CompAMa
www.compama.co.usb.ve

Bull. Comput. Appl. Math., Vol.5, No.2, 2017
ISSN 2244-8659

Surrogate reservoir models for CSI well probabilistic production forecast

Saúl Buitrago [1], *Olivo Romero* [2]

CompAMa Vol.5, No.2, pp.29-45, 2017 - Accepted Sep 26, 2017

Abstract

The aim of this work is to present the construction and use of Surrogate Reservoir Models capable of accurately predicting cumulative oil production for every well stimulated with cyclic steam injection at any given time in a heavy oil reservoir in Mexico considering uncertain variables. The central composite experimental design technique was selected to capture the maximum amount of information from the model response with a minimum number of reservoir models simulations. Four input uncertain variables (the dead oil viscosity with temperature, the reservoir pressure, the reservoir permeability and oil sand thickness hydraulically connected to the well) were selected as the ones with more impact on the initial hot oil production rate according to an analytical production prediction model. Twenty five runs were designed and performed with the STARS simulator for each well type on the reservoir model. The results show that the use of Surrogate Reservoir Models is a fast viable alternative to perform probabilistic production forecasting of the reservoir.

Keywords: Surrogate model, approximation model, response surface, experimental design, cyclic steam injection, probabilistic production forecast.

[1]Departamento de Cómputo Científico y Estadística, Universidad Simón Bolívar (USB), Caracas 1080-A, Venezuela (sbutrago@usb.ve).
[2]Spectrum Servicios Técnicos México SA de CV, D.F., México (olivo-romero@gmail.com).

1 Introduction

The modeling and simulation of reservoirs is a critical step in the planning and development of oil fields. Numerical reservoir simulation has become an industry standard tool for hydrocarbon reservoir management. It is now used in all phases of field development in the oil and gas industry.

Before a reservoir model can be accepted for the forecast of future production, the model has to be updated with historical production data. On the other hand, the quality of the data used to construct the reservoir model is most of the time poor, leading to a high uncertainty of production forecasts.

As the reservoir models (RMs) run in a wide variety of time scales, several hours or even days, the problem intensifies when we realize that in many cases, the uncertainty of several variables has to be considered in order to make reliable forecasts. Then sensitivity analysis of uncertain variables and probabilistic forecasting and risk analysis becomes a must and several RMs runs must be made for different combinations of uncertain variables values.

Surrogate Reservoir Models (SRMs) are prototypes of the RMs that can run in fractions of a second rather than in hours or days. If properly designed, they can mimic the capabilities of the RM with high accuracy. SRMs are attractive tools to be used as an efficient substitution of RMs. The SRM is built on the basis of modeling the response of the reservoir simulator with a limited number of cases chosen intelligently. It is not necessary to know the simulation code operates (or even to understand it), only the input-output behaviour of the reservoir model is important. SRMs can be developed regularly off-line as new versions of the RMs become available, and can efficiently be used for forecasting behaviour under uncertainty conditions as well as for real-time decision making (see [1–7]).

Consequently, to improve the confidence of production forecasts, a methodology is introduced, base upon Surrogate Reservoir Models, to build replacements for the reservoir model.

The aim of this work is to present the construction and use of Surrogate Reservoir Models (SRMs) capable of accurately predicting cumulative oil production for every well stimulated with cyclic steam injection (CSI) at any given time in a heavy oil reservoir in Mexico considering uncertain variables.

Section 2 describes the reservoir in terms of crude oil type, API density, viscosity, depth and pressures. Additionally, the numerical models of wells considered are listed (conventional CSI, selective CSI and horizontal CSI for the extra heavy oil and the heavy oil reservoirs), as well as the variables that have the greatest influence on the production behaviour (the dead oil viscosity with temperature, the reservoir pressure, the reservoir permeability and oil sand thickness hydraulically connected to the well). Section 3 describes the construction of the surrogate reservoir models. The central composite experimental design technique was selected to capture the maximum amount of information from the model response with a minimum number of reservoir models simulations. Section 4 details the numerical model associated to each well type to be performed with the STARS simulator [8]. Section 5 discusses the construction of the field-to-study model, based on the surrogate reservoir model of each well type and the activity of the wells for the period 2012-2027. Finally, in section 6, the conclusions of this work are listed.

2 Reservoir description

The project geographically comprises a site located southeast of Mexico, state of Tabasco, where the presence of heavy and extra-heavy viscous oil is present in the shallow sands field (depth 600 m to 2200 m) of the Pliocene and Pleistocene of the Tertiary.

The reservoir type is black oil with a density ranging from 5 to 10 degrees API for extra-heavy oil (XP) with a viscosity of 6000-45000 centipoises and between 12 to 23 degrees API with a viscosity of 200-2000 centipoises for the heavy oil (P).

The original pressure reported for Heavy Oil Field S in 1964 was between 150 and 200 kg/cm^2. According to the pressure behaviour observed during the different production periods (1964 to 2010), it indicates that these deposits are a combination of volumetric and compartmentalized, where original values of pressure at intervals pertaining to a sandy packet, but not connected and behaving as separate reservoirs or flow units (see [9–11]).

The numerical models of wells considered in this work are: SXP conventional cyclic steam injection (CSI), SXP selective CSI, SXP horizontal CSI, SP conventional CSI, SP cyclic hot water injection (CHWI).

We analyzed the variables that have the greatest influence on the production behaviour in extra-heavy oil wells subjected to cyclic steam injection, through sensitivities made with the Boberg-Lantz model (see [12]).

The selected variables with the greatest impact resulting from this analysis for vertical wells were (a) permeability, (b) pressure (c) the open thickness, and (d) the viscosity of the oil. In the case of horizontal wells, (a) the per-

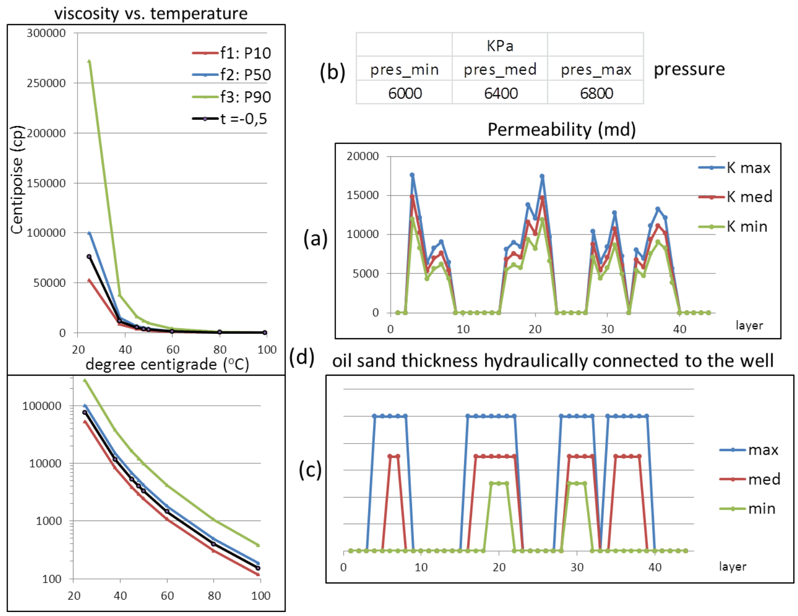

Fig. 1: Variation range for the 4 selected variables for the model SXP conventional CSI.

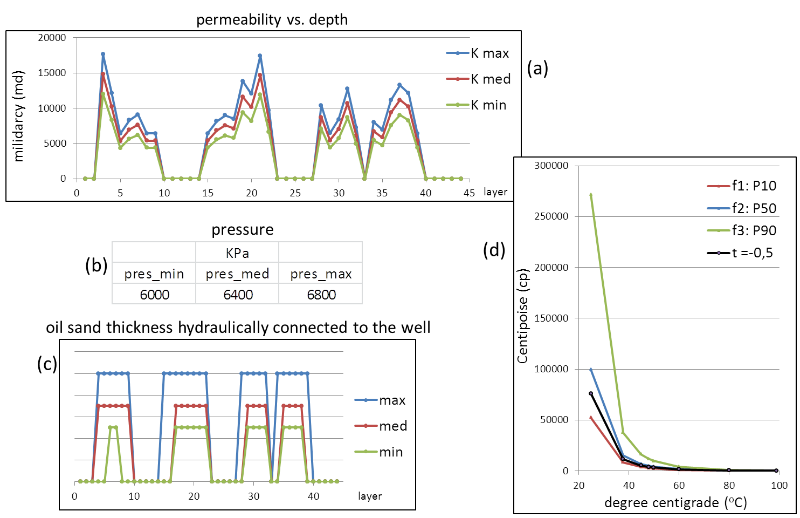

Fig. 2: Variation range for the 4 selected variables for the model SXP selective CSI.

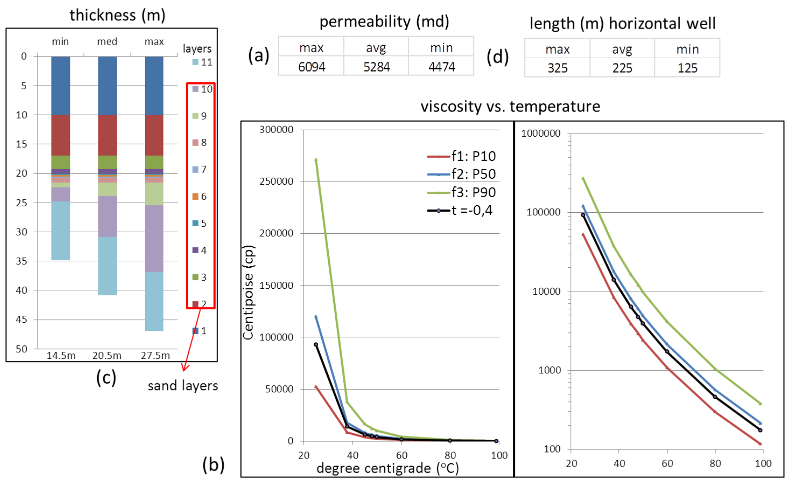

Fig. 3: Variation range for the 4 selected variables for the model SXP horizontal CSI.

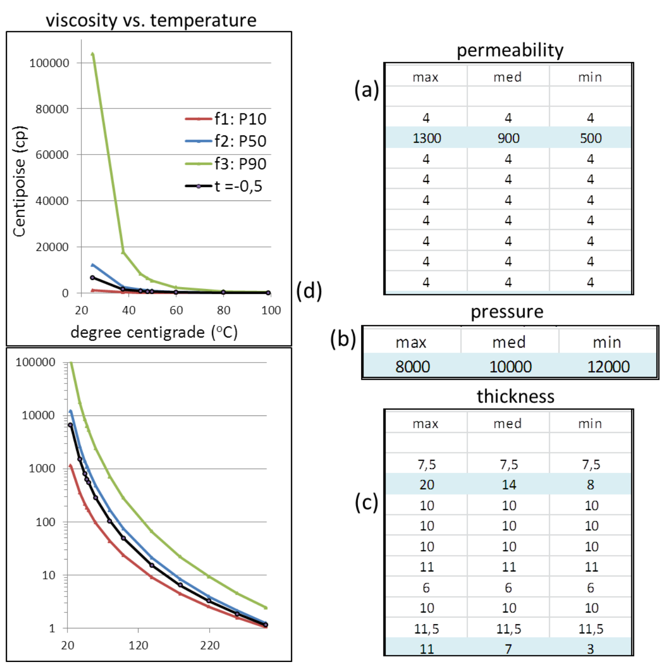

Fig. 4: Variation range for the 4 selected variables for the model SP CSI and SP CHWI.

meability, (b) the viscosity of the oil, (c) the open thickness, and (d) the horizontal length were chosen. Figs. 1, 2, 3 and 4 show the variation of the variables with uncertainty, where the colors red, blue and green were used to represent the minimum, average and maximum respectively.

3 Surrogate reservoir model (SRM)

Surrogate models are compact scalable analytic models that approximate the multivariate input/output behavior of complex systems, based on a limited set of computational expensive simulations.

In this context, a SRM is an approximation to the numerical simulation model by means of functions that represent the different responses of the reservoir simulator. These are models for specific problems and never substitute the numerical simulation model.

The generation of a "simple" or "greater precision" model depends on the objective of the problem: sensitivity analysis or risk analysis. In this work, multivariable quadratic functions will be used.

Steps for the determination of the SRM:

Selection of variables. At this stage, we choose the variables that are considered uncertain and that affect the response of the reservoir simulator. Variation ranges are assigned to these variables, for their subsequent evaluation and quantification of the effects, and migration of the uncertainty in the variables, on the response of the simulator (production response).

Reduction of variables. This step is very important if you have a large number of variables considered uncertain and should determine which of them have a significant influence on the reservoir production response.

Generation of Response Surface. The objective of this stage is to determine an analytical function which can be evaluated as many times as desired, at a low cost. For this purpose it is proposed to use multivariable 2nd-degree polynomials for each step time, for example annually, up to the proposed forecast time. The step prior to the determination of the coefficients of these polynomials is the design of an experimental design, which will allow selecting the combinations of the variables values for which the numerical simulation must be run.

An experiment design type Central Composite Design was chosen. Given n variables and two levels on each variable, this design consists in a 2^n factorial, where the points or experiments are augmented with $2n$ axial points

$(\pm\alpha, 0, 0, \ldots, 0)$, $(0, \pm\alpha, 0, \ldots, 0)$, $\ldots$, $(0, 0, \ldots, \pm\alpha, 0)$, $(0, 0, 0, \ldots, \pm\alpha)$, and the central point $(0, 0, 0, \ldots, 0)$. We have a total of $2^n + 2n + 1$ points or experiments. The following calculations are made for the case of three variables to keep the simplicity. Thus, for the three variables (x_1, x_2, x_3), we have $2^3 + 2 \times 3 + 1 = 15$ points or experiments to perform. α, which ensures the design to be rotatable, is calculated as $(2n)^{1/4}$.

The multivariable 2nd degree polynomial in case of 3 variables, which gives the cumulative oil production, and in combination with the selected design of experiment, is the following:

$$\begin{aligned} N_p &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 \\ &\quad + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 \ . \end{aligned} \tag{1}$$

This leads to the following linear system of equations:

$$A\beta = b \ \text{ con } A = x^T x, \ b = x^T N_p \ , \tag{2}$$

where the matrix x is of dimension 15×10, and the vector β y N_p are of dimension 10×1 and 15×1 respectively (see equations in 3).

$$\begin{aligned} x &= \begin{pmatrix} 1 & -1 & -1 & -1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & -1 & -1 & -1 & -1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & -1 & 1 & -1 & -1 & 1 & 1 & 1 \\ 1 & -1 & 1 & -1 & -1 & 1 & -1 & 1 & 1 & 1 \\ 1 & -1 & -1 & 1 & 1 & -1 & -1 & 1 & 1 & 1 \\ 1 & 1 & -1 & 1 & -1 & 1 & -1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & -1 & 1 & 1 & -1 & -1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}, \\ \beta &= (\beta_1, \beta_2, \beta_3, \beta_{12}, \beta_{13}, \beta_{23}, \beta_{11}, \beta_{22}, \beta_{33})^T, \\ N_p &= (N_{p_1}, N_{p_2}, N_{p_3}, \ldots, N_{p_{15}})^T. \end{aligned} \tag{3}$$

The solution of (2) and (3) is given directly by the expression

$$\beta = A^{-1}N_p = (x^T x)^{-1}(x^T x)x^T N_p \ . \tag{4}$$

Finally, the calculated coefficients of the polynomials are obtained for each prediction time. These allow obtaining a response equivalent to that provided by the numerical simulation model for the selected values of the variables within their ranges of variation.

In some cases we can obtain that the cumulative oil production for time step $i-1$ is greater than the cumulative for time step i, since each linear system is solved independently of the time step. To avoid this, the following extra condition is added:

$$N_{p_{i-1}} \leq N_{p_i}, \ \ \text{para } i \geq 2, \ \text{y } N_{p_1} \geq 0 \ . \tag{5}$$

This leads us to rethink the problem as the linear system $A\beta = b$ given by equations (2) and (3) with the constraints set forth in (5), and to the use of free derivative optimization methods, such as that proposed by Buitrago et al. in [13, 14], to solve it.

4 Numerical well models

SXP conventional cyclic steam injection. The characteristics of the numerical model are: radial meshing of 18×44 cells, four producing sands, depth at the top of 660 meters, gross thickness of 111 meters, net thickness of 30 meters and drainage radius of 120 meters. The wells do not have cold production, injection of 4635 tons of steam per cycle, the period of injection-soaking lasts 30 days, and the production period lasts 16 months. Finished the production cycle a new steam cycle is injected until 5 cycles. The production and cumulative oil response for this type well is shown in Fig. 5.

SXP selective cyclic steam injection. The behaviour of this well type was determined by a numerical simulation model with characteristics similar to the SXP conventional CSI well type. In this case the open thickness was 42 meters. Injection of 5800 tons of water equivalent to 140 tons per meter of open sand, the period of injection-soaking lasts 30 days, the production period lasts 16 months. Once the production period is over, the well is injected with a new steam cycle up to 5 cycles. The drainage radius was

120 meters. The production and cumulative oil response for this well type is shown in Fig. 6.

SXP horizontal cyclic steam injection. The characteristics of the numerical model are the following: a Cartesian meshes of $21 \times 25 \times 11$ cells (includes supra and infra adjacent layers of 10 m each), sand thickness of 21 meters, discretized in 9 layers of variable thicknesses. The open horizontal length of the well was 325 meters, and an area of 625 meters $\times$ 425 meters. Wells do not have cold production, injection of 10500 tons of steam per cycle, the injection-soaking period lasts 35 days, and the production period lasts 18 months. After the production cycle, a new steam cycle is injected for up to 5 cycles. The flowing bottom pressure was 51 kg/cm^2. The production and cumulative oil response for this type well is shown in Fig. 7.

SP conventional cyclic steam injection. The characteristics of the numerical model are the following: a radial meshing of 18×10 cells, radius of 100 meters, discretized in 18 rings with widths from 30 cm to 22 meters, gross thickness of 97 meters, two producing sands with a thickness of 21 meters, depth to the top of 1100 m. Injection of 4800 tons of steam per cycle, the period of injection-soaking lasts 30 days, and the production period lasts 15 months. After the production cycle, a new steam cycle is injected for up to 5 cycles. The drainage radius was 100 meters. The production and cumulative oil response for this type well is shown in Fig. 8.

SP cyclic hot water injection. The behaviour of this well type was determined using a numerical simulation model with characteristics similar to the SP conventional CSI model. Injection of 4800 tons of water per cycle, the period of injection-soaking lasts 30 days; the production period lasts 15 months. After the production cycle, a new cycle of water is injected for up to 3 cycles. The drainage radius was 100 meters. The production and cumulative oil response for this type well is shown in Fig. 9.

Finally, twenty five runs were designed and executed with the STARS reservoir simulator [8] for each well type based on the corresponding reservoir model, as shown in Figs. 10 to 14 for the SXP conventional CSI, SXP selective CSI, SXP horizontal CSI, SP conventional CSI and SP CHWI. Here the production is given in thousands of cubic meters. This is the information used for the generation of the surrogate model for each type well.

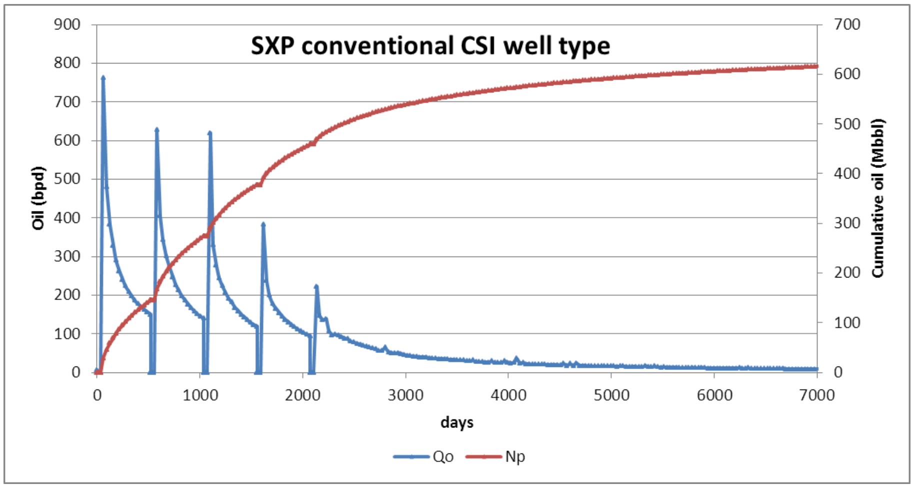

Fig. 5: Oil producction rate and cumulative for the SXP conventional CSI well type model.

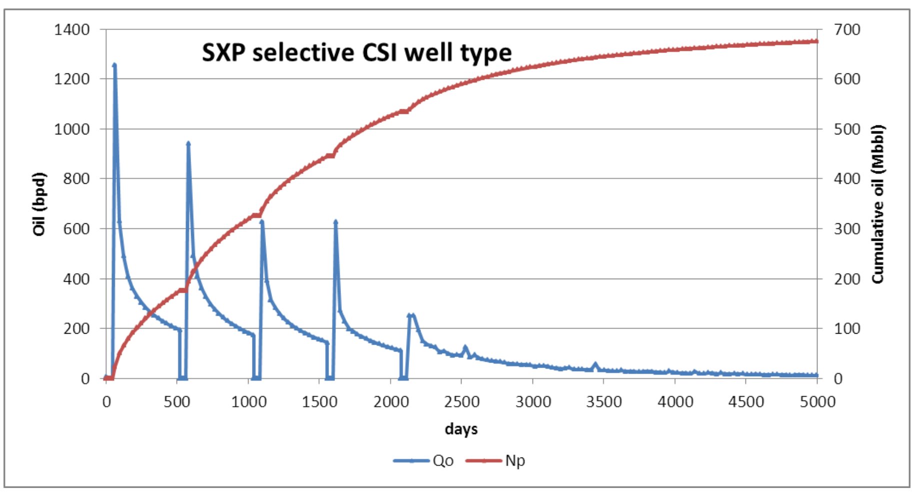

Fig. 6: Oil producction rate and cumulative for the SXP selective CSI well type model.

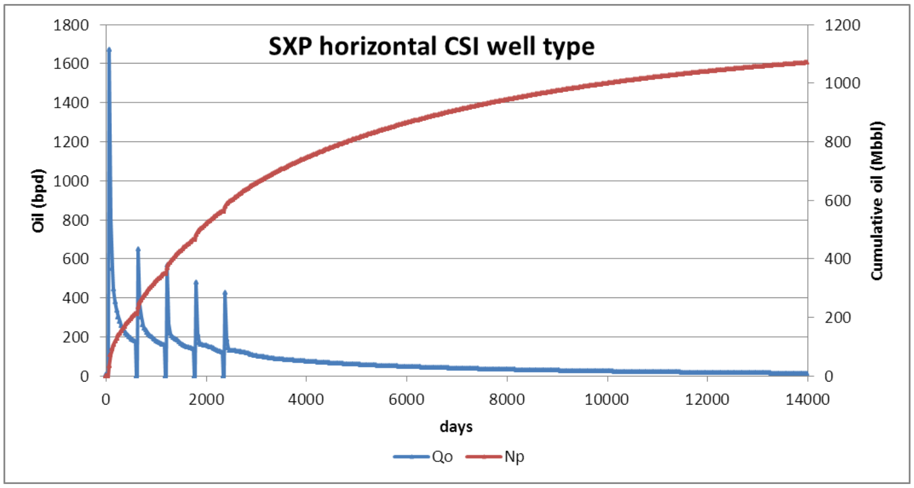

Fig. 7: Oil producction rate and cumulative for the SXP CSI horizontal well type model.

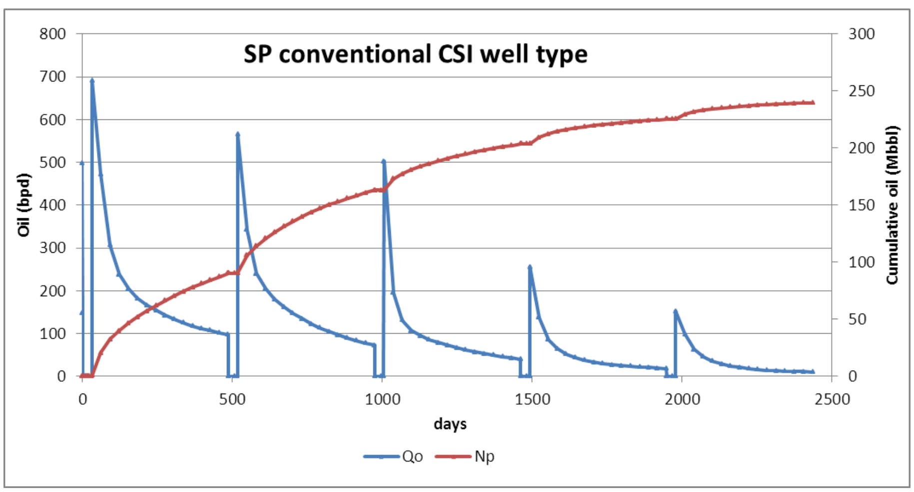

Fig. 8: Oil producction rate and cumulative for the SP conventional CSI well type model.

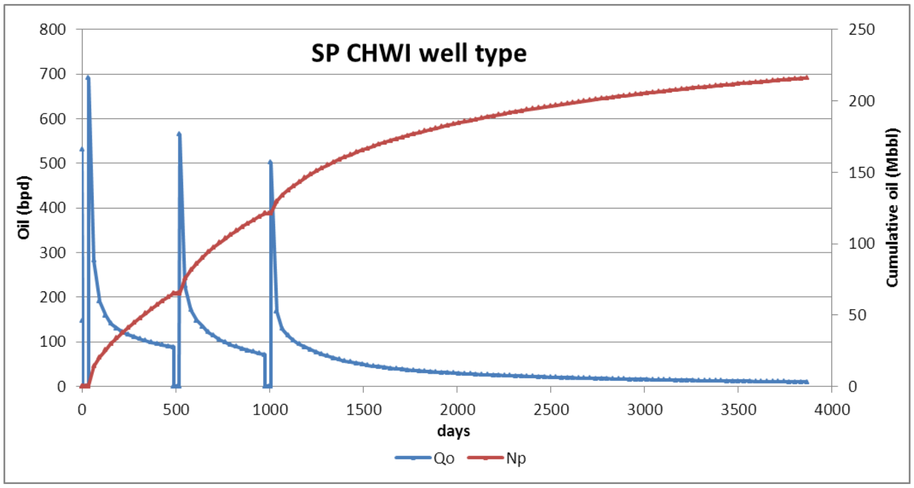

Fig. 9: Oil producction rate and cumulative for the SP cyclic hot water injection well type model.

5 Probabilistic production profiles

The minimum, mean and maximum curves were generated for each of the selected variables (see section 2) for each well type, as shown in Figs. 1 to 4. A probability distribution (Beta Pert type), based on its parameters, was assigned to each variable depending on its type.

Tab. 1: Well activity in the period 2012-2027 for the SXP field.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	Total 2013-2027
Directional wells - low angle	21	60	4	0	0	0	0	0	0	0	0	0	0	0	0	0	64
Directional wells - low angle - selective	8	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Horizontal wells	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5
Workover: major repairs with equipment	1	2	1	0	2	6	19	10	14	6	6	12	15	10	7	4	114
Workover: minor repairs	0	3	29	63	15	25	20	20	5	0	0	0	0	0	0	0	180
Steam cycles in directional wells	15	43	60	63	63	42	61	53	0	0	0	0	0	0	0	0	385
Steam cycles in horizontals wells	0	0	0	3	3	0	3	2	0	0	0	0	0	0	0	0	11
Selective steam cycles in directional wells	4	6	10	6	5	9	7	2	0	0	0	0	0	0	0	0	45

Tables. 1 and 2 show the well activity for the period 2012-2027 for the SXP and SP fields. Using the well activity information, the SRMs of each well type, and the probabilistic distributions assigned to the selected variables, we calculated the probabilistic oil rate and cumulative oil production profiles (percentiles 10, 50 and 90) for the fields SXP and SP (production bands), using the Monte Carlo method. These probabilistic profiles, oil rate and cumulative oil production, are shown in Figs. 15 and 16 respectively.

Tab. 2: Well activity in the period 2012-2027 for the SP field.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	Total 2013-2027
Directional wells - low angle	38	7	2	0	0	0	0	0	0	0	0	0	0	0	0	0	9
Horizontal wells	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Workover: major repairs with equipment	15	18	34	27	18	15	10	10	6	5	0	1	2	1	0	0	147
Workover: minor repairs	4	18	38	7	2	0	0	0	0	0	0	0	0	0	0	0	65
Steam cycles in directional wells	0	0	0	31	24	19	19	31	24	7	0	0	0	0	0	0	155
Hot water cycles in directional wells	0	0	0	8	16	20	21	13	8	1	0	0	0	0	0	0	87

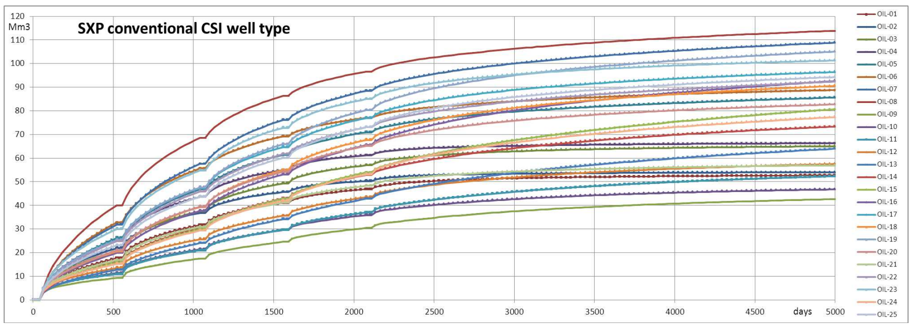

Fig. 10: Cumulative oil production for the 25 experiments associated to SXP conventional CSI well type model.

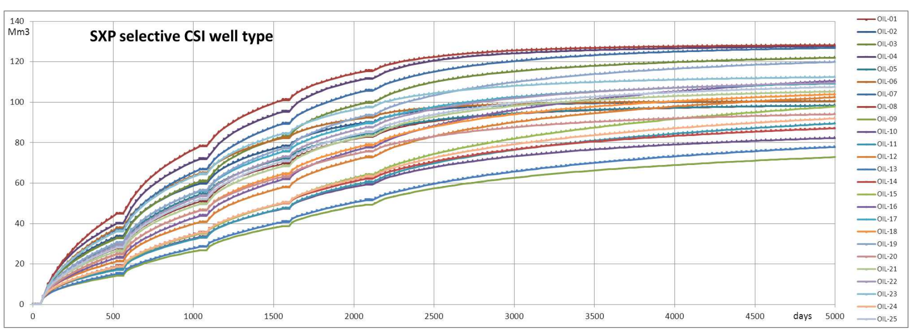

Fig. 11: Cumulative oil production for the 25 experiments associated to SXP selective CSI well type model.

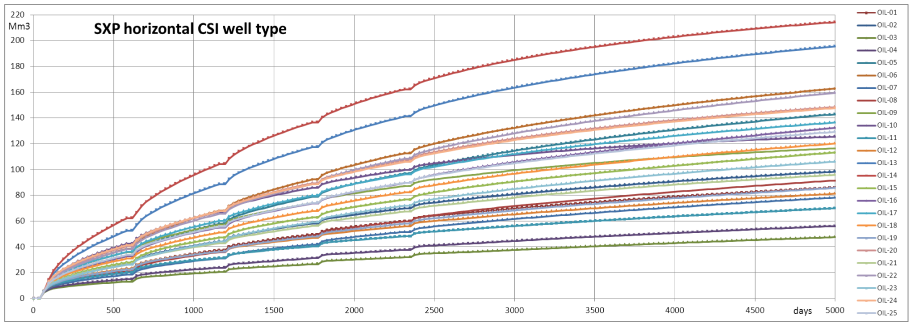

Fig. 12: Cumulative oil production for the 25 experiments associated to SXP CSI horizontal well type model.

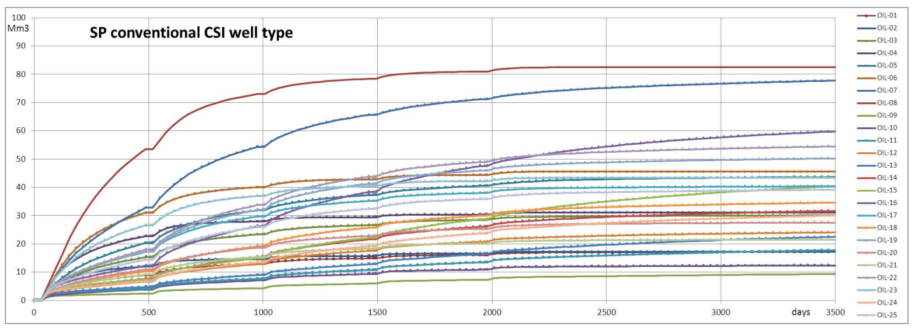

Fig. 13: Cumulative oil production for the 25 experiments associated to SP conventional CSI well type model.

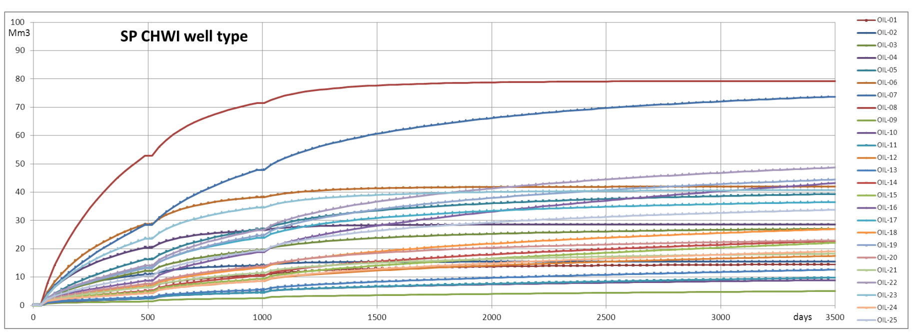

Fig. 14: Cumulative oil production for the 25 experiments associated to SP cyclic hot water injection well type model.

6 Conclusions

- The essential steps to be taken into account in order to develop an surrogate model (SRM) of a reservoir were identified.
- The results show that the use of surrogate models is a fast alternative way to calculate the probabilistic production forecasts of oil fields.

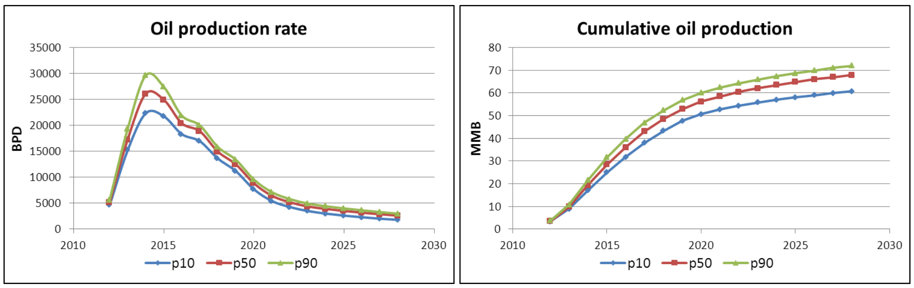

Fig. 15: Probabilistic response for the SXP field

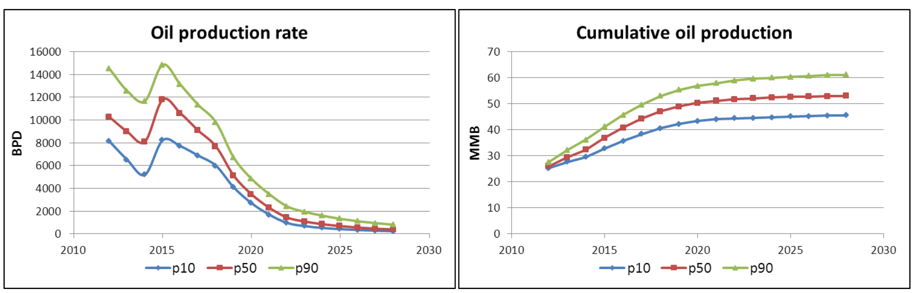

Fig. 16: Probabilistic response for the SP field

References

[1] S.D. Mohaghegh, A. Modavi, H.H. Hafez, M. Haajizadeh, M. Kenawy, and S. Guruswamy. Development of surrogate reservoir models (SRM) for fast track analysis of complex reservoirs. *Society of Petroleum Engineers*, (SPE 99667):1–9, 2006. doi: 10.2118/99667-MS.

[2] S.D. Mohaghegh, H.H. Hafez, R. Gaskari, M. Haajizadeh, and M. Kenawy. Uncertainty analysis of a giant oil field in the Middle East using surrogate reservoir model. *Society of Petroleum Engineers*, (SPE 101474):1–13, 2006. doi: 10.2118/101474-MS.

[3] S.D. Mohaghegh. Quantifying uncertainties associated with reservoir simulation studies using surrogate reservoir models. *Society of Petroleum Engineers*, (SPE 102492):1–13, 2006. doi: 10.2118/102492-MS.

[4] D.I. Zubarev. Pros and cons of applying proxy-models as a substitute for full reservoir simulations. *Society of Petroleum Engineers - Annual Technical Conference and Exhibition*, 9(3, SPE 86883):1–23, 2009. doi: 10.2118/124815-MS.

[5] G. Rojo-Ruiz, L.A. Rojas-Bejarano, and J. Quintero-Contreras. Uso de modelos de aproximación basados en superficies de respuestas polinómicas multivariables (MDA PEP) para la generación de pronósticos de producción probabilistas a partir de los resultados de simulación de yacimientos. *Ingeniería Petrolera*, LI(7):47–60, 2011. https://www.scribd.com/document/234523049/Julio.

[6] S.D. Mohaghegh, A. Shohreh, G. Vida, G. Razi, and G.S. Bromhal. Grid-based surrogate reservoir modeling (SRM) for fast track analysis of numerical reservoir simulation models at the gridblock level. *Society of Petroleum Engineers, Western Regional Meeting*, (SPE 153844):1–13, 2012. doi: 10.2118/153844-MS.

[7] S.D. Mohaghegh, J. Liu, R. Gaskari, M. Maysami, and O. Olukoko. Application of well-based surrogate reservoir models (SRMs) to two offshore fields in Saudi Arabia, case study. *Society of Petroleum Engineers, Western Regional Meeting*, (SPE 153845):1–13, 2012. doi: 10.2118/153845-MS.

[8] CMG. *STARS - Thermal and advanced processes reservoir simulator*. Computer Modelling Group, Calgary, Alberta, Canada, 2016. http://www.cmgl.ca/stars.

[9] A. Aguilar-Rodríguez, M. Arteaga-Cardona, M.G. Aguilar-Aguilar, T. Flores-de Dios-Mosqueda, O. Cruz-Samberino, and E.A. Isidro Torres. Perforación de pozos horizontales

para producir aceite extrapesado en samaria. *Horizonte Sur*, 61:31–42, 2012. https://drive.google.com/file/d/0B2-yk6QC4qeVTGdiVG9jZnAyYkE/view.

[10] M. Arteaga-Cardona, A. Aguilar-Rodríguez, and J.B. Atamirano-Rayón. Prueba piloto de inyección cíclica de vapor campo samaria neógeno – primera etapa. *Ingeniería Petrolera*, 52(3):5–20, 2012. ISSN: 0185-3899, https://www.scribd.com/document/345325866/Ingenieria-Petrolera-Marzo2012-LII-3.

[11] M. Arteaga-Cardona. Logros y retos de la primera prueba piloto de inyección de vapor en México. *Ingeniería Petrolera*, 53(8):486–503, 2013. ISSN: 0185-3899, http://132.248.9.34/hevila/Ingenieriapetrolera/2013/vol53/no8/4.pdf.

[12] T.C Boberg and R.B Lantz. Calculation of the production rate of a thermally stimulated well. *Journal of Petroleum Technology*, 18(12, SPE-1578-PA):1613–1623, 1966. doi: 10.2118/1578-PA.

[13] S. Buitrago, E. Rodríguez, and D. Espin. Global optimization techniques in gas allocation for continuous flow gas lift systems. In *Proceedings of the 1996 SPE Gas Tecnology Simposium, SPE 35616, Calgary, Canada, 28 April-1 May 1996*, volume 1, pages 375–383, april 1996. doi: 10.2118/35616-MS.

[14] S. Buitrago and E. Rodríguez. Global optimization techniques in the oil industry. In *Métodos Numéricos en Ingeniería y Ciencias Aplicadas, Ed: N. Troyani, M. Cerrolaza*, pages OP47–OP58, march 2000. ISBN: 980-00-1639-2.