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RESERVOIR CHARACTERISATION USING ARTIFICIAL BEE COLONY OPTIMISATION

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ABSTRACT

To obtain an accurate estimation of reservoir performance, the reservoir should be properly characterised. One of the main stages of reservoir characterisation is the calibration of rock property distributions with flow performance observation, which is known as history matching. The history matching procedure consists of three distinct steps: parameterisation, regularisation and optimisation. In this study, a Bayesian framework and a pilot-point approach for regularisation and parameterisation are used. The major focus of this paper is optimisation, which plays a crucial role in the reliability and quality of history matching.

Several optimisation methods have been studied for history matching, including genetic algorithm (GA), ant colony, particle swarm (PS), Gauss-Newton, Levenberg-Marquardt and Limited-memory, Broyden-Fletcher-Goldfarb-Shanno. One of the most recent optimisation algorithms used in different fields is artificial bee colony (ABC). In this study, the application of ABC in history matching is investigated for the first time. ABC is derived from the intelligent foraging behaviour of honey bees. A colony of honey bees is comprised of employed bees, onlookers and scouts. Employed bees look for food sources based on their knowledge, onlookers make decisions for foraging using employed bees' observations, and scouts search for food randomly.

To investigate the application of ABC in history matching, its results for two different synthetic cases are compared with the outcomes of three different optimisation methods: real-valued GA, simulated annealing (SA), and pre-conditioned steepest descent. In the first case, history matching using ABC afforded a better result than GA and SA. ABC reached a lower fitness value in a reasonable number of evaluations, which indicates the performance and execution-time capability of the method. ABC did not appear as efficient as PSD in the first case. In the second case, SA and PDS did not perform acceptably. GA achieved a better result in comparison to SA and PSD, but its results were not as superior as ABC's.

ABC is not concerned with the shape of the landscape, that is, whether it is smooth or rugged. Since there is no precise information about the landscape shape of the history matching function, it can be concluded that by using ABC, there is a high chance of providing high-quality history matching and reservoir characterisation.

KEYWORDS

History matching, inverse problem, evolutionary algorithms, optimisation, reservoir characterisation, landscape shape, artificial bee colony.

INTRODUCTION

One of the main purposes of reservoir simulation is to predict the future performance of hydrocarbon fields with the aim of field developments or investment decisions. Accurate reservoir simulation requires high-quality reservoir characterisation and geomodelling. In geomodels, porosity and permeability distributions are usually considered as uncertain parameters; however, they are also the principal parameters in reservoir simulation. Porosity and permeability distributions in geomodels are generated using geostatistical correlations (Journel and Huijbregts, 1978). Although many developments have been made in geostatistics such as co-kriging, sequential Gaussian simulation, and sequential indicator simulation (Kelkar and Perez, 2002), porosity and permeability remain uncertain parameters for reservoir simulation due to the limited number of sample data (Oliver, 1994). Only about one-billionth of the whole reservoir is measured and the rest is estimated using the geostatistical correlations (Berta et al, 1994).

Hence, history matching is applied to calibrate geomodel parameters and possibly other input data of the reservoir simulator, such as well skins and aquifer strength with observed data. The observed data is typically information about well performance during the production period—for instance: well oil performance rate, well bottomhole pressure, and well water cut in each time step (Oliver and Chen, 2010). This calibration is called history matching, which is a non-linear inverse problem (Ballester and Carter, 2007). The non-linearity, measurement errors in observed data, excessive computation time, and large number of variables make history matching a complicated inverse problem, which suffers from ill-posedness. Ill-posed problems have more than one solution with similar fitness values (Sun, 1994).

The history matching procedure, like other inverse problems, consists of three sections: variables definition (parameterisation), objective function definition, and optimisation (Oliver and Chen, 2010). As the number of gridblocks in geomodels is large, it is unfeasible to carry out history matching while treating porosity and permeabilities in each gridblock as decision variables. Therefore, a parameterisation should be used to reduce the quantity of unknown parameters to a reasonable number. In parameterisation, it is essential to define the minimum parameters representing the whole model with enough accuracy (Tarantola, 1987); however, it is a complex task due to reservoir heterogeneity. Several approaches have been introduced such as zonation (Jacquard, 1965), pilot points (De

Marsily et al, 1984, Bissell et al, 1997), spectral decomposition of prior covariance (Reynolds et al, 1996), and so on. These parameterisation approaches are not the focus of this study. In this paper, a pilot-point approach and a full parameterisation have been used. Full parameterisation corresponds to a system that does not include parameterisation and in which all variables (gridblocks) are taken for granted as decision variables. In such a case, the number of gridblocks should be small.

The next section is objective function definition. The objective function can be defined in different ways. The most famous approaches in history matching regarding the objective function definition are the square of differences between observed data (history) and simulation results (L^2 the norm of misfit), and Bayesian form, which is derived from Bayes' theorem (Sivia and Skilling, 2006; Carter, 2004). In the Bayesian framework, prior knowledge is used to stabilise problems and make them well-posed. The prior information performs as a penalty term in the objective function. In this study, the Bayesian approach is used for the definition of the objective function. After defining the decision variables with or without parameterisation and defining the objective function, finding the global minimum (optimisation) is the next step, and plays a key role in history matching.

Various optimisation methods have been used in history matching, such as simulated annealing (Ouenes et al, 1993), genetic algorithm (GA) (Romero and Carter, 2001), particle swarm (Mohamed et al, 2010), ant colony (Hajizadeh et al, 2011) and several classical optimisation methods—for example: Gauss-Newton, Levenberg-Marquardt and Limited-memory, Broyden-Fletcher-Goldfarb-Shanno (LBFGS) (He et al, 1997, Zhang et al, 2005). Each method has its own capabilities and weaknesses, and the method selection should be based on conditions—especially the shape of landscape. Due to the large dimensionality of the space, providing a precise assessment for the landscape shape is not possible (Oliver and Chen, 2010). Thus, the selection of the optimisation method is controversial and no unique approach has been developed thus far. It should be mentioned that ensemble Kalman filtering (Liang et al, 2009, Lorentzen et al, 2009, Nævdal et al, 2003) is another algorithm that was developed for assisted history matching.

Classical (gradient) optimisers converge much faster and more efficiently than stochastic optimisers, (Zhang et al, 2005), but they have some restrictions, especially in systems with multiple local minima and/or discrete decision variables. On one hand, classical methods are sensitive to the initial guess, and the objective function is required to be derivable. On the other hand, stochastic methods are slow in convergence and cannot perform appropriately in systems with a large number of variables (Oliver and Chen, 2010). To find the global minimum in systems with many local minima, however, one of the best options is making use of stochastic optimisers. The ABC method introduced by Karaboga in 2005 is one of the most recent evolutionary optimisation methods. ABC was inspired by studying the swarm behaviour of honey bees. Its applications have been studied in different fields, such as digital IIR filters (Nurhan, 2009), heat-transfer coefficient (Zielonka et al, 2011) and several numerical functions (Karaboga and Akay, 2009). In this study, the application of the ABC algorithm in automatic history matching and reservoir characterisation is investigated for the first time, and its advantages and disadvantages explored by evaluating its performance on two different synthetic models.

HISTORY MATCHING

As previously stated, the main goal of history matching is to calibrate the input data—especially the geomodel—with the observed data. This means that an estimated set of parameters (m) using some observed data (d_{obs}) that contains measurement error is required (Equation 1). Measurement error is almost always assumed to be Gaussian with a zero mean, and it is also assumed that observed data is not correlated with each other (Sun, 1994). Therefore, the covariance matrix (C_d) of observed data is a diagonal matrix whose elements are standard deviations of the measurement error (noise). The matrix is shown in Equation 2. The decision variables form a column vector, m, in Hilbert space (H_1), and the number of elements is N_m. Similarly, d_{obs}, d_{cal} are column vectors in Hilbert space (H_2) containing the observation and calculation data, respectively, and with a quantity denoted by N_{dobs}. The vectors m and d_{cal} are related to each other by g, a non-linear operator from space H_1 to space H_2. As shown in Equation 3 (Stark, 1987), g is the reservoir simulator in the history matching problem, which is ECLIPSE E100 in this paper.

$$m = \begin{bmatrix} m_1 \\ \vdots \\ m_{N_m} \end{bmatrix}, \quad d_{obs} = \begin{bmatrix} d_{obs_1} \\ \vdots \\ d_{obs_{N_{dobs}}} \end{bmatrix} \tag{1}$$

$$C_d = \begin{bmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_{N_{dobs}} \end{bmatrix} \tag{2}$$

$$d_{cal} = g(m) \tag{3}$$

Equation 3 is the forward problem, but in history matching it is desirable to estimate m using observed data; this requires solving an inverse problem. The elements of m can be any uncertain or unknown parameter—such as porosities—in some or all of the gridblocks, or well skins, aquifer data and so on. To estimate m, an objective function should be defined. As previously stated, to overcome ill-posedness and stabilise the solution, a Bayesian framework can be applied to define the objective function. In the Bayesian framework, the main objective is to find a set of variables (m) that maximises the posterior probability function: $p(m|d_{obs})$. Using Bayes' theorem (Equation 4), Equation 5 can be derived with the assumption of Gaussian distribution of m, and Gaussian noise in the observed data (Sivia and Skilling, 2006). The matrix, C_m, is the covariance of prior knowledge and C_D is the covariance matrix of observed data, which is defined in Equation 6. The second term in Equation 6 (C_T) is the numerical simulation error, which is assumed to be zero in this study. With the purpose of finding the solution (m_∞), it is necessary to maximise Equation 5—or similarly minimise Equation 7. The first term in Equations 5 and 7 is likelihood and the second term is prior knowledge. The prior knowledge term depends on the availability and certainty of information about decision variables, and can be omitted if there is no prior knowledge for the decision variables.

$$P(m|d_{obs}) = \frac{P(d_{obs}|m).P(m)}{P(d_{obs})} \tag{4}$$

$$P(m|d_{obs}) \cong c.exp\left\{-\frac{1}{2}(g(m)-d_{obs})^t C_D^{-1}(g(m)-d_{obs}) - \frac{1}{2}(m-m_{prior})^t C_M^{-1}(m-m_{prior})\right\} \tag{5}$$

$$C_D = C_d + C_T \qquad \rightarrow \qquad C_D \cong C_d \tag{6}$$

$$S(m) = \left\{\frac{1}{2}(g(m)-d_{obs})^t C_D^{-1}(g(m)-d_{obs}) + \frac{1}{2}(m-m_{prior})^t C_M^{-1}(m-m_{prior})\right\} \tag{7}$$

An optimisation is required to minimise Equation 7. Several methods of optimisation exist, but reaching an acceptable solution and being efficient in computation time requires a discerning selection of optimisation method. In this study, the objective function of history matching is defined by Equation 7. The observed data is field and well performance in each time step. The decision variables (m) are the porosity in each gridblock. In the first case study, they are directly assumed to be variables due to full parameterisation. In the second case, pilot-point parameters construct the element of m, then by making use of pilot-point parameters and ordinary kriging, porosities in the whole gridblocks are calculated. Hence, the porosity in each gridblock is indirectly the unknown parameter in the second case study. The parameter definitions are discussed in more detail in the case studies. In this study, an assessment for the landscape shape was made to determine whether S(m) has several local minima or not; however, this is only an estimate. The following optimization methods were then applied: simulated annealing (SA), genetic algorithm (GA), pre-conditioned steepest descent (PSD), and ABC. Their outcomes were compared together. In this paper, the application of ABC for history matching is investigated in detail, and its usefulness and efficiency in different cases is evaluated.

ARTIFICIAL BEE COLONY

The natural behaviour of a honey bee's colony

To survive through winter, bees have to produce adequate honey. Hence, honey bees need to explore and exploit the area around them for food as efficiently as possible and store enough food. To carry out efficient exploitation and exploration, they not only memorise the locations with highest profitability, but also share their information with each other (Panigrahi et al, 2011). The profitability of a food source depends on its distance from the hive, richness and the ease of extraction (Karaboga, 2005). The main stage of efficient exploration and exploitation involves sharing information and communicating with each other through a dancing language—a waggle dance. In this dance, they explain the profitability of food sources, directions and distances (Panigrahi et al, 2011). By this means, they share their knowledge and are consequently able to focus more on areas with highest profitability. Bees' exploration and exploitation of their surrounding area is one of the most well organised in nature.

Artificial bee colony (ABC) algorithm

Using honey bee behaviour as inspiration, an algorithm for optimisation was developed by Karaboga in 2005. The colony of ABC comprises employed bees, onlookers and scouts, just like real honey bees. In the first attempt, employed bees search for food randomly and then memorise the locations. In the next attempt, an employed bee looks for a food source based on her knowledge. This means employed bees always looked for better locations around the previous ones. They also share their information about food source profitability and their locations with onlooker bees. Onlookers collect information from all employed bees, then make decisions based on the observations. If the nectar amount increases, the number of onlookers looking for it will increase (Karaboga, 2005). This means locations with the highest profitability are exploited by more onlooker bees. Scouts search randomly and usually look for a new home or food source. Scouts usually comprise only 5% of the whole population. If an employed bee cannot extract any more food from its corresponding area after a number of tries (i.e. they cannot find a better location with a higher level of nectar) it becomes a scout bee.

In the ABC algorithm, defining colony size (N_b) and the dimension of the problem (N_m) are the first steps. Usually half of the colony is assumed to be employed bees and the rest are onlooker bees, and the number of food sources (N_f) is equal to the number of employed bees (Karaboga and Basturk, 2008). An initial population should then be generated. It is shown as a matrix (Equation 8), which is typically generated randomly. Each possible solution (m_i=[m_{i1}... m_{iNm}]) is then evaluated. After that, each employed bee looks around one m_i for a better solution—if she gets a better result, she memorises the new location (solution), otherwise she keeps the previous location (solution) in mind. Each employed bee is an agent for a solution (m_i). After all the employed bees search around their m_i, they share their knowledge with an onlooker based on the fitness of each solution.

$$Initial\ Pop = \begin{bmatrix} m_{11} & \cdots & m_{1N_m} \\ \vdots & \ddots & \vdots \\ m_{N_f1} & \cdots & m_{N_fN_m} \end{bmatrix} \quad (8)$$

Onlookers then use the fitness values provided by the employed bees to forage around the food sources. Consequently, most onlookers exploit around an m_i with a lower fitness value (a higher profitability) rather than search for an m_i with a higher fitness (a lower profitability). It is a repetitive procedure: in each cycle, each employed bee searches for a better fitness using their own knowledge and each onlooker searches for food after collecting the knowledge of the employed bees. These cycles are repeated until the required satisfaction is gained, or one of the stopping criteria is met. During the cycles, it is necessary to define a limitation; if an employed bee cannot improve the fitness of a specific location after a limited number of iterations, she should become a scout bee and look for a new solution randomly (Karaboga, 2005; Karaboga and Basturk, 2007a, 2007b).

In this study, the above algorithm—which was coded in MATLAB by Karaboga in 2007—is used. In the following sections two famous functions, which are usually used to benchmark the capability of optimisation methods, are selected to investigate the searching behaviour of ABC.

Searching behaviour of ABC using the Ackley function

The Ackley function is a multi-dimensional model that is extensively used to test optimisation methods; this function has several local minima and one global minimum. In this study, to be able to draw the function and investigate the searching behaviour, a 2D Ackley function is used. The global minimum is (0,0) with a zero fitness value: (f(0,0) = 0). The function is displayed in Figure 1 for -2 < x, y < 2. The function is written in Equation 9, assuming a = 20, b = 0.2, and c = 2π (Molga and Smutnicki, 2005). Classical optimisation methods cannot perform properly to find the global optimum of such a system and they usually get stuck in a local minimum. For these kinds of functions, evolutionary algorithms must be applied.

$$F(x,y) = -ae^{\left(-b\sqrt{\frac{1}{2}(x^2+y^2)}\right)} - e^{\frac{1}{2}(\cos(cx)+\cos(cy))} + a + e \quad (9)$$

The ABC algorithm was run on the Ackley function with 50 iterations and a colony size of 30. The point (3.9×10^{-10}, -3.2×10^{-10}) was found as a final solution with a fitness of 1.4×10^{-9}, which is very close to the exact solution. The total number of evaluations was 1,500. Figure 2 exhibits the exploration and exploitation of ABC on this function. Each dot point shows a location that is evaluated either by employed, onlooker or scout bees. Notice that even though the landscape contains many local minima, ABC converges quickly to the global minimum.

Searching behaviour of ABC using the Schwefel function

A similar procedure is used for the Schwefel function, which is shown in Equation 10. For this study, x and y are between -500

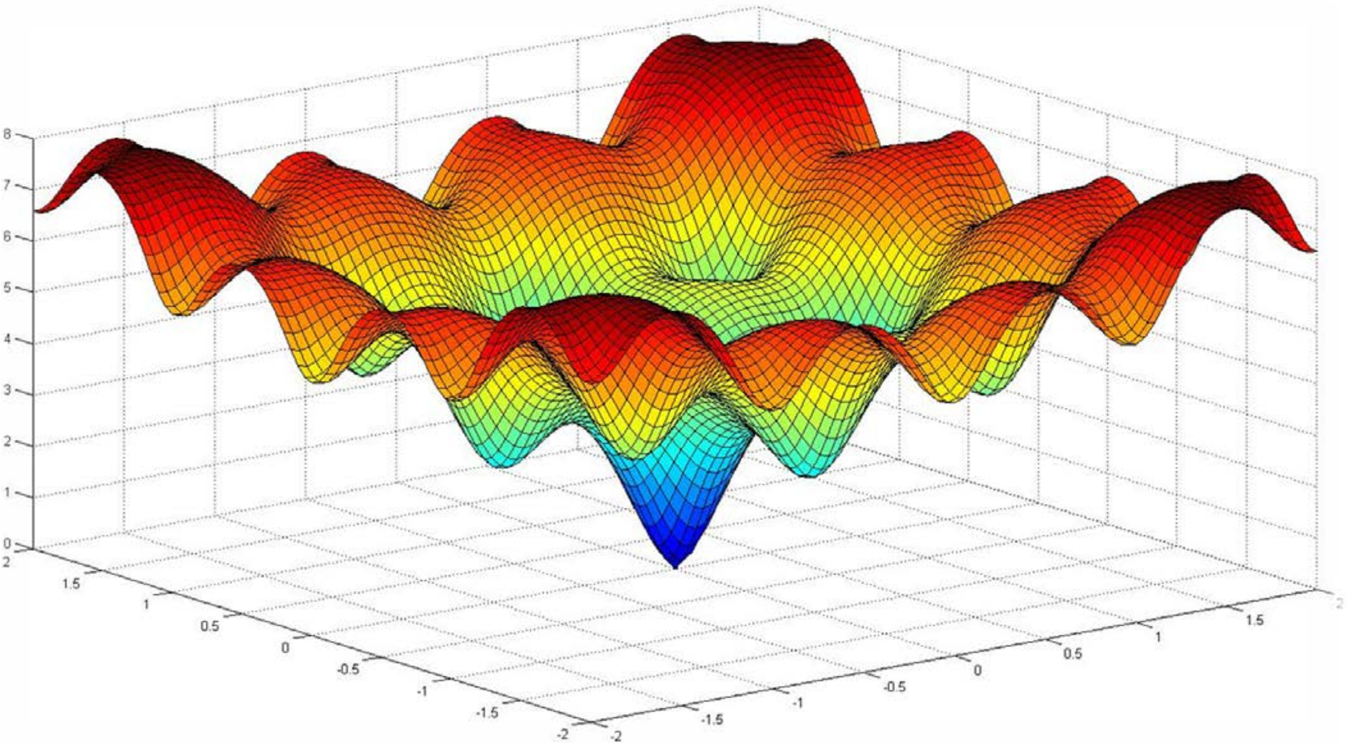

Figure1. 2D Ackley function.

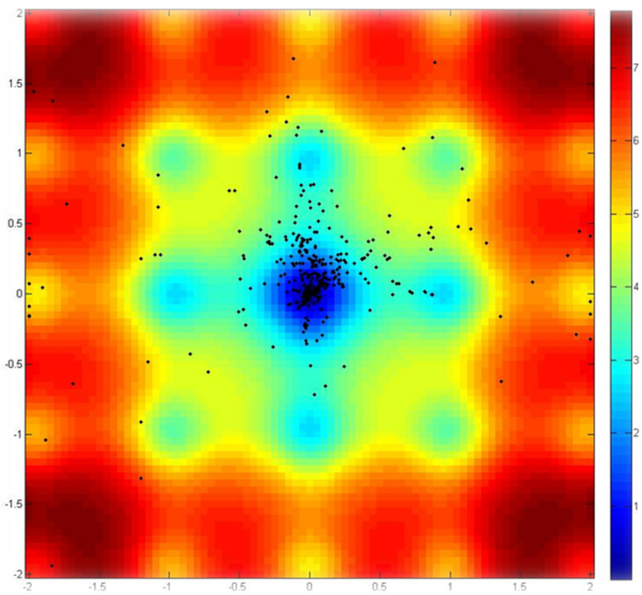

Figure 2. Searching behaviour of ABC on the Ackley function.

and 500, and the global minimum is -837.9658, which is located at (x, y) = (420.9687, 420.9687). Schwefel is a multi-dimensional function, which is problematic even for stochastic optimisation algorithms due to its highly rugged landscape shape (Fig. 3) (Molga and Smutnicki, 2005). ABC was run for the function with 70 iterations and colony size of 30. The following results were obtained—x and y of the solution were equal to 420.9688 and 420.9688, respectively, and its fitness was -837.966, which is close to the exact solution. Figure 4 exhibits the convergence behaviour of ABC on Schwefel function.

$$F(x,y) = -x(\sin\left(\sqrt{|x|}\right) - y(\sin\left(\sqrt{|y|}\right) \tag{10}$$

The searching behaviour of ABC demonstrates high-quality exploration and exploitation of the landscape and fast convergence to the solution.

Application of ABC in history matching

In the above examples, the capability of ABC in exploration and exploitation is shown. In this study, the application of ABC in automatic history matching and its advantages and disadvantages are studied using two synthetic examples. To automate the history matching, MATLAB was coupled with ECLIPSE (E100) to run the reservoir simulation at each function evaluation. MATLAB was also coupled with SGeMS for geostatistical data generation (Remy et al, 2009). The coding for the geostatistics section was done by Thomas Mejer Hansen from 2004–08 and can be found at http://mgstat.sourceforge.net/. The coding for the ABC algorithm used in this study was done by Karaboga (2009) and can be found at http://mf.erciyes.edu.tr/abc/. To evaluate the capacity of ABC, a comparison of its results with other optimisation methods is required. Thus, two stochastic optimisers (a real-valued genetic algorithm and simulated annealing), and a classical method (pre-conditioned steepest descent (Tarantola, 1987) are used. For the genetic algorithm and simulated annealing optimisation, the MATLAB global optimisation toolbox was used.

RESULTS

For this study, two synthetic models were constructed to evaluate the proposed optimisation method in the history matching process. Since synthetic cases do not have any flow performance history, they should be simulated for a period of time to generate such a history. A Gaussian noise was added to the history (observed vector) to make it more realistic. At this point, the history used for geomodel calibration was ready. Subsequently, the decision variables needed to be defined. The porosities of each gridblock were assumed to be the decision variables. Then, with history matching, the decision variables were assessed using the objective function defined in Equation 7 and an optimisation method. Finally, the estimated values obtained by different optimisation methods were compared with the reference values (exact solutions) that were used to produce the history for the synthetic cases. A real case was not used in

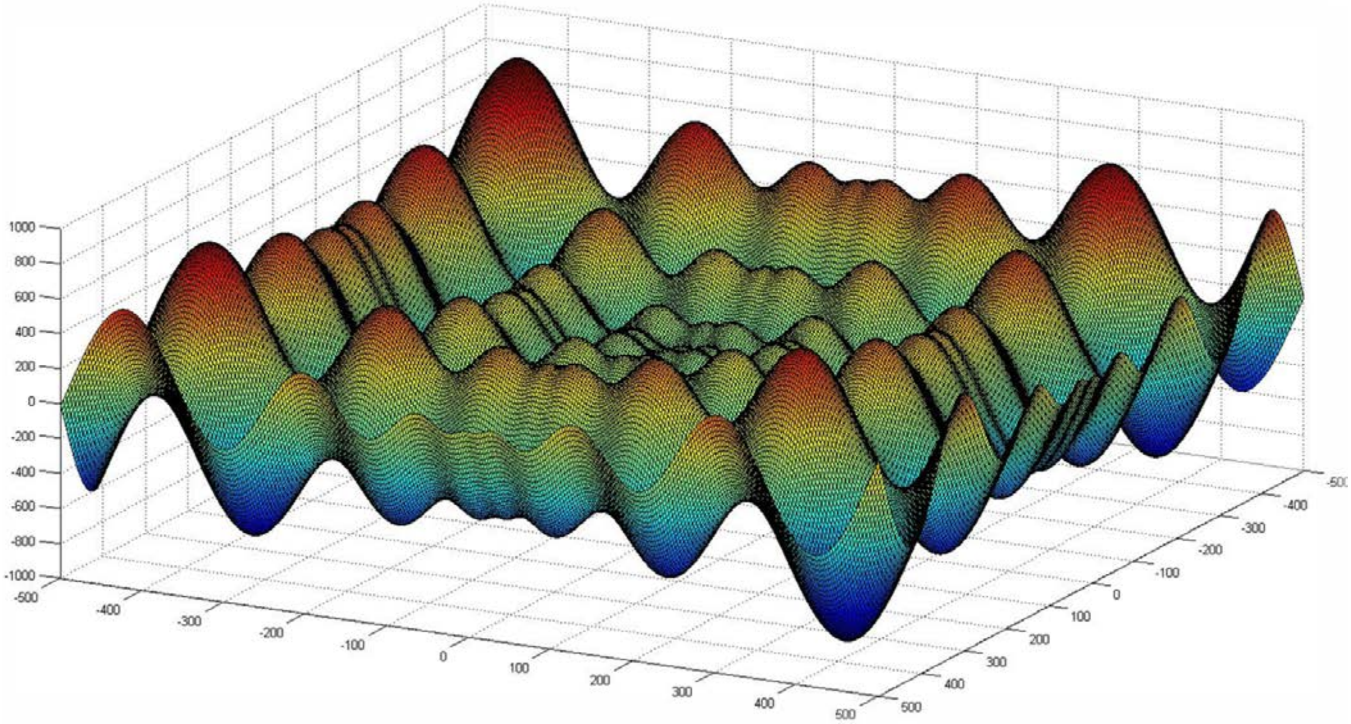

Figure 3. 2D Schwefel function.

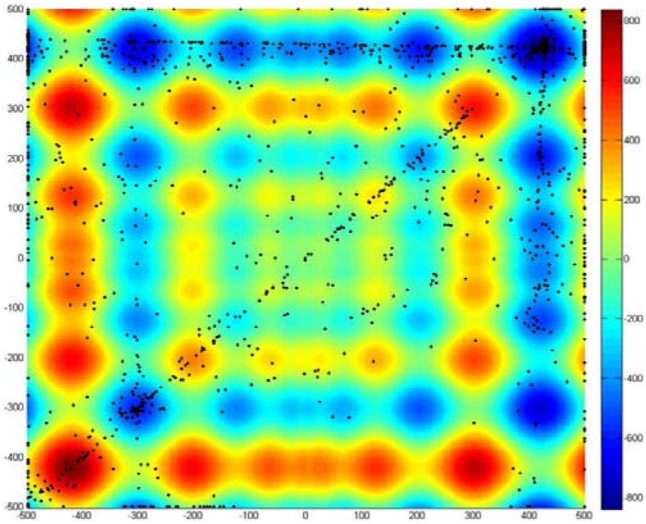

Figure 4. Searching behaviour of ABC on Schwefel function.

the evaluation of the proposed method since its corresponding true solution was not necessarily known, and so further verification of the solution acquired by different methods was not possible or reliable. To sum up, the goal was to reproduce the reference porosity distribution using historical performance data and prior knowledge, if available.

Case one

The first case consisted of 75 large gridblocks in three layers; each layer had 25 gridblocks. The permeability of each gridblock is calculated using the Kozeny-Carman equation with some simplifications, shown in Equation 11. Permeability in the x and y directions were set as equal. The permeability in the vertical direction (z) was 10% of the permeability in the horizontal direction (x, y). The porosity in each gridblock was similar to the corresponding gridblocks of other layers. The porosities for one layer were considered as the decision variable. Thus, there were only 25 unknown parameters and no need to reduce the number of unknown variables with parameterisation. It was assumed that the porosity distribution of the reference case was totally heterogeneous and therefore uncorrelated. More detail about the case is shown in Table 1. Although this case was unrealistic, it is useful to investigate the outcomes of different approaches on simple cases.

Table 1. Reservoir properties.

Property	Value
Average permeability in X and Y direction	517 md
Average porosity	0.2471
Number of gridblocks in X, Y, Z direction	5, 5, 3
Dimension of gridblocks in X, Y, Z direction	183 m, 183 m, 18.3 m
Rock compressibility	0.000058 1/bar
Reservoir top	2,926 m
Phases	Oil, water, gas and dissolved gas
Oil viscosity	2 cp @ 413 bar
Initial pressure	269 bar @ 1851 m

$$k = 30{,}000 \times \phi^3 \tag{11}$$

Porosity for the reference case was generated using a normal distribution, with a mean of 25 and standard deviation (σ) of 7. As it is uncorrelated, the covariance matrix (C_M) was diagonal. The porosity distribution of the reference case is shown in Figure 5. History was generated for 2,210 days in 38 time steps. The history consisted of well bottomhole pressures, well liquid production rates, well gas production rates, and well oil production rates in each time step; the total observation data is equal to 798 elements. Gaussian noise was then added to the history with a zero mean and σ of 2. The observed performances were not correlated, therefore the covariance matrix (C_D) is a diagonal matrix whose elements are 4 (σ^2). This case is a nine-spot water flooding system, with five injectors and four producers.

To generate a prior knowledge, Gaussian noise was added to the reference porosity with zero mean and σ of 3. Therefore, this can be considered as the initial estimation for all 25 unknown variables (prior knowledge); Figure 6 shows the prior distribution. The objective function is defined by Equation 7. Although the prior distribution seems close to the reference case, its fitness value is in the order of 10^7 (5.04×10^7) and the difference between prior (here $m_{prior} = m_\infty$) and the reference porosity is 9.5%, based on Equation 12. In this equation, m_r is the reference value and m_∞ is the final solution. The main goal of history matching is to reduce the difference between the solution and the reference (Equation 12) by minimising the result of Equation 7.

$$O(m_\infty) = \frac{1}{N_m} \sum_{i=1}^{N_m} \frac{|m_{\infty i} - m_{ri}|}{m_{ri}} \tag{12}$$

For full parameterisation cases with porosities and/or permeabilities as variables, the authors believe the shape of landscape is smooth and is more likely to have only one minimum. As mentioned before, it is almost impracticable to precisely estimate the landscape shape for the history matching objective function; it is only a rough estimation. What led the authors to this conclusion is the landscape shape for the 2D system, and that classical methods can converge to the optimal solution. To draw a 2D landscape, the porosity of 23 out of 25 gridblocks was fixed to the reference values and the other two assumed as variables. The fitness value has been drawn for different porosity values of the two gridblocks, as shown in Figure 7. As it can be seen, the graph is fairly smooth.

The results of different optimisation methods for the 2D case are shown in Table 2. Since stochastic methods (SA, GA and ABC) use random numbers, they were run 10–20 times with different seed numbers and different algorithm options; the best ones (i.e. lower fitness values) were then selected. SA, ABC, real-coded GA, and pre-conditioned steepest descent (PSD) converged to the optimal point. The classical method also works properly. This can be due to the existence of only one minimum. The main difference is the number of times the evaluation function has been evaluated, which causes a huge impact on computation costs/time. The method performances are ranked from the lowest computation time to the highest: 1. PSD; 2. SA; 3. ABC; and, 4: GA. For PSD, calculation of the sensitivity matrix (which is estimated numerically in this study) is necessary. For such cases with smooth landscapes, classical methods are much more efficient than evolutionary algorithms.

The performance results of the methods in the 2D case could not clearly discern between the methods' capabilities and strong points. The main challenge is the case with 25 variables. The next section investigates which of the classical or stochastic methods are more efficient for the case with 25 variables.

The results of solving the 25 variables system with the different methods are shown in Table 3. One of the main advantages of using ABC in history matching is the opportunity of considering prior knowledge for selecting the starting points. At the beginning, ABC starts looking for a solution around the initial food sources. Hence, if a prior knowledge is available and incorporated into the optimisation, there will be a higher probability that ABC converges at a more rapid pace into the global optimum. Since prior knowledge is only a point (vector), and the initial food source consists of a set of points (matrix), noise is added to the prior knowledge to define the initial food source.

As previously mentioned, the main goal is to reduce the value of Equation 12 by minimising Equation 7. For this case, there was an initial estimation for all variables (prior knowledge) and its difference with the reference (real solution) was 9.5%. As the observed data contains noises, the value of Equation 7 for the reference is around 742.82. A genetic algorithm was run several times and each time got stuck at a different point. The result in Table 3 for GA is the best one, and it could not reduce the value to less than 481,800. The difference between its solution and reference is 15.75%; hence, it is concluded that GA at its present configuration cannot provide a good result for this case.

SA was also applied. In SA, an initial point is required and because of having prior knowledge, it is possible to use it as the initial guess. The main problem with this method is its slow convergence speed. It reached S(m) = 74,579 after 70,200 iterations, but its results are acceptable and close to the reference. The value of Equation 12 using SA solution is 5.2%. As SA needs more time to get better results, it is not efficient, especially in a real case.

Pre-conditioned steepest descent worked properly in this case, as was expected. Not only it did achieve a better result compared to the stochastic optimisers, but it also converged faster to the optimal solution. The final solution of PSD is close to the reference, and the difference is only 0.2%. Thus, it is recommended that a classical optimiser should be implemented for this type of case.

In this study, the main focus is on the application of ABC in history matching. For this case, the outcome of history matching using ABC demonstrates ABC can provide a better result compared to other stochastic optimisers. The difference between its solution and the reference is 2.55%. In contrast to the other two stochastic methods, ABC reached a lower fitness

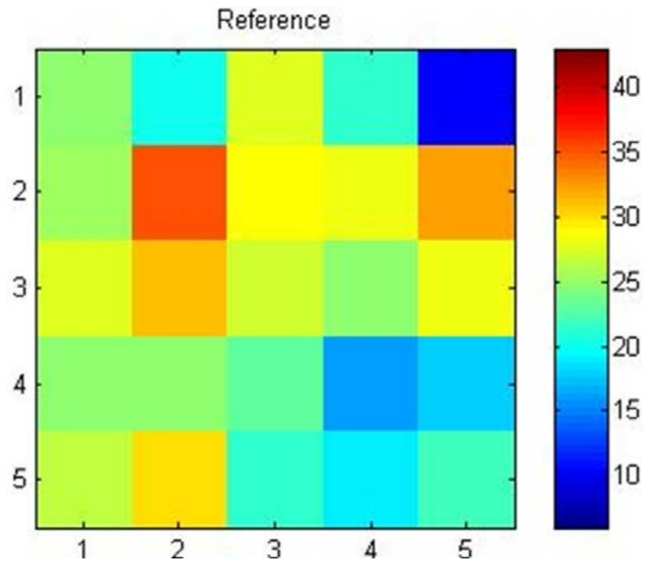

Figure 5. Porosity distribution for the reference case.

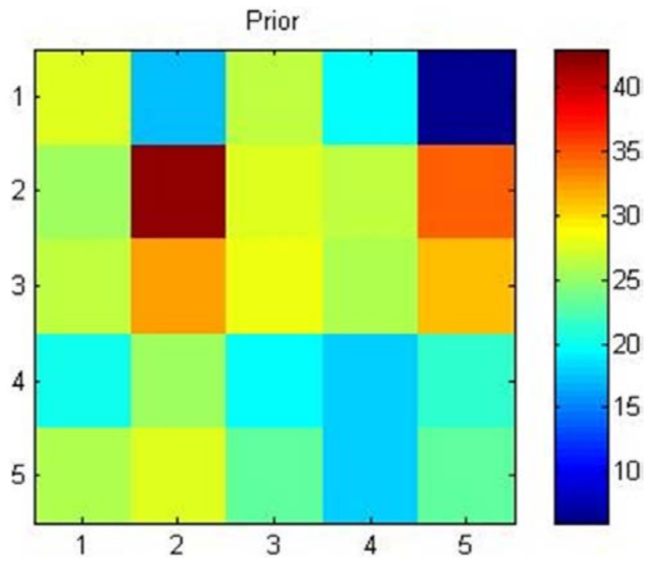

Figure 6. Prior porosity distribution.

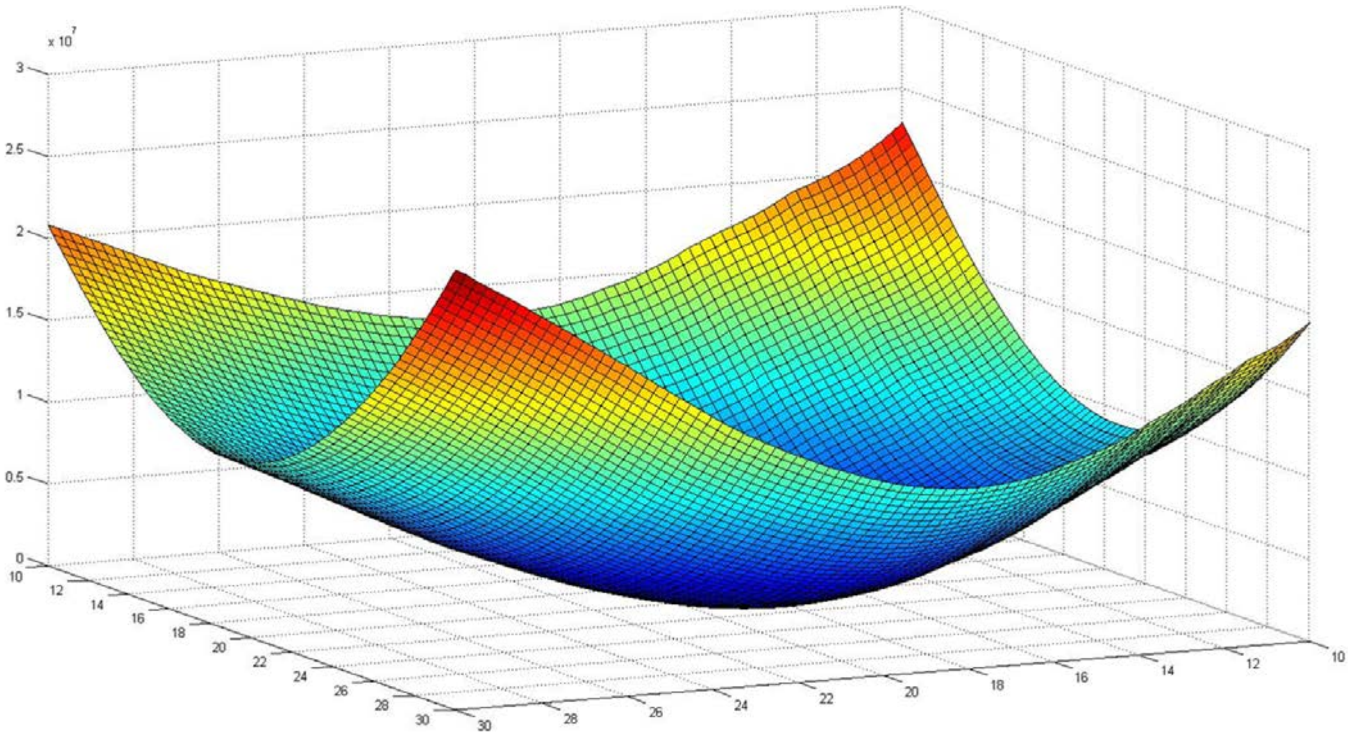

Figure 7. Landscape for case one.

Table 2. Results for the first case with two variables.

Method	Options	No. of Evaluations	Fitness value	Parameters
Solution	-	-	725.9	[20.28...18.96]
SA	Initial point: [15...15]	113	724	[20.28...18.96]
	Fast annealing			
	Exponential temp. update			
	10 initial temp with 100 iterations interval			
ABC	Colony size = 30	280 (12 generations)	725	[20.28...18.96]
	Cycles = 12			
	Limit = 100			
Real-valued GA	Pop. size = 10	780 (25 generations)	724.7	[20.28...18.96]
	Crossover: 90%; heuristic ratio: 1.2			
	Mutation: 10% constrained dependent			
	Elite: 2			
	Selection: stochastic uniform			
PSD	Initial point: [15...15]	36 (nine iterations)	725	[20.28...18.96]

value in a reasonable number of evaluations. This demonstrates the performance and execution time capability of the method. Although GA exhibited more power in exploration of the solution space than ABC, ABC can overcome this deficiency in exploration with its exploitation ability. It is fair to state that ABC did not appear as efficient as PSD in this case.

Case two

Since real cases consist of a large number of gridblocks, more gridblocks were defined for the second case (35 × 35 × 3 grids in x, y and z directions, respectively). Similar to the previous case, it is assumed the porosity is unknown in each gridblock. The permeability is calculated from Equation 11, and the permeability is the same in x and y directions. The permeability in the vertical direction is 10% of the horizontal. This case is a system with two phases (water and oil), and is also a nine-spots water-flood system with five injectors and four producers. The injector wells are connected to the first and second layers, and the production wells are completed only into the second layer. The history (observed vector) was generated by simulating the reference case in 38 time steps for 2,210 days. Its elements are well bottomhole pressures, well oil production rates, well liquid production rates, field oil production rate, field pressure, and field water production rate at each time step. Gaussian noise with a σ of 2 and a zero mean was added to the observed vector.

This case has 3,675 gridblocks, and the aim is to estimate the porosity in each gridblock. There are nine wells in the system with known porosity values in the gridblocks where wells exist. Hence, the number of variables is 3675 – (3×9) = 3,648. It is impractical to optimise a system with 3,648 variables; thus, a parameterisation method should be applied to reduce the variables to a reasonable number. The pilot-point approach introduced by de Marsily in 1984 is used in this study. Pilot points act as pseudo wells and can alter the property distribution with their parameters, which are their locations and their values—in this

Table 3. Results for the first case with 25 variables.

Solutions	Prior	Reference	SA	GA	ABC	PSD
Options	-	-	Initial point: prior	Pop size = 120 Elite = 1	Initial food source: prior + Gaussian noise	Initial point: prior
			Fast annealing	Crossover: 70% scattered	Colony size = 30	
			Exponential temp. update	Mutation: 30% constrained dependent	Cycles = 1,550	
			10 initial temp with 30 iterations interval	Selection: roulette wheel	Limit = 100	
Parameters	27.528	24.563	26.476	36.663	24.323	24.489
	25.404	25.546	25.332	19.036	25.352	25.653
	26.451	27.444	27.455	27.057	27.162	27.437
	20.250	24.817	20.932	22.600	24.777	24.861
	25.867	26.286	27.428	26.700	26.126	26.321
	17.320	20.283	18.552	25.603	19.394	20.291
	42.022	35.238	42.291	39.756	35.590	35.289
	32.067	30.868	31.440	33.116	32.114	30.722
	25.563	24.549	24.858	30.590	24.641	24.413
	27.441	29.874	28.568	34.173	29.559	29.881
	26.744	27.519	27.670	26.948	27.113	27.511
	27.879	28.600	26.817	14.128	29.299	28.581
	28.126	27.305	26.775	28.591	27.638	27.251
	19.573	22.834	21.806	13.514	24.059	22.999
	23.335	21.038	21.318	20.885	20.867	21.037
	19.438	21.489	21.684	24.942	21.466	21.463
	26.420	28.444	26.106	31.067	27.854	28.462
	25.988	24.552	23.306	21.207	24.580	24.515
	18.136	16.313	18.606	11.534	19.258	16.455
	18.112	18.959	17.527	23.754	17.617	18.901
	6.540	10.565	10.510	10.637	10.546	10.566
	34.384	32.213	30.945	29.661	32.512	32.151
	31.135	28.522	28.775	27.967	28.297	28.517
	21.335	17.927	17.742	18.673	18.694	17.965
	23.342	21.903	23.667	18.735	22.853	21.898
Fitness value	5.04 × 107	742.84	74,579	481,800	19,735	733
No. of evaluations	-	-	70,200	36,120 (300 generations)	48,100 (1,550 cycles)	32,400 (1,200 iterations)
Difference using Eq. 12 (%)	9.5%	0%	5.2%	15.74%	2.55%	0.2%

case, porosity. A limited number of the gridblocks are described by pilot points and the rest are calculated using geostatistical interpolations based on the pilot points and well data. In this study, a fixed number of pilot points are used to describe the reservoir and their values (porosity), and locations are considered as decision variables. Therefore, it is only necessary to find the best locations and the best values for pilot points, and the rest of gridblocks are calculated using geostatistical correlation.

In this case, it is assumed there are seven pilot points in each layer and their locations are defined in a polar coordinate system. Each pilot point is located on a specific fixed radius, but could be located at any angle. In each layer, seven pilot points are available but their values and angles are unknown (2×7=14); thus, there are 42 decision variables. After history matching, the location and value of all the 21 pilot points are obtained. The rest of the gridblocks are estimated using geostatistical correlations. In this study, ordinary kriging is used; it is assumed the variogram parameters are all known for further simplification of the problem.

The objective function is defined in the same way as the previous case, but in this case there is no prior knowledge; it is unreasonable to provide prior knowledge for the locations of pilot points. Therefore, the objective function is only the first term (likelihood) of Equation 7. The porosity of the reference case was constructed by assuming a set of values for the pilot points' location and value (m_r). The permeability distribution for each layer of the reference case is shown in Figure 8. Using only data from the nine wells, the distributions for each layer are calculated and the corresponding fitness value is 1.6036×10^6 (Fig. 9). The difference in generated porosity between nine samples and 16 samples (nine wells plus seven pilot points), based on Equation 13, is 17.34%. In Equation 13, p_∞ denotes the generated porosity using the final solution (m_∞), and p_r denotes the reference porosity, which is generated using m_r.

$$O(m_\infty) = \frac{1}{3675} \sum_{i=1}^{3675} \frac{\left|p_{\infty i} - p_{r_i}\right|}{p_{r_i}} \tag{13}$$

Similar to the first case, the shape of the landscape was estimated first. As the location and value of a pilot point are related to each other, a rugged landscape is expected so to prove this, all the values and locations of the pilot points are assumed known except for one. The value for this single pilot point and its angle are the unknown parameters; its corresponding landscape was calculated and is shown in Figure 10. As it can be seen, there are some local minima and one global minimum. This shape is only for one pilot point. It is expected that the landscape exhibits a more rugged behaviour in cases with more pilot points. Consequently, it is difficult for a classical method to solve these kinds of problems.

In this case, four different optimisation methods—ABC, PSD, GA and SA—were investigated on both the 2-dimensional and 42-dimensional problems. In the pilot points ap-

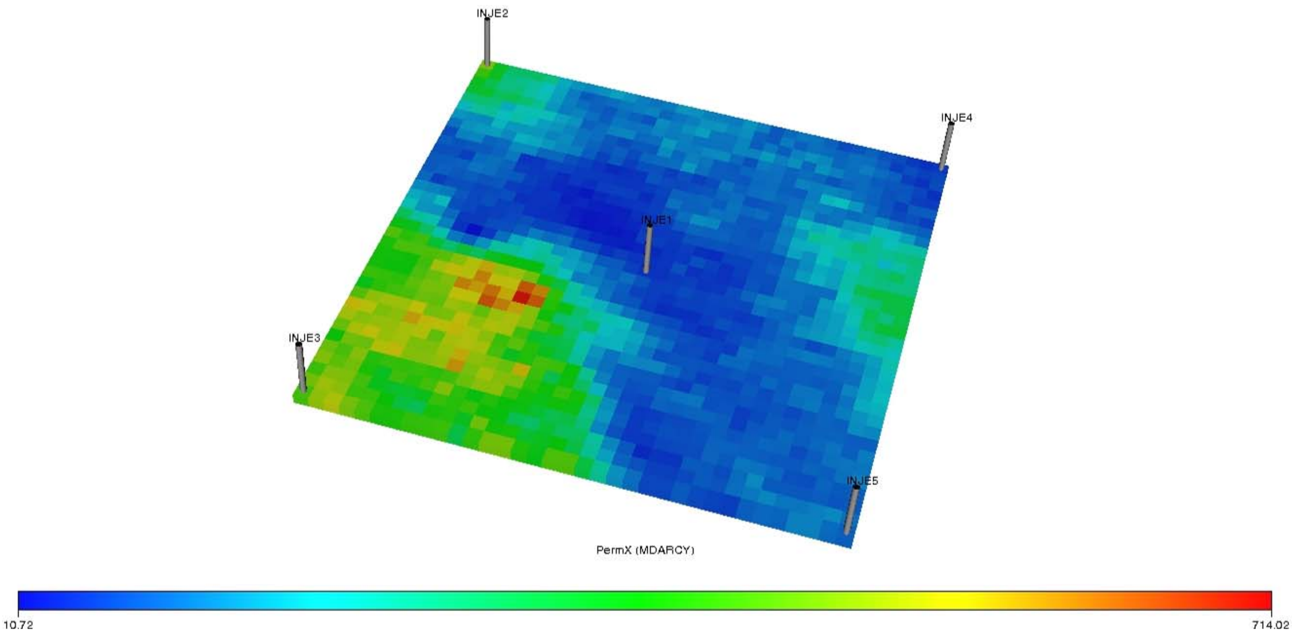

Figure 8a. Reference first layer.

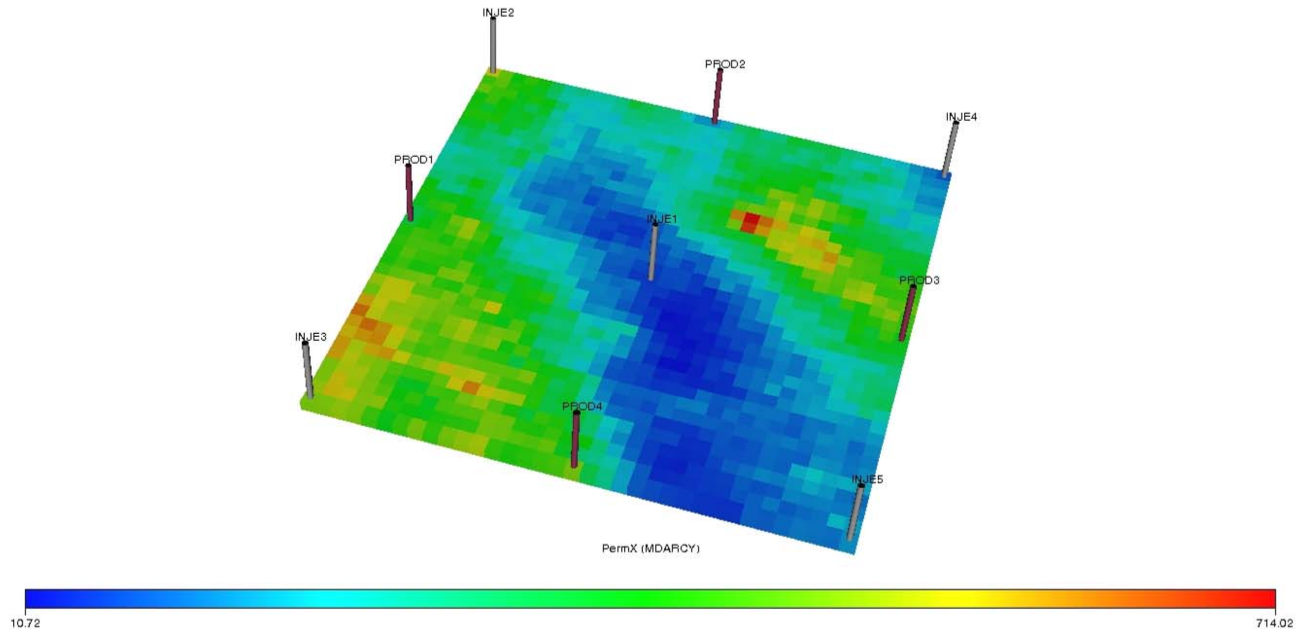

Figure 8b. Reference second layer.

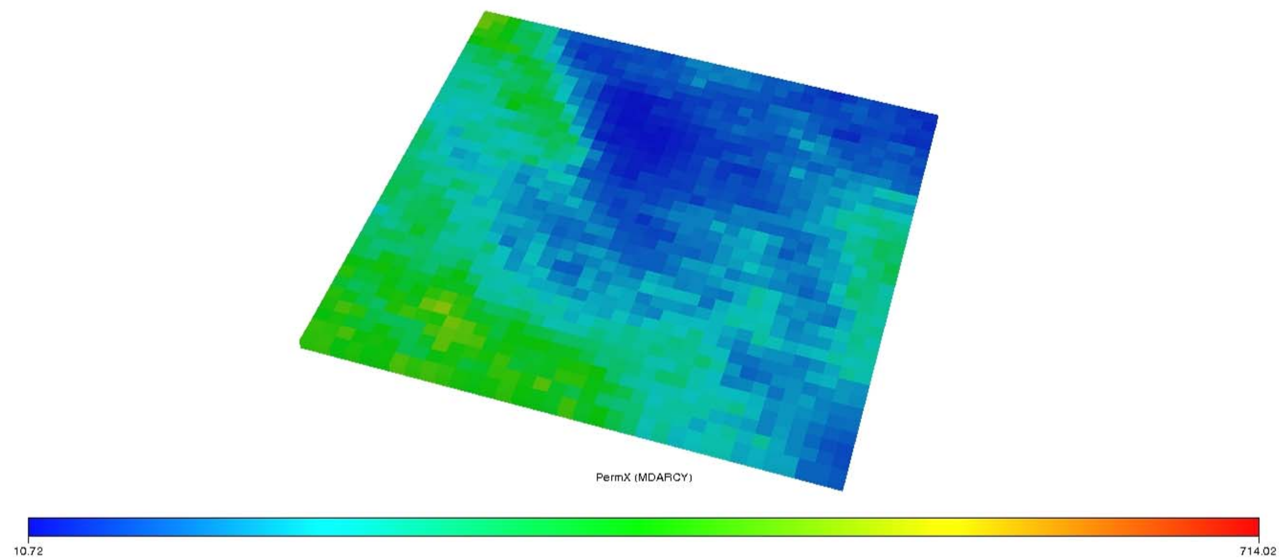

Figure 8c. Reference third layer.

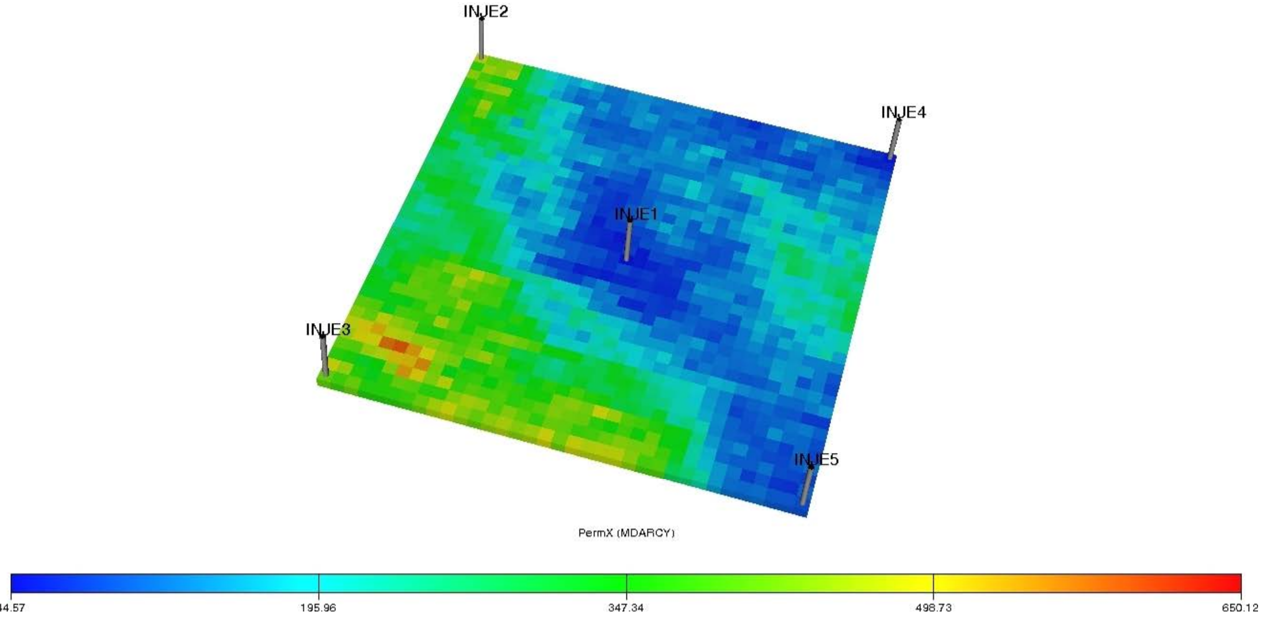

Figure 9a. Generated permeability of first layer (with only nine wells' data).

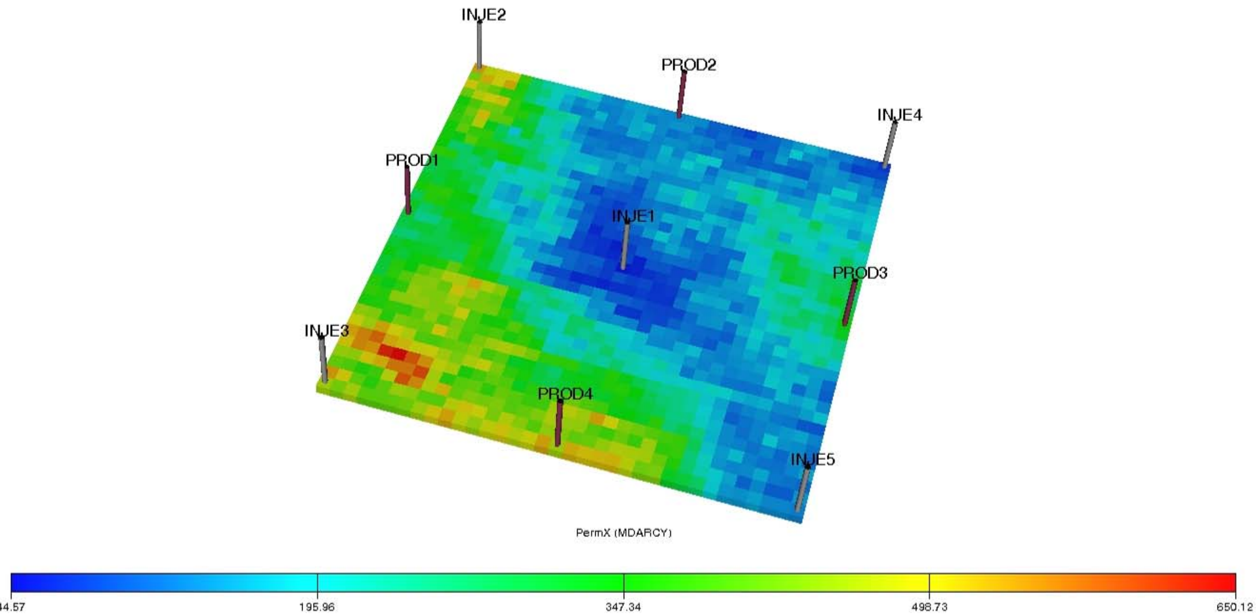

Figure 9b. Generated permeability of second layer (with only nine wells' data).

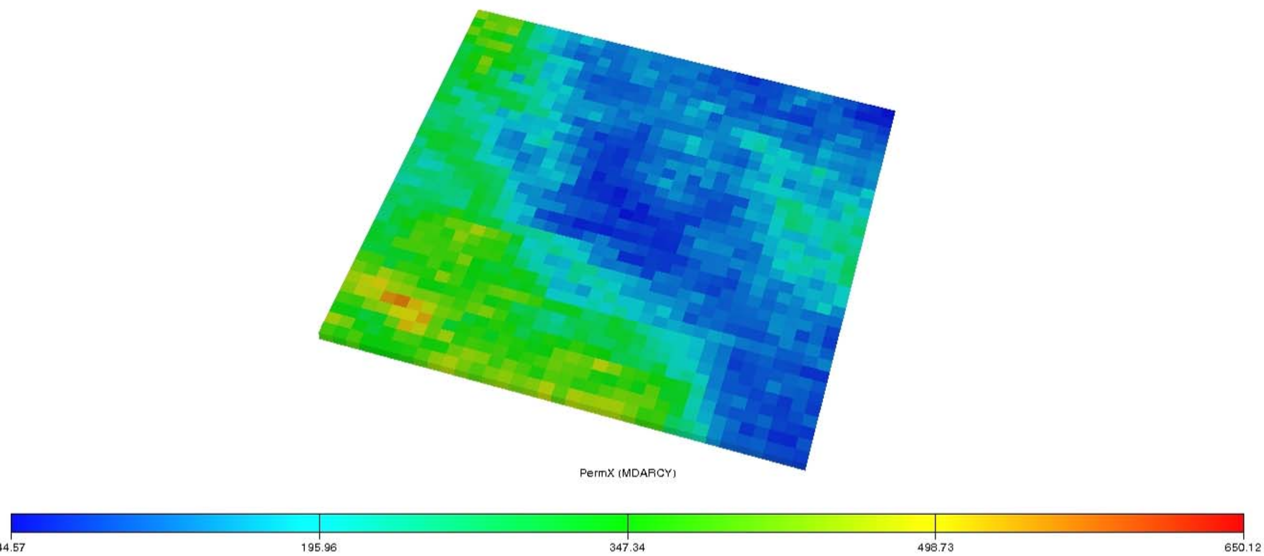

Figure 9c. Generated permeability of third layer (with only nine wells' data).

proach, different sets of parameters (m) may lead to the same answer (p). Thus, in this section the final porosity distributions (p_∞) are compared, based on Equation 13. For the 2D problem, the classical method got stuck in a local minimum as expected, but all stochastic optimisers provided appropriate solutions. The results of the four different optimisers can be seen in Table 4. The real challenge is for the case with 42 decision variables.

For the 42-dimensional problem, pre-conditioned steepest descent could not reduce the fitness value to less than 601,810, and the difference between reference porosity distribution and the generated porosity distribution based on Equation 13 is 16.78%. For the pilot-point approach, it is not feasible to provide a proper initial guess. This can be a reason why classical methods were stuck in a local minimum. In those cases where decision variables are dependent, stochastic optimisers are recommended. The outcomes of the different optimisers are shown in Table 5.

SA did not perform acceptably in this case. After 28,430 iterations, the fitness value (S(m)) was 207,890. SA not only failed to reduce the value of Equation 13—in fact, this value was observed to increase; however, the fitness value was reduced compared to the case without pilot points. The genetic algorithm reduced the value of S(m) to 26,127 with 15,540 evaluations in 258 generations, and the corresponding $O(m_\infty)$ value is 16.75%, which is better than the results from SA and PSD. The ABC outperformed the other optimisers in performance and $O(m_\infty)$ and $S(m_\infty)$ values. ABC reduced the value of fitness to 9,142.2, which is much better than the other algorithms. More importantly, the difference between the reference and the calculated porosity after history matching, based on Equation 13, is 12.55%. More details are provided in Table 5.

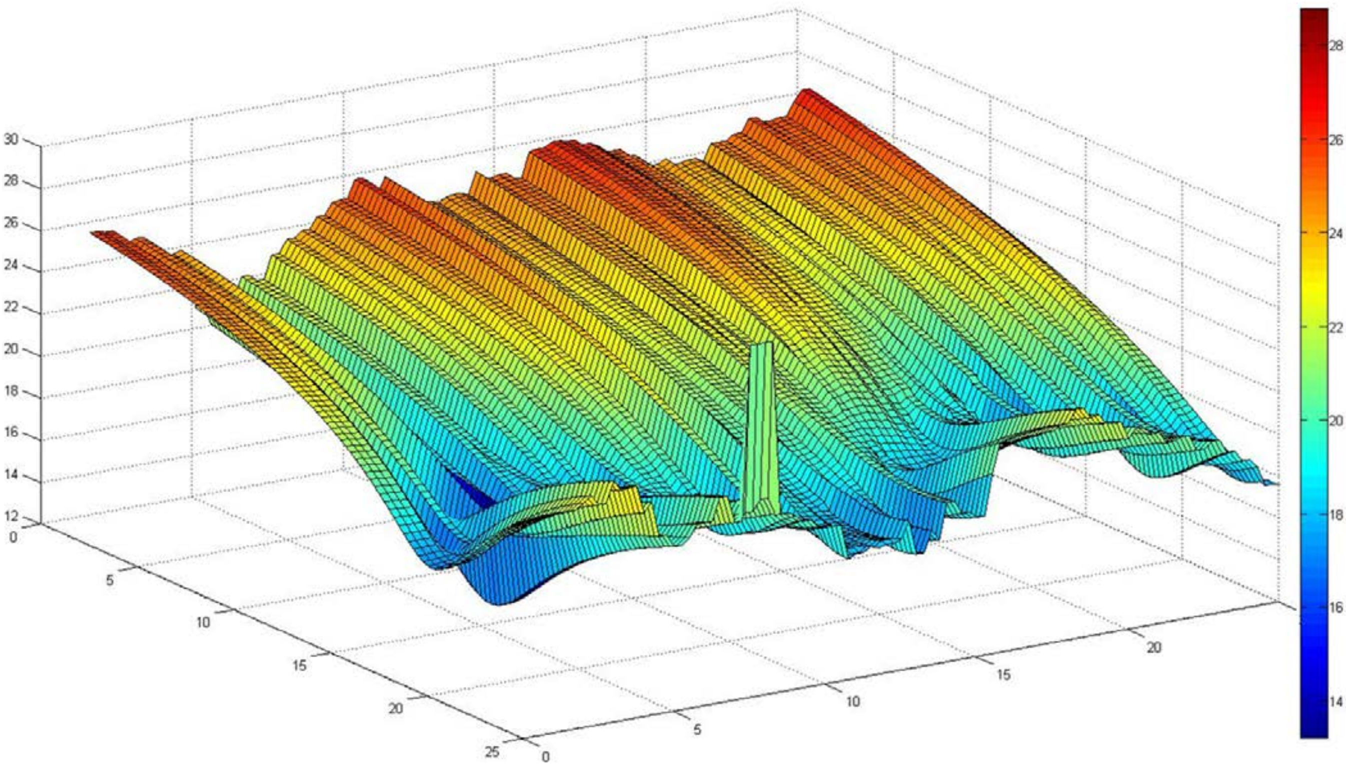

Figure 10. Landscape shape for case two.

Table 4. Results for case two with two variables.

Method	Options	No. of Evaluations	Fitness value	Difference based on Eq. 13 (%)	Parameters
Solution	-	-	739.29	0	[5.1998...15.4701]
SA	Initial point: [10...10]	61	739.44	0.003	[5.2527...15.4942]
	Fast annealing				
	Exponential temp. update				
	10 initial temp. with 30 iterations interval				
ABC	Colony size = 20	280 (14 generations)	739.32	0.0015	[5.3053...15.4681]
	Cycles = 14				
	Limit = 100				
Real-valued GA	Pop size = 20	340 (16 generations)	739.31	0.0008	[5.2771...15.4765]
	Crossover: 80%; heuristic ration: 0.8				
	Mutation: 20% constrained dependent				
	Elite: 1				
	Selection: stochastic uniform				
PSD	Initial point: [10...10]	800 (200 iterations)	7,129.0	1.73	[10.797...24.581]

Table 5. Results for case two with 42 variables.

Method	Options	No. of evaluations	Fitness value	Difference based on Eq. 13 (%)
Solution	-	-	739.29	0
Distribution with nine wells' data	-	-	1,603,600	17.34
SA	Initial point: [10, 10]	28,430	207,890	17.45
	Fast annealing			
	Exponential temp. update			
	Five initial temp with 100 iterations interval			
ABC	Colony size = 30	26,100 (870 generations)	9,142.9	12.55
	Cycles = 870			
	Limit = 150			
Real-valued GA	Pop. size = 60	15,540 (258 generations)	26,127	16.75
	Crossover: 90% scattered			
	Mutation: 10% constrained dependent			
	Elite: 1			
	Selection: roulette wheel			
PSD	Initial point: [20, 20]	6,600 (150 iterations)	601,810	16.78

This study shows that the ABC method works properly in history matching problems. ABC is not concerned with the shape of the landscape, that is, whether it is smooth or rugged. The main problem is the computation time, which makes it an inefficient method in systems with smooth landscapes. Since there is no precise information about the landscape shape, it can be concluded that by using ABC, there is a high chance of providing high-quality history matching and reservoir characterisation.

CONCLUSION

In this study, the application of ABC optimisation in history matching and reservoir characterisation was investigated using two different synthetic cases. The outcomes of ABC were compared with the results of different optimisation methods—PDS, SA and real-coded GA. The comparison indicates ABC worked properly in convergence speed and the final solution in both cases. In the first case where a full parameterisation was used, although a classical method provided a better result than the other methods, ABC also performed properly. In the second case where pilot-point parameterisation was used, ABC gave the best result in comparison to the other three methods.

Due to the high dimensionality of history matching, there is no straightforward technique to predict the landscape shape of the objective function; hence, the selection of an optimisation method among the variety of options is always controversial. In this study, it was shown that ABC can perform properly both on rugged or smooth landscapes. The major drawback of ABC is the long computing time, which is a result of the slow convergence speed due to its preference for exploitation rather than exploration, in contrast to GA.

Providing one solution for industrial problems is risky, especially for investment and field-development decisions; thus, a set of solutions along with their reliability should be provided. Future studies could expand the knowledge area of this matter. It is recommended for such work to include an uncertainty analysis. It is also fair to state that evolutionary algorithms can almost never find the exact optimal solution in cases with continuous variables. To find the global optimum, it is recommended that a hybrid ABC be implemented by coupling ABC with a classical method.

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NOMENCLATURE

d_{obs}	Column vector of observed data
d_{sim}	Column vector of simulated data
m	Column vector consists of model parameters
m_{prior}	Column vector consists of prior model parameters
g	Forward problem
C_d	Covariance matrix of observed data
C_m	Covariance matrix of model data
C_T	Covariance matrix of calculation error
$S(m)$	Bayesian objective function
N_d	Number of observed data
S(m)	An objective that shows the difference of reference and solution
σ	Standard deviation
m_∞	Solution of optimisation
p_∞	Porosity distributions for
$O(m_\infty)$, $O(m)$	Difference of reference and solution

REFERENCES

BALLESTER, P.J. AND CARTER, J.N., 2007—A parallel real-coded genetic algorithm for history matching and its application to a real petroleum reservoir. Journal of Petroleum Science and Engineering, 59, 157–68.

BERTA, D., HARDY, H.H. AND BEIER, R.A., 1994—Fractal Distributions of Reservoir Properties and Their Use in Reservoir Simulation. International Petroleum Conference and Exhibition of Mexico. Veracruz, Mexico: Society of Petroleum Engineers.

BISSELL, R.C., DUBRULE, O., LAMY, P., SWABY, P. AND LEPINE, O., 1997—Combining Geostatistical Modelling With Gradient Information for History Matching: The Pilot Point Method. SPE Annual Technical Conference and Exhibition, San Antonio, Texas, 5–8 October.

CARTER, J., 2004—Using Bayesian Statistics to Capture the Effects of Modelling Errors in Inverse Problems. Mathematical geology, 36 (2), 187–216.

DE MARSILY, G., LAVEDAN, G., BOUCHER, M. AND FASANINO, G., 1984—Interpretation of interference tests in a well field using geostatistical techniques to fit the permeability distribution in a reservoir model. In: Verly, G., David, M., Journel, A.G. and Marechal, A. (eds) Geostatistics for Natural Resources Characterization, Part 2, 831–49.

HAJIZADEH, Y., CHRISTIE, M. AND DEMYANOV, V., 2011—Ant colony optimization for history matching and uncertainty quantification of reservoir models. Journal of Petroleum Science and Engineering, 77 (1), 78–92.

HE, N., REYNOLDS, A.C. AND OLIVER, D.S., 1997—Three-Dimensional Reservoir Description From Multiwell Pressure Data and Prior Information. SPE Journal, 2 (3), 312–27.

JACQUARD, P., 1965—Permeability Distribution From Field Pressure Data. SPE Journal, 5 (4), 281–94.

JOURNEL, A.G. AND HUIJBREGTS, C., 1978—Mining geostatistics. London; New York: Academic Press.

KARABOGA, D., 2005—An idea based on honey bee swarm for numerical optimization. Kayseri, Turkey: Erciyes University.

KARABOGA, D. AND AKAY, B., 2009. A comparative study of Artificial Bee Colony algorithm. Applied Mathematics and Computation, 214, 108-132.

KARABOGA, D. AND BASTURK, B., 2007a—Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems Foundations of Fuzzy Logic and Soft Computing. In: Melin, P., Castillo, O., Aguilar, L., Kacprzyk, J. and Pedrycz, W. (eds). Berlin; Heidelberg: Springer.

KARABOGA, D. AND BASTURK, B., 2007b—A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm. Journal of Global Optimization, 39 (3), 459–71.

KARABOGA, D. AND BASTURK, B., 2008—On the performance of artificial bee colony (ABC) algorithm. Applied Soft Computing, 8 (1), 687–97.

KARABOGA, N., 2009—A new design method based on artificial bee colony algorithm for digital IIR filters. Journal of the Franklin Institute, 346 (4), 328–48.

KELKAR, M. AND PEREZ, G., 2002—Applied geostatistics for reservoir characterization. Richardson, Texas: SPE.

LIANG, B., SEPEHRNOORI, K. AND DELSHAD, M., 2009—A Weighted Ensemble Kalman Filter for Automatic History Matching. Petroleum Science and Technology, 27 (11), 1062–91.

LORENTZEN, R.J., FLORNES, K.M. AND NÆVDAL, G., 2009—History Matching Channelized Reservoirs Using the Ensemble Kalman Filter. International Petroleum Technology Conference, Doha, Qatar, 7–9 December.

MOHAMED, L., CHRISTIE, M.A. AND DEMYANOV, V., 2010—Reservoir Model History Matching with Particle Swarms: Variants Study. SPE Oil and Gas India Conference and Exhibition, Mumbai, India, 20–22 January, SPE 129152.

MOLGA, M. AND SMUTNICKI, C., 2005—Test Functions for optimization needs, 1–43.

NÆVDAL, G., JOHNSEN, L.M., AANONSEN, S.I. AND VEFRING, E.H., 2003—Reservoir Monitoring and Continuous Model Updating Using Ensemble Kalman Filter. SPE Annual Technical Conference and Exhibition, Denver, Colorado, 5–8 October.

OLIVER, D., 1994—Incorporation Of Transient Pressure Data Into Reservoir. In Situ, 18 (3), 243–75.

OLIVER, D. AND CHEN, Y., 2010—Recent progress on reservoir history matching: a review. Computational Geosciences, 1–37.

OUENES, A., BREFORT, B., MEUNIER, G. AND DUPERE, S., 1993—A New Algorithm for Automatic History Matching: Application of Simulated Annealing Method (SAM) to Reservoir Inverse Modeling. SPE.

PANIGRAHI, B.K., SHI, Y. AND LIM, M.-H., 2011—Handbook of swarm intelligence: concepts, principles and applications. Berlin: Springer.

REMY, N., BOUCHER, A. AND WU, J., 2009—Applied geostatistics with SGeMS: a user's guide. Cambridge: Cambridge University Press.

REYNOLDS, A.C., HE, N., CHU, L. AND OLIVER, D.S., 1996—Reparameterization Techniques for Generating Reservoir Descriptions Conditioned to Variograms and Well-Test Pressure Data. SPE Journal, 1 (4), 413–26.

ROMERO, C.E. AND CARTER, J.N., 2001—Using genetic algorithms for reservoir characterisation. Journal of Petroleum Science and Engineering, 31 (2–4), 113–23.

SIVIA, D.S. AND SKILLING, J., 2006—Data analysis: a Bayesian tutorial. Oxford: Oxford University Press.

STARK, H., 1987—Image recovery—theory and application. Orlando: Academic Press.

SUN, N.-Z., 1994—Inverse problems in groundwater modeling. Dordrecht; Boston: Kluwer Academic.

TARANTOLA, A., 1987—Inverse problem theory: methods for data fitting and model parameter estimation. Amsterdam; Oxford: Elsevier.

ZHANG, F., SKJERVHEIM, J.-A., REYNOLDS, A.C. AND OLIVER, D.S., 2005—Automatic History Matching in a Bayesian Framework, Example Applications. SPE Reservoir Evaluation & Engineering, 8 (3), 214–23.

ZIELONKA, A., HETMANIOK, E. AND SŁOTA, D., 2011—Using the Artificial Bee Colony Algorithm for Determining the Heat Transfer Coefficient. Berlin; Heidelberg: Springer.

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APPEA