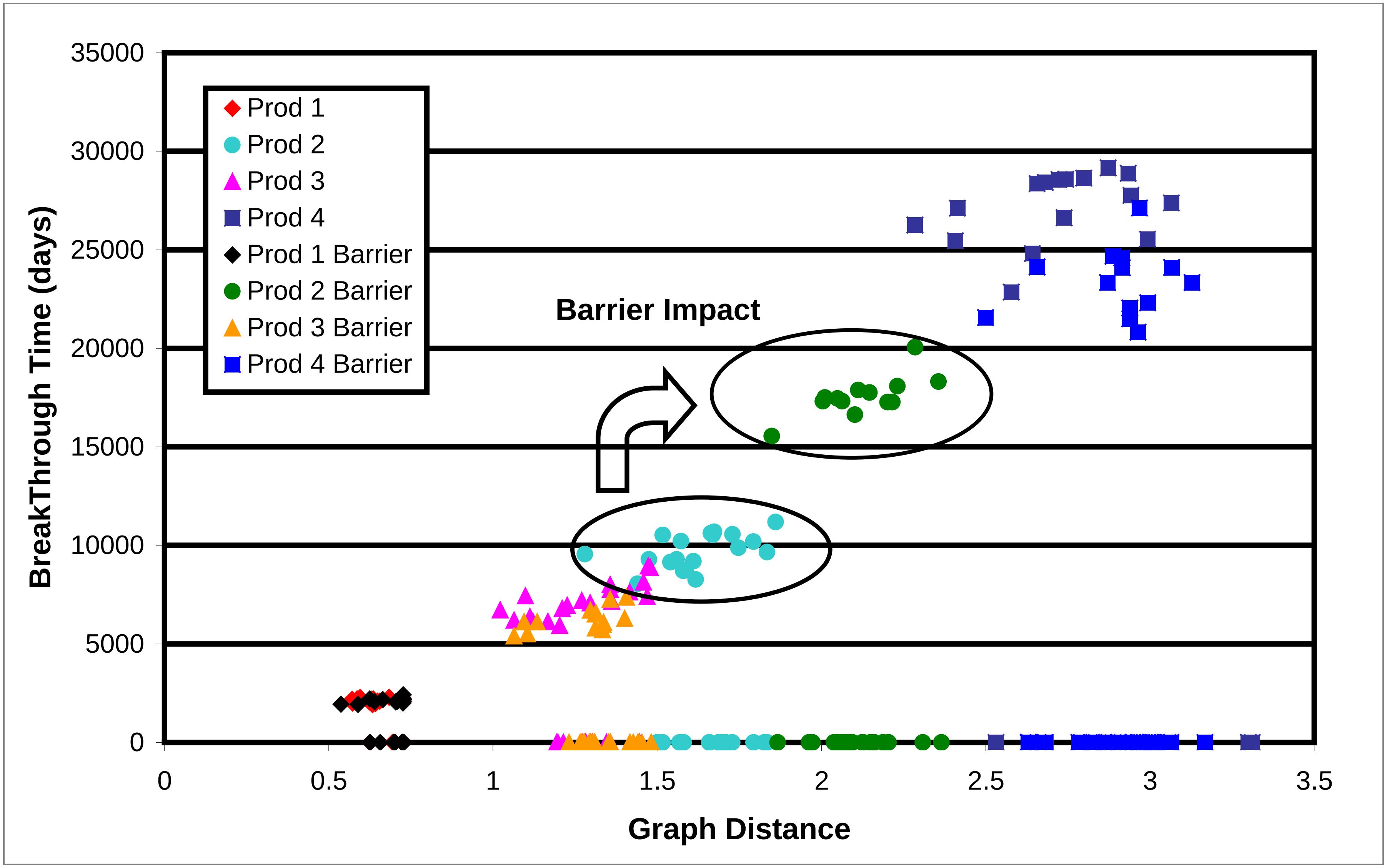

Figure 3. Breakthrough time versus injector-producer graph distance: Case 1 (without fault barrier), and Case 2 (with fault barrier).

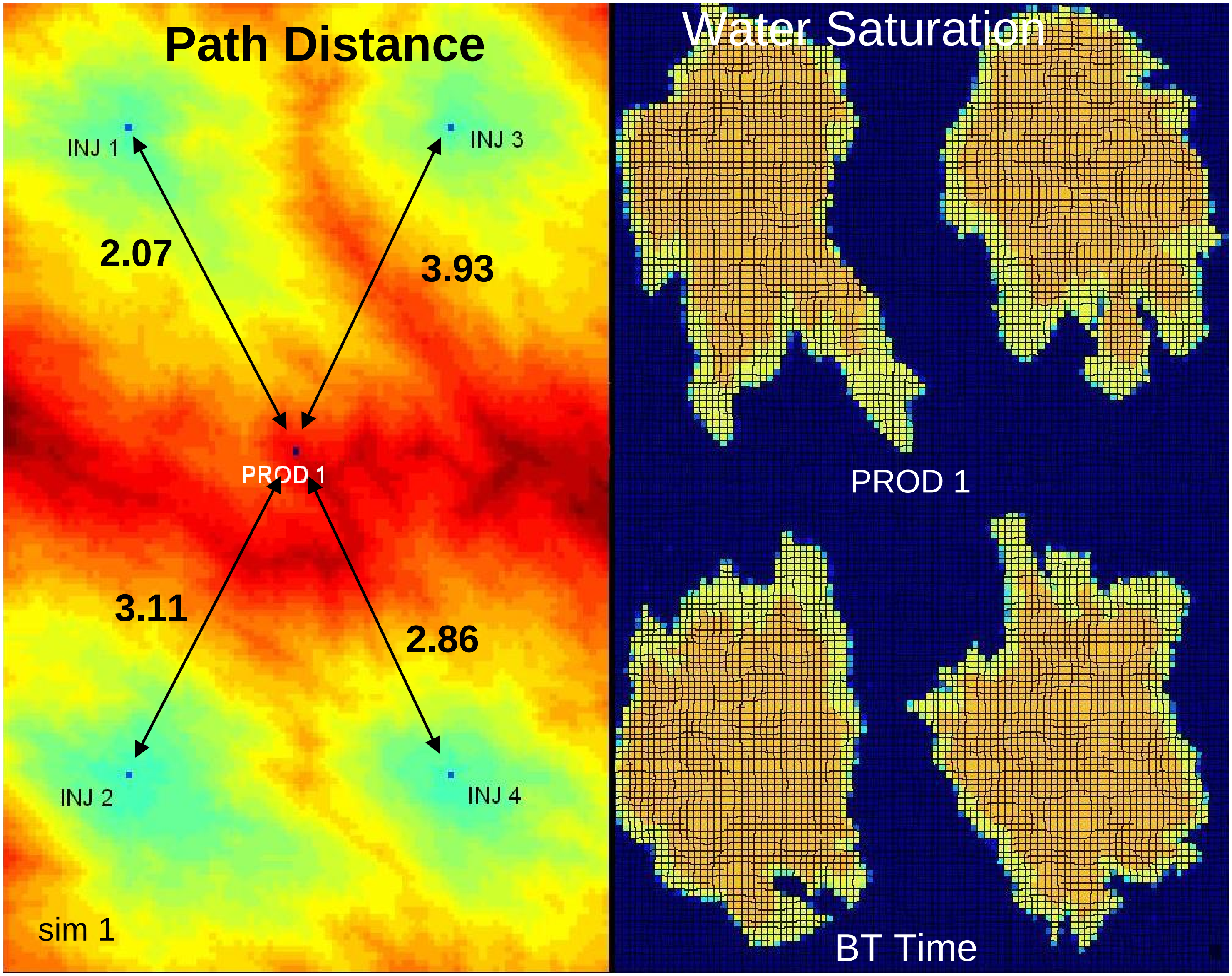

Figure 4. Graph distances between wells (left). Water saturation map at breakthrough time (right).

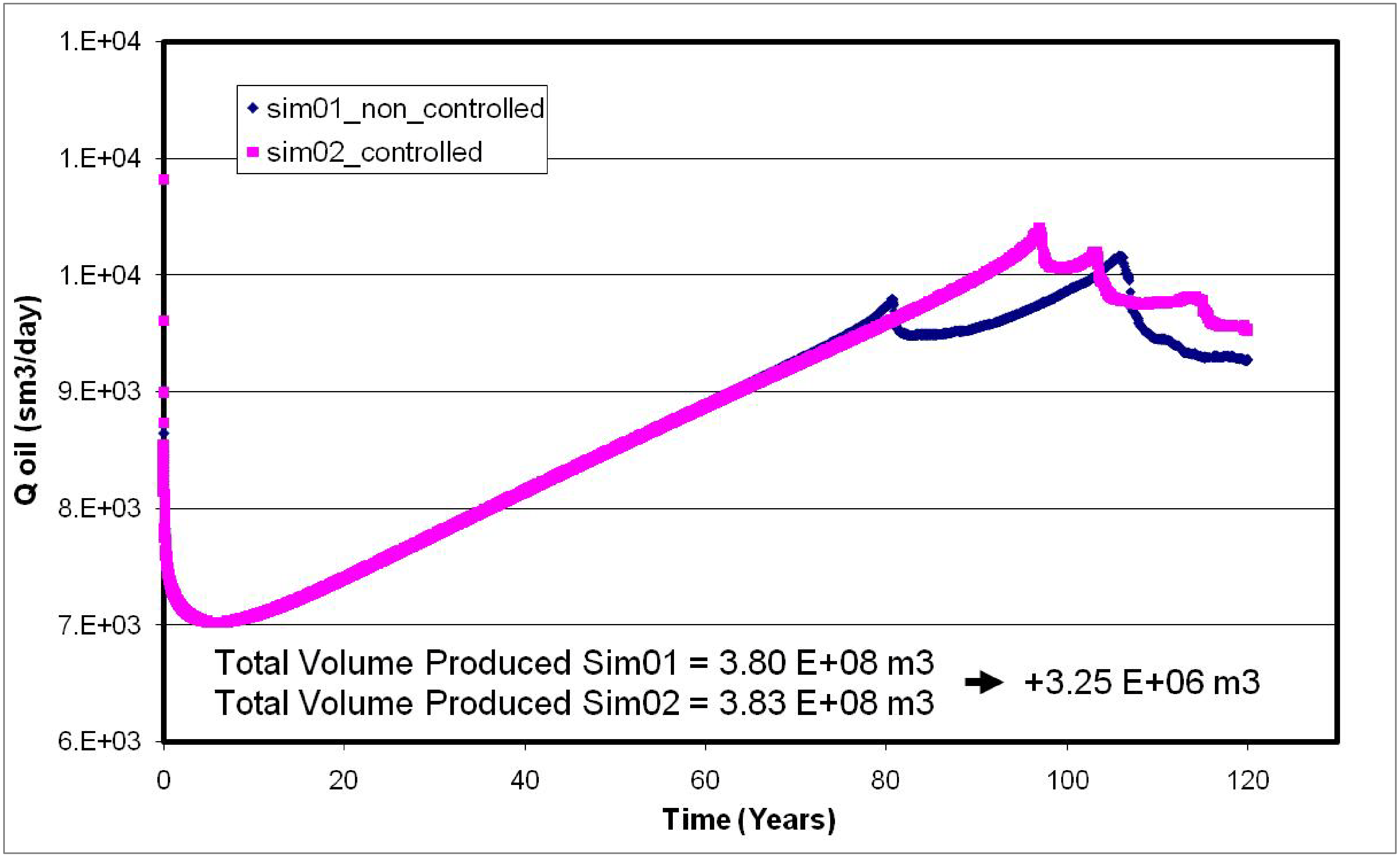

Figure 5. Oil rate for the initial (sim 1) and controlled (sim 2) injection rates.