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An Optimization Methodology of Alkaline-Surfactant-Polymer Flooding Processes Using Field Scale Numerical Simulation and Multiple Surrogates

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Abstract

After conventional waterflood processes the residual oil in the reservoir remains as a discontinuous phase in the form of oil drops trapped by capillary forces and is likely to be around 70% of the original oil in place (OOIP). The EOR method so-called alkaline-surfactant-polymer (ASP) flooding has been proved to be effective in reducing the oil residual saturation in laboratory experiments and field projects through reduction of interfacial tension and mobility ratio between oil and water phases.

A critical step to make ASP floodings more effective is to find the optimal values of design variables that will maximize a given performance measure (e.g. net present value, cumulative oil recovery) considering a heterogeneous and multiphase petroleum reservoir. Previously reported works using reservoir numerical simulation have been limited to sensitivity analyses at core and field scale levels because the formal optimization problem includes computationally expensive objective function evaluations (field scale numerical simulation).

The proposed methodology estimates the optimal values for a set of design variables (slug size and concentration of the chemical agents) to maximize the cumulative oil recovery from a heterogeneous and multiphase petroleum reservoir subject to an ASP flooding. The surrogate-based optimization approach has been shown to be useful in the optimization of computationally expensive simulation-based models in the aerospace, automotive, and oil industries. In this work we have extended this idea along two directions: i) using multiple surrogates for optimization, and ii) incorporating an adaptive weighted average model of the individual surrogates.

The proposed approach involves the coupled execution of a global optimization algorithm and fast surrogates (ì.e. based on Polynomial Regression, Kriging, and a Weighted Average

Model) constructed from field scale numerical simulation data. The global optimization program implement the DIRECT algorithm and the reservoir numerical simulations are conducted using the UTCHEM program from the University of Texas at Austin.

The effectiveness and efficiency of the proposed methodology is demonstrated using a well-known field scale case study.

Introduction

After conventional waterflood processes the residual oil in the reservoir remains as a discontinuous phase in the form of oil drops trapped by capillary forces and is likely to be around 70% of the original oil in place (OOIP)[1]. The EOR method so-called alkaline-surfactant-polymer (ASP) flooding has been proved to be effective in reducing the oil residual saturation in laboratory experiments and field projects through reduction of interfacial tension and mobility ratio between oil and water phases. Some ASP pilot tests reported in the literature have reached an oil recovery over 60% OOIP[2-5].

In ASP floodings the surfactant is responsible for reducing the interfacial tension between oil and water phases to a level that promotes the mobilization of trapped oil drops. The alkaline agent is intended to react with the acids to generate *in situ* surfactant to attain ultralow tension[6] and to overcome the surfactant depletion in the liquid phases due to retention. The role of the polymer is to increase the viscosity, reducing the mobility ratio and hence reaching a greater volumetric swept efficiency. Details of the physical processes taking place can be found in Shah and Schechter[7].

The design of an ASP flooding process must achieve three main objectives: propagation of the chemicals in an active mode, the injection of enough chemicals accounting for the retention, and a complete swept of the area of interest[8]. Achieving these objectives is significantly affected by the selection of the chemicals, the concentration of the ASP solution and the slug size, among other factors.

Previous works toward the optimization of ASP processes have concentrated mainly around identifying formulations that will achieve minimum interfacial tension using laboratory experiments and empirical correlations[9-12], and sensitivity analyses using numerical simulation at core and field scale levels[13-17]. Table 1 presents a summary of these works and shows that formal optimization of ASP flooding has not been addressed. The latter is a critical step to find the optimal

parameters that will maximize a given performance measure (e.g. net present value, cumulative oil recovery) considering a heterogeneous and multiphase petroleum reservoir.

The cited formal optimization has been limited due to the high computational cost exhibited by the numerical simulations at the reservoir level, which makes impractical the coupled execution of the simulator and optimization algorithms. The surrogate-based optimization approach has been shown to be useful in the optimization of computationally expensive simulation-based models in the aerospace[18,19], automotive[20,21], and oil industries[22,23]. Surrogate-based design makes reference to the idea of constructing an alternative fast model (surrogate) from numerical simulation data and using it for optimization purposes. In this work we have extended this idea along two directions: i) using multiple surrogates for optimization, and ii) incorporating an adaptive weighted average model of the individual surrogates.

The proposed methodology estimates the optimal parameters (slug size and concentration of the chemical agents) to maximize the cumulative oil recovery from a heterogeneous and multiphase petroleum reservoir subject to an ASP flooding. The methodology involves the coupled execution of a global optimization algorithm and surrogates (based on Polynomial Regression, Kriging, and a Weighted Average Model) constructed from field scale numerical simulation data.

The methodology is evaluated using a field scale case study based on an ASP flooding pilot available in the sample data archives of the UTCHEM[24] program of the University of Texas at Austin.

Problem of Interest
The optimization of an ASP flooding process. More specifically:

$$find\ x \in X \subseteq R^p$$

such that

$$f(x)\ is\ maximized$$

where f is the cumulative oil recovery (computationally expensive objective function), x represents p design variables, namely, slug size and the chemical concentrations, and X denotes simple bounds constraints ($x_{i\ min} < x_i < x_{i\ max}$; with $i = 1,2\ ...\ p$). Note that the computationally expensive nature of the objective function evaluations limits the possible solution approaches to those satisfying the time restrictions typically present in the oil industry.

Solution methodology
With reference to Fig. 1, the proposed methodology involves the following steps:
1. Generate a sample of the design variables space using a modified latin hypercube experimental design. This sampling procedure has been shown to be very effective for selecting values of input variables for the analysis of the output of a computer code[25].
2. Conduct numerical simulations (via UTCHEM) using the sample (input) from the previous step and obtain the corresponding objective function values (output).

3. Using the input/output pairs obtained in the previous steps, construct multiple surrogate models based on Polynomial Regression, Kriging and a Weighted Average Model. This surrogate models will be discussed later in this section.
4. Solve the optimization problem of interest by coupling the execution of a global optimization algorithm (a modified Lipschitzian method called DIRECT[26]) with each of the surrogates constructed in step 3.
5. Conduct numerical simulations using the optimal values obtained in the previous step to confirm their performance level. The designer now selects among the best confirmed design values the solution that satisfy the most his preference structure.

Surrogate Modeling. It is an inverse problem where due to the limited amount of available data: i) alternative surrogates can provide reasonable approximations to function f, and ii) each surrogate may offer the best fit to f depending on the region of the design space. Since the location of the optimal design values is unknown we suggest to use multiple surrogates considering they can be constructed at no significant additional computational cost. Two alternative (approximating and interpolating schemes) surrogate models, namely, Polynomial Regression (PRG) and Kriging (KRG), will be considered. In addition, a Weighted Average Model (WAV) of these surrogates will also be included in the study. The WAV can be shown to reduce the variance estimation with respect to that of the individual surrogates[27]. Throughout this section, given the stochastic nature of the surrogates, the available data is considered a sample of a population.

Polynomial Regression model. The regression analysis is a methodology that studies the quantitative association between a function of interest y, and m prediction variables z^j, where there are n values of the function of interest y_i, for a set of prediction variables $z_i^{j\ [28]}$. For each observation i a linear equation is formulated:

$$y_i = \sum_{i=1}^{m} \beta_j z_i^j + \varepsilon_i \quad E(\varepsilon_i) = 0 \quad V(\varepsilon_i) = \sigma^2 \ ....(1)$$

where the errors ε_i are independents with expected value equal to zero and variance σ^2. The estimated parameters $\hat{\beta}_j$ (by least squares) are unbiased and have minimum variance.

Eq.1 is expressed in matrix form as:

$$y = Z\beta + \varepsilon \quad E(\varepsilon) = 0 \quad V(\varepsilon) = \sigma^2 I \ ....(2)$$

where Z is a $n \times m$ matrix with the prediction variable values. The vector of the estimated parameters is:

$$\hat{\beta} = \left(Z^T Z\right)^{-1} Z^T y \ ....(3)$$

Considering a new set of design values z, the variance of the predicted response $z^T \hat{\beta}$ is:

$$V(y(z)) = \sigma^2 \left(z^T \left(Z^T Z\right)^{-1} z + 1 \right) ....(4)$$

In this work the regression model considered is a second-order polynomial model of the form:

$$y = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \sum_{i=1}^{p} \sum_{j=1}^{p} \beta_{ij} x_i x_j \quad\text{.................................(5)}$$

Kriging model. These models suggest estimating deterministic functions as:

$$y(x_j) = \mu + \varepsilon(x_j) \quad\text{.......................................(6)}$$

where, y is the function to be modeled, μ is the mean of the population, and ε is the error with zero expected value, and with a correlation structure that is a function of a generalized distance between the sets of design values. In this work we use a correlation structure[29] given by:

$$\text{cov}(\varepsilon(x_i), \varepsilon(x_j)) = \sigma^2 \exp\left(-\sum_{h=1}^{p} \theta_h \left(x_i^h - x_j^h\right)^2\right) \quad\text{.........(7)}$$

where, p denotes the number of dimensions in the set of design variables x; σ, identifies the standard deviation of the population, and, θ_h is a parameter which is a measure of the degree of correlation among the data along the h direction.

Specifically, given a set of n input/output pairs (x, y), the parameters, μ, σ, and θ are estimated such that the likelihood function is maximized (Sacks et al.[29]). The model estimates for a new set of design values is given by:

$$\overline{y}(x) = \overline{\mu} + r^T R^{-1}(y - L\overline{\mu}) \quad\text{...(8)}$$

where the line above the letters denotes *estimates*, r identifies the correlation vector between the new set of design values and the points used to construct the model, R is the correlation matrix among the n sample points, and L denotes an n-vector of ones.

The estimation variance is given by:

$$s^2(x) = \sigma^2 \left[1 - r^T R^{-1} r + \frac{\left(1 - L^T R^{-1} r\right)}{L^T R^{-1} L}\right] \quad\text{....................(9)}$$

Weighted Average model. This model suggests to estimate deterministic functions as:

$$y_{WAV}(x) = \sum_{i=1}^{k} \alpha_i(x) y_{surr\,i}(x) \quad\text{..(10)}$$

where y_{WAV} is the weighted average model, $y_{surr\,i}$ is the prediction, and α_i the weight of the surrogate i, and k the number of surrogates. Note the adaptive nature of the model since the weights are a function of x.

Assuming unbiased and independent predictions, the unbiased weighted average model has minimal variance when the weights are determined as follows.

$$\alpha_i = \frac{\dfrac{1}{V(i)}}{\displaystyle\sum_{j=i}^{k} \dfrac{1}{V(j)}} \quad\text{..(11)}$$

where $V(i)$ is the prediction variance of the i surrogates. In this case the individual surrogates are PRG and KRG (k=2).

Case Study

As previously stated the problem of interest is to find the values of the design variables, namely, concentration of alkaline, surfactant and polymer, and ASP slug size (expressed in the form of the injection time) that maximize the cumulative oil production. The ranges of the design variables are presented in Table 2. The cumulative oil production is calculated at 487 days.

As illustrated in Fig. 2, the ASP flooding pilot has an inverted five-spot pattern and a total of 13 vertical wells, 9 producers and 4 injectors. The reservoir is at a depth of 4150 ft., has an average initial pressure of 1770 psi, and the porosity is assumed to be constant throughout the reservoir and equal to 0.3. The numerical grid is composed of 19x19x3 blocks in the x, y and z directions. Figures 3, 4 and 5 show the initial reservoir pressure, initial water saturation and horizontal permeability fields, respectively. The OOIP is 395,427 bbls, the crude oil viscosity is 40 cp, the initial brine salinity is 0.0583 meq/ml and the initial brine divalent cation concentration is 0.0025 meq/ml. The injection scheme is described in Table 3. This is the reference configuration whose details can be found in the sample data archives of the UTCHEM program.

Three flowing phases and eleven components are considered in the numerical simulations. The phases are water, oil and microemulsion, while the components are water, oil, surfactant, polymer, chloride anions, divalent cations (Ca^{++}, Mg^{++}), carbonate, sodium, hydrogen ion, and oil acid. The ASP interactions are modeled using the reactions: *in situ* generated surfactant, precipitation and dissolution of minerals, cation exchange with clay and micelle, and chemical adsorption.

Note the detailed chemical reaction modeling, and the heterogeneous and multiphase petroleum reservoir under consideration.

Results and discussion

With reference to the case study, a sample of 86 sets of values in the four-dimensional design space was generated using a modified latin hypercube experimental design. Then, the corresponding cumulative oil recovery was calculated for each of the cited set of values. Among these input/output pairs the maximum, average, and minimum values for cumulative oil recovery are 33.58% OOIP (132,784 bbl), 24.27% OOIP (95,970 bbl), and 18.06% OOIP (71,414 bbl), respectively. Note that the performance of the ASP flooding is significantly affected by the values of the design variables, so their optimal specification is a critical issue.

Table 4 presents the optimal values for the design variables obtained through the coupled execution of DIRECT and each of the surrogate models. For each of these sets of values numerical simulations were conducted to assess its true performance. For the optimal values suggested by each of the surrogates the cumulative oil recovery was greater than those obtained within the sample.

The optimization with the PRG model resulted in the greatest objective function value (best solution found), that is, 35.70% OOIP (134,634 bbl). This point has maximum values of surfactant and polymer concentration and injection time. On the other hand, the interior solution obtained using the WAV

model represents a 5% reduction with respect to the best solution found, but with 55%, 13% and 10% lower values of surfactant, and polymer concentrations, and injection time, respectively which would result in lower costs. The solution found using the KRG model has an objective function value slightly higher than the corresponding to WAV but with a maximum value for polymer concentration.

The WAV model presents the smallest difference between the surrogate estimations for cumulative oil recovery and the corresponding values obtained using UTCHEM. This confirms the better modeling capabilities of the WAV model (through variance reduction) with respect to the individual surrogates.

The proposed methodology showed to be effective and efficient (requires a relatively low number of field scale numerical simulations) within the context of the case study, can benefit from the increasing availability of parallel computing environments, and holds promise to be useful in more general scenarios of ASP flooding optimization.

Conclusions

- An optimization methodology of ASP flooding processes has been proposed. The methodology involves the coupled execution of a global optimization algorithm and fast surrogates (ì.e. based on Polynomial Regression, Kriging, Weighted Average Model) constructed from field scale numerical simulation data. The global optimization program implement the DIRECT algorithm and the reservoir numerical simulations are conducted using UTCHEM from the University of Texas at Austin.
- For the set of optimal values suggested by each of the surrogates the cumulative oil recovery was greater than those obtained within the sample.
- The interior solution obtained using the WAV model represents a 5% reduction with respect to the best solution found (corresponding to PRG), but with 55%, 13% and 10% reduction of the surfactant, polymer concentration and injection time, respectively which results in lower costs.
- The WAV model presents the smallest difference between the surrogate estimations for cumulative oil recovery and the corresponding values obtained using UTCHEM. This confirms the better modeling capabilities of the WAV model (through variance reduction) with respect to the individual surrogates.
- The proposed methodology showed to be effective and efficient (requires a relatively low number of field scale numerical simulations) within the context of the case study, can benefit from the increasing availability of parallel computing environments, and holds promise to be useful in more general scenarios of ASP flooding optimization.

Nomenclature

α = weights of the WAV model

$\hat{\beta}$ = estimated parameters

ε = error

μ = mean of the population

θ = correlation parameter

σ = standard deviation

f = objective function

I = identity matrix

k = number of surrogates

KRG = Kriging model

L = n-vector of ones

p = number of variables

r = correlation vector

R = correlation matrix

PRG = Polynomial Regression model

s^2 = kriging variance

V = variance

x = the design variables

X = constraints set

WAV = Weighted Average Model

y = function of interest

z = prediction variables

Z = matrix of the prediction variables

Subscripts

$surr$ = surrogate model

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TABLE 1 – SUMMARY OF PREVIOUS WORK TOWARD ASP FLOODING OPTIMIZATION							
Authors	Parameters	Optimum formulation study		Sensitivity		Detailed chemical reactions	Optimization
		Lab experiments	Core floods	Core scale	Field scale		
Salager et al. (1978)[9] Salager et al. (1978)[10]	Salinity, ACN, alcohol, surfactant, temperature, WOR	Yes	No	-	-	-	No
Bourrel et al. (1980)[11]	Salinity, ACN, EON of the surf., alcohol, hydrophobic molecular weight of the surf., temperature	Yes	No	-	-	-	No
Zhijian et al. (1998)[13]	Chemical agents, chemical concentrations, slug size, fluid-rock interactions	Yes	No	No	Yes	Yes	No
Manrique et al. (2000)[14]	Salinity, chemical agents, chemical concentration, temperature, fluid-rock interactions	Yes	Yes	Yes	No	No	No
Qi et al. (2000)[15]	Salinity, chemical agents, chemical concentrations, pH, fluid-rock interactions	Yes	Yes	Yes	No	No	No
Hernández et al. (2001)[16]	Salinity, chemical agents, chemical concentration, temperature, fluid-rock interactions	Yes	Yes	Yes	No	No	No
Wei-Ju Wu (1996)[17]	Reservoir properties, chemical agents, chemical concentrations, chemical reactions, fluid-rock interactions, slug size, chemical adsorption	No	No	Yes	Yes	Yes	No
Zerpa et al. (Present work)	Chemical concentration, slug size	No	No	No	No	Yes	Yes

TABLE 2 – DESIGN VARIABLE RESTRICCIONS

DESING VARIABLE	RANGE		UNITS
	Min	Max	
Alkaline Concentration (Na_2CO_3)	0	0.5898	meq/ml
Surfactant Concentration	0.001815	0.01	Vol. fract.
Polymer Concentration	0.0487	0.1461	wt%
Injection time	111	326	days

TABLE 3 – INJECTION SCHEME

Slug	Inj. time (days)	PV	Component concentration								
			Cw^1	$Csurf^1$	$Cpol^2$	Ccl^3	Cca^3	Cmg^3	$Cco3^3$	Cna^3	$Ch^{+\,3}$
Polymer preflush	26	0.05	1.0	0	0.0974	0.015667	0.0019	0.004774	0.009122	0.01461	111.0034
AS preflush	25	0.1	0.99574	0.00426	0	0.07168	0.0034	0.0067	0.3339	0.52517	111.0767
ASP slug	715	0.41	0.99637	0.00363	0.0974	0.04948	0.0067	0.00831	0.3351	0.3929	111.839
Polymer drive	50	0.5	1.0	0	0.05	0.03586	0.00665	0.00132	0.0164	0.09	111.0034
Postflush	275	1.0	1.0	0	0	0.0135	0.00185	0.004774	0.008	0.0146	111.0034

1. Conc. unit = Vol. fract.
2. Conc. unit = wt%
3. Conc. unit = meq/ml

TABLE 4 –OPTIMIZATION RESULTS

MODEL	Surrogate-based optimal solution				Objective function (COP %OOIP)	
	Cna [meq/ml]	Csurf [Vol. fract.]	Cpol [wt%]	Injection time [days]	Surrogates	UTCHEM
Polynomial Regression	0.3080	4.9993E-03	0.1200	326	32.17 (127,218 bbl)	35.70 (141,167 bbl)
Kriging	0.3060	3.8196E-03	0.1200	282	36.40 (143,929 bbl)	34.84 (137,767 bbl)
Weighted Average Model	0.3058	2.2934E-03	0.1047	292	34.05 (134,634 bbl)	33.86 (133,892 bbl)

Sampling of the design space (input)

↓

Objective function evaluations for the input sample (output)

↓

Construction of surrogate models using input/output pairs

↓

Surrogate-based optimization

↓

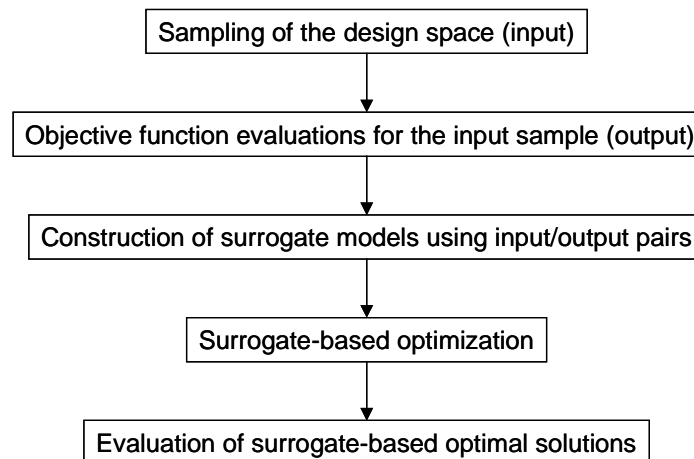Evaluation of surrogate-based optimal solutions

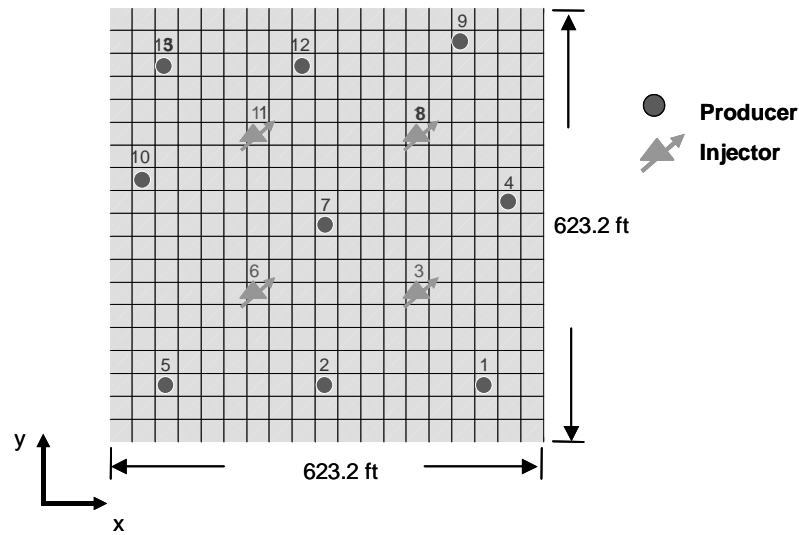**Fig. 1 – Architecture of the proposed methodology**

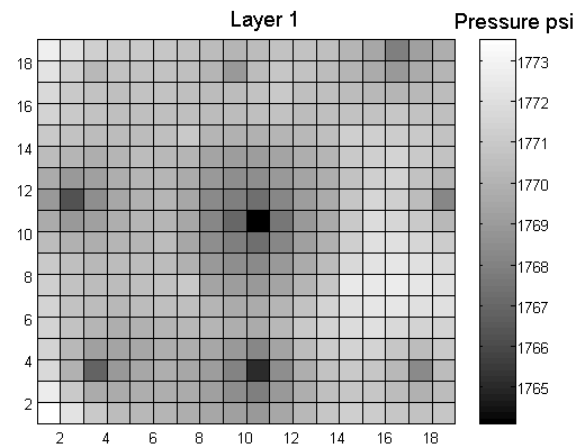Fig. 2 – Well pattern illustration

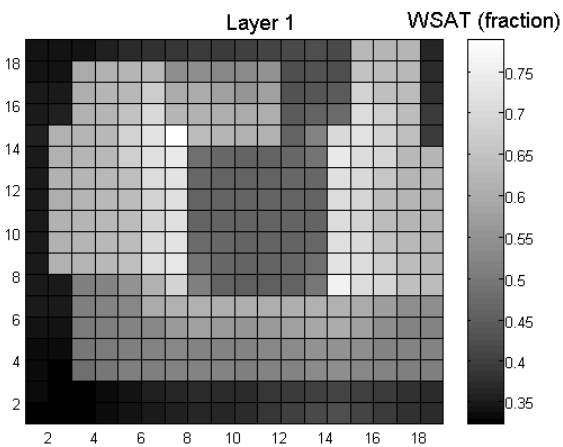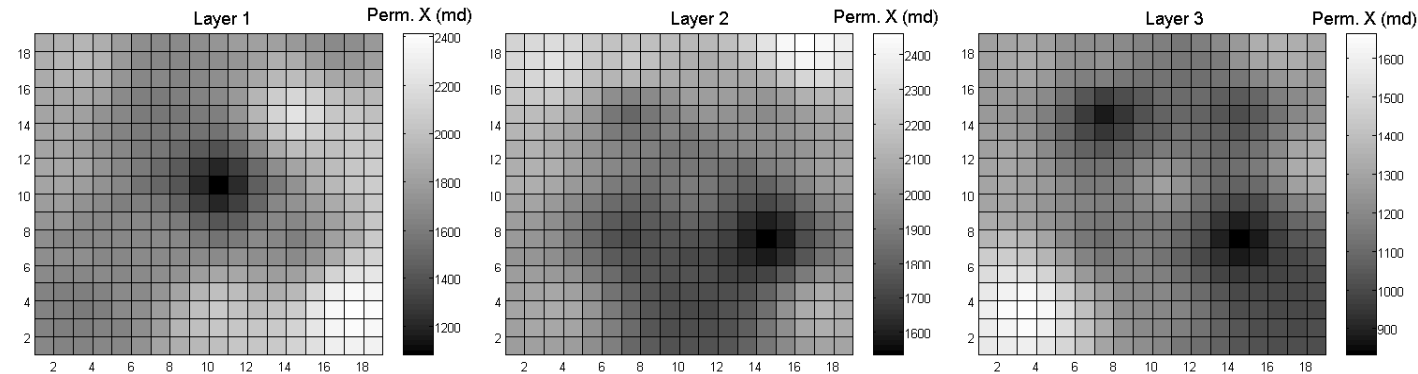Fig. 3 – Initial reservoir pressure distribution

Fig. 4 – Initial water saturation field

Fig. 5 – Horizontal permeability field