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A Novel Assisted History Matching Workflow and its Application in a Full Field Reservoir Simulation Model

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ABSTRACT

The significant increase in using reservoir simulation models poses significant challenges in the design and calibration of models. Moreover, conventional model calibration, history matching, is usually performed using a trial and error process of adjusting model parameters until a satisfactory match is obtained. In addition, history matching is an inverse problem, and hence it may have non-unique solutions. In typical reservoir simulation problems with a large number of unknown parameters, the problem could be ill-posed. In recent years, assisted history matching approach has been offered to solve this problem hopefully. In this paper, proposes an efficient assisted history matching workflow is recommended, and its application in a full field reservoir simulation model of a mature gas-cap reservoir is presented. In addition, Sobol sequence experimental design technique, Kriging proxy modeling, and three novel metaheuristic optimization algorithms are used to assist the history match of 28 years of historical production and pressure data. Finally, the results are compared with those obtained using a manual history matching procedure and with those obtained using the most widely used assisted history matching workflow. Also, in the proposed workflow, a significant improvement in terms of match quality and solution time is shown.

Keywords: Assisted History Matching, Experimental Design, Proxy Modeling, Optimization Algorithms, Reservoir Simulation Workflow.

INTRODUCTION

History matching is the process of calibrating reservoir models with actual production and pressure data. The model is considered calibrated if it can reproduce the historical data of the presented reservoir. Only history matched models can be used to predict the reservoir future performance under different scenarios. Traditional history matching is carried out through trial and error sequences of adjusting model parameters until a satisfactory match is obtained. Furthermore, history matching is an inverse problem, and hence it may have non-unique solutions. History matching process is an ill posed problem, and it is often very time consuming. In recent years, several approaches have been introduced to assist the history matching process. Assisted history matching

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concept is inspired by the optimization theory which has been first introduced by Kantorovich [1] in the area of mathematical programming. The history matching problem is converted to an optimization problem with the objective of minimizing the difference between observed and simulated data. The workflow of assisted history matching is usually composed of three main procedures: experimental design, proxy modeling, and optimization.

This paper introduces a new assisted history matching workflow and presents its application in a field case. The proposed workflow involves introducing a superior technique in each element of the typical assisted history matching workflow. The Sobol sequence is the proposed experimental design technique [2] whereas Kriging is used as the proxy modeling method [3]. Three recently developed metaheuristic global optimization algorithms (firefly optimization (FFO), bee colony optimization (BCO), and harmony search optimization (HSO)) are used to optimize the created proxy model. This work is divided into two main parts.

The first part presents the methodology followed to prove the superiority of the newly proposed technique(s) in each sub-step of the three main steps of the assisted history matching procedure. To show the effectiveness of the proposed methods, their performance in solving assisted history matching problems is compared with the latest algorithms commonly used in commercial assisted history matching programs. Three synthetic history matching problems of different reservoir engineering applications with variable complexity are used as test problems to compare the results with each other and validate the paper conclusions. A performance indicator is developed to quantify the relative error between the estimated values of history matching parameters using the studied algorithms and the exact solutions.

The second part of the paper presents the application of the proposed assisted history matching workflow in a real field reservoir simulation model for a mature gas-cap reservoir with 28 years of historical pressure and production observed data. To emphasize the superiority of the proposed workflow, the resultant history matched models are compared with those obtained either manually or with those developed models from other recent assisted history matching workflows.

The following sections discuss the newly proposed technique(s) in each sub-step of the three main steps of the assisted history matching procedure.

EXPERIMENTAL PROCEDURE

Experimental Design

An experimental design is a technique used to guide the choice of the experiments (simulation runs) to be conducted in an efficient way. In assisted history matching, experimental design is used to explore the uncertainty range of the reservoir history matching parameters. Samples are selected from the search space of the uncertain parameters in order to obtain the maximum amount of information from fewer experiments (simulation runs). The chosen samples are used to build the scoping runs. Once analytical or numerical simulation scoping runs are conducted, the objective function is calculated. The objective function is a formula which represents the difference between historical and simulated data. Although the experimental design technique was first proposed by Ronald Fisher [4] for agricultural applications, it was first applied in reservoir engineering practices by Damsleth et al [5]. An experimental design technique to perform a sensitivity analysis study for a field in the North Sea with a minimum number of simulation runs was used by Damsleth et al [5]. In addition, it was stated by Damsleth et al that applying experimental design approach helped reduce the number of required simulation runs by 30-40% compared with varying one parameter at a time. Seeing the studies of Shams et al [2] for a summarized literature review of the different concepts of experimental design techniques and their previous applications in reservoir simulation assisted history matching is helpful. It was stated by Montgomery [6] that Latin hypercube (LHC) design is the most commonly used experimental design technique. Our experience in reservoir engineering applications also confirms that most commercial assisted history matching software tools use LHC as the preferred experimental design technique. The previous work introduced the Sobol sequence as the preferred experimental design technique [2]. It is the proposed technique to be used in the worked flow presented here too. A comparative study between LHC, Sobol, and Halton sequence experimental design techniques in assisted history matching applications was conducted to show how experimental design techniques of Sobol and Halton sequences can enhance the assisted history matching process in reservoir engineering applications in comparison with LHC [2].

Sobol sequence, Halton sequence, and LHC are individuals of an experimental design family called space-filling design. The space-filling design concept is based on spreading the samples around the design space without following a specific factor leveling scheme. The number of the selected samples is predefined by the designer and does not depend on the number of problem factors or their levels.

In LHC sampling technique, proposed by Mackay et al [7], samples are selected according to a uniform distribution. The typical calculations of the LHC method are carried out by calculating two matrices (Q_{Nxk} and R_{Nxk}). The columns of Q matrix are random permutations of the integer values from 1 to N. And R is a matrix of random values that are uniformly distributed within the default range of [0, 1]. The samples matrix, S, can be expressed by using the following equation (Equation 1):

$$S=\frac{1}{N}(Q-R) \quad (1)$$

Each sample element of S is located over a matrix X by a cumulative distribution function, D, where:

$$X_{i,j}=D_j^{-1} \quad (2)$$

In case of a normal Gaussian distribution, the cumulative distribution function is expressed by using Equation 3:

$$D(x)=\frac{1}{2}\left\{1+\operatorname{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right\} \quad (3)$$

where μ is the mean value, and σ is the standard deviation. On the other hand, and as it has been stated by Sobol [8], Sobol sequence experimental design method is based on generating sets of random numbers Φ: [0, 1] which are applied iteratively to build a matrix γ_k where:

$\gamma_k=\Phi(\gamma_{k-1})$, for k=1,2,… (4)

The quasi-random Van der Corput sequence [9] is used to choose Φ with a uniform distribution. In Van der Corput sequence, a base b ≥ 2 is given, and the further successive numbers n are created according to the following formula (Equation 5):

$$n=\sum_{j=1}^{T} a_j b^{j-1} \quad (5)$$

where a_j is the matrix of the expansion coefficients. The number of the sequence is given by Θ_b, as seen in Equation 6.

$$\theta_b = \frac{\sum_{j=1}^{T} a_j}{b^j} \tag{6}$$

For more clarification, in case when b=2 and n=4, the coefficients of the expansion are a_1=0, a_2=0, and a_3=1. The fourth number of the sequence, $\Theta_2(4)$, can be calculated as follows by using Equation 7:

$$\Theta_2(4) = \frac{0}{2} + \frac{0}{4} + \frac{1}{8} = \frac{1}{8} \tag{7}$$

In Halton sequence technique, base-two Van Der Corput sequence for the first dimension, the base-three sequence in the second dimension, base-five in the third dimension, and so on are used. In Sobol sequence method, only one base for all dimensions is used, and so the reordering task becomes more difficult and more complex than Halton sequence technique. Sobol sequence and LHC methods for efficiency on a number of test problems of various complexity for which analytic quadrature is available have been compared with each other by Bianchetti [10]. It has been concluded by Bianchetti that the Sobol sequence technique performs better than LHC as it fulfills three main requirements: (1) best uniformity of distribution, (2) good distribution for fairly small initial sets, and (3) uniform-looking filling of the space, even for small numbers of required samples. It has been also stated by Bianchetti that although there has been a significant progress in improving space filling properties of LHC, due to the high cost of optimization involved, even the most efficient techniques cannot be applied for solving high dimensional problems. It has been stated by Saltelli et al [11] that an important practical drawback of LHC is that new points cannot be added sequentially. On the other side, additional stratification properties of the Sobol sequence scheme results in increased uniformity of the Sobol sampling. The standard LHC sampling does not possess additional stratification properties in higher dimensions.

Proxy Modeling

The proxy model is the analytical function that relates the independent variables (e.g. the uncertain reservoir parameters) to the objective function values. The first researchers who introduced the proxy modeling concept in the literature were Box and Wilson [12]. It was suggested by Box and Wilson that the first-degree polynomial model would be suitable to approximate a variable response. It has been pointed out by Nocedal [13], Nocedal and Wright [14], Byrd et al [15], and Zhu et al [16] that proxy models have been used to speed up optimization problems since the 1970s. According to Eide et al [17], the quality of a proxy model may be highly restricted by the number of input parameters. As input parameters increase, the number of required function evaluations significantly increases. Moreover, the least square method was developed by Gauss [18] as a data fitting technique. It minimizes the sum of the squared residuals among the scattered points and the function values. The least squares methods has been subdivided into linear and nonlinear sub-categories by Bates and Watts [19]. Linear least square problems are solved through a closed scheme. They are not accurate and can only be appropriate for guessing the major trends of the variables response. The non-linear square problems are solved iteratively. First, the initial values of the interaction coefficients are chosen, then they are updated iteratively. The Kriging method for estimation/prediction problems in geostatistics has been introduced by

Krige [20]. Kriging method can be thought of as an interpolation technique that is based on regression against the values of the surrounding observed data points. These data points are weighted according to a spatial covariance model. Kriging method is a data exact technique, as it reproduces the observed value at a sampled location.

Thin plate splines (TPS) proxy modeling technique has been introduced by Wold [21]. TPS refers to the analogy of bending a thin metal plate. TPS functions are piecewise polynomials of order K. The joining points of the pieces are called knots. The concept of this method is that the function values and the first (K-1) derivatives agree at the knots. Given a set of data points, a weighted combination of TPS centered on each data point gives the interpolation function that passes through all points exactly. Radial basis function (RBF) proxy modeling is a generalized version of the multi-quadric method for interpolating multi-dimensional scattered data introduced by Hardy [22]. A common feature of the RBF is that its complexity does not increase by the increase of the dimensions of the interpolation. RBF is valuable because it creates a proxy model covering the whole design space, and hence it is valuable for global optimization. The major drawback of this method is its inaccuracy at the boundaries.

The artificial neural network (ANN) as a fitting technique has been introduced by Freeman and Skapura [23] and Veelenturf [24]. ANN is a fitting algorithm which is inspired by the learning process performed in the human brain. It includes modification of connections between the neurons based on experimental knowledge. Proxy modeling technique was coupled with Monte Carlo simulation for uncertainty quantification by Mohaghegh [25]. The usage of ANN as a proxy method instead of the expensive forward simulation runs was introduced by Christie et al [26]. ANN models are trained by data obtained during the initial searches within the parameter design space. Once the neural networks are trained, they can be used to predict the objective function values for other combinations of uncertain parameters in the history matching problem. Seeing the studies of Shams et al [3] for a summarized literature review of proxy models applications in assisted history matching is helpful and constructive. A comparative study of several proxy modeling methods has been presented by Yeten et al. In addition, the performances of polynomial regression, TPS, Kriging, and ANN techniques have been compared with each other by Yeten et al. It is concluded by them that all proxy generation methods strongly depend on the model complexity, dimensions of the design space, and quality of the input dataset. In addition, it has been highlighted by them that among the studied proxy modeling techniques, only Kriging reproduces exact outcome at sampled points. On the contrary, the use of proxy for history matching particularly for cases which have a large number of uncertain parameters was not recommended by Zubarev [28].

This work provides three comparative studies between four powerful proxy modeling techniques (TPS, RBF, kriging, and ANN) using three different reservoir engineering assisted history matching test problems. The objective of the presented proxy modeling comparative studies is to recommend the best performing technique(s) to be used in the newly proposed assisted history matching workflow.

Optimization Techniques

In assisted history matching, the created proxy model is optimized (minimizing the error function) using an optimization algorithm. The results of this optimization process are the model parameters which yield a history matched model capable of reproducing the historical fluid rates and pressure data. Optimization techniques have evolved through two generations: deterministic and stochastic algorithms. Deterministic optimization is the classical approach of optimization methods which completely rely on the linear algebra as they require the computation of the gradients of the mathematical model with respect to the optimized model parameterization to minimize the objective function. Due to their deterministic nature, the deterministic optimization algorithms search for stationary points in the search space. Moreover, as a consequence, the resultant solution could be a local optimum and not the global optimum. Local maxima or minima optimum is not the correct optimal solution. In our area of interest and due to the non-uniqueness nature of the history matching problem, it is expected by us to encounter several local minima, and therefore the deterministic algorithms are not expected to work efficiently. In addition, several attempts to use deterministic optimization methods in assisted history matching are presented by Anterion et al [29]. On the other hand, the stochastic optimization concept is based on employing randomness in the search procedure. Many of the stochastic optimization algorithms are nature inspired. The application of simulated annealing stochastic optimization method in reservoir engineering was introduced by Ouenes et al [30, 31, and 32] introduced. The heat-bath algorithm which can be considered as a new version of simulated annealing was discussed by Sen et al [33]. In addition, heat-bath algorithm performed better in large simulation cases. Genetic algorithm (GA) was introduced by Holland [34], and it belongs to the group of evolutionary based optimization methods. GA is inspired by Darwin's theory of natural evolution which demonstrates the concept of the survival of the fittest. Moreover, different versions of GA for the history matching of reservoir simulation cases have been employed by Romero et al [35] Williams et al [36], Castellini et al [37], Ballester and Carter [38].

The evolutionary strategy optimization algorithm was first introduced by Rechenberg [39] and later used by Schulze-Riegert et al [40], Haase et al [41], and Selberg et al [42] for assisted history matching applications. In addition, this technique is efficient for global and local optimization of continuous and discrete search parameters as it uses mutation and recombination operators to find optimum solutions. Moreover, the scatter search optimization algorithm in the history matching of two simple reservoir model cases with a small number of uncertain parameters was applied by Sousa et al [43]. Branchs et al. [44], Gao et al. [45], and Jia et al. [46] used the simultaneous perturbation stochastic approximation algorithm for history matching purposes was used by Branchs et al [44], Gao et al. [45], and Jia et al [46]. Ensemble Kalman Filters (EnKF) for history matching geological facies was introduced by Liu and Oliver [47] introduced, and the results with the gradient based randomized-maximum-likelihood method were compared. Moreover, better history matched models from fewer simulations using

EnKF in comparison with the gradient method were obtained. The application of EnKF workflow to the history matching of different scale reservoir simulation models were presented by Valles and Naevdal [48], Sarma and Chen [49], and Pajonk et al [50]. Although EnKF method has a wide application in assisted history matching problems, it (like any other optimization method) suffers from several drawbacks. Also, three problems which may occur in EnKF by under-sampling were investigated by Petrie [51]. Moreover, under-sampling happens when the number of ensemble members is small compared to the size of the state. Moreover, three drawbacks of EnKF, i.e. (1) inbreeding, (2) filter divergence, and (3) the development of long range spurious correlations were also discussed by Petrie [51]. In addition, a problem of localization called the Schur product has also reported by her. In addition, two proposed methods to overcome these problems: covariance inflation and covariance localization have been studied by Petrie. For her specific case studies, it was reported by her that these two methods cannot effectively help prevent the problems of EnKF. It was reported by Jardak et al [52] that for nonlinear observation operators, standard EnKF, even when applying localization and inflation does not provide good estimates. The use of paired and coupled EnKF as a possible remedy to the inconsistency problem in EnKF which was observed by Lorentzen et al [54] was investigated by Valles and Naevdal [53]. It has been stated by Franssen and Kinzelbach [55] that EnKF performs worse in the problems that exhibit strongly non multi Gaussian properties.

Particle swarm optimization (PSO) is developed by Kennedy and Eberhart [56] and it is inspired by the social behavior of a flock of birds, particles, trying to reach an unknown destination. PSO algorithm for obtaining history-matched models was applied by Kathrada [57], Mohamed et al [58], and Fernandez et al [59]. In addition, good results in reasonable solution time were obtained by them. The ant colony optimization algorithm to reservoir simulation assisted history matching was introduced by Hajizadeh [60]. The ant colony algorithm is inspired by the behavior of food search of ant colonies. According to Hajizadeh [60], the ant colony optimization algorithm is very powerful if its tuning parameters are carefully selected and handled.

The following part of this work introduces the FFO, BCO, and HSO techniques to reservoir engineering assisted history matching. This work presents the first time of employing the proposed optimization techniques in reservoir engineering applications.

Firefly Optimization (FFO)

FFO is a stochastic optimization algorithm developed by Yang [61] and inspired by flashing behavior of firefly insects. In nature, the fireflies use flashing behavior to attract other fireflies by sending signals to the opposite sex. Attractiveness is proportional to the brightness of each firefly. A Firefly that has less brightness will move towards the brighter one. The flashing light can be referred to the value of the objective function. For a minimization problem, the brightness can be set with an inverse proportional relationship with the objective function value. According to Yang [61], the FFO algorithm can be presented in the flow chart shown in Figure 1.

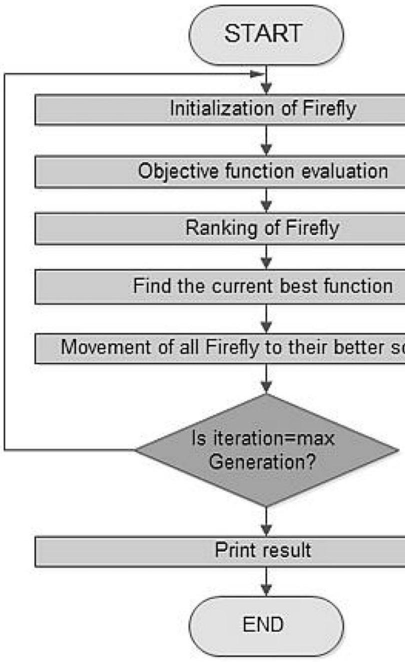

Figure 1: Flow chart of FFO pseudo code.

The most important feature of the FFO is the strategy of fireflies movement. When the less bright firefly moves towards the brighter ones, each firefly creates 'M' number of new fireflies using inversion mutation strategy. Length of their mutation cycle, L, is determined by the following formula:

$$L=\text{random}\ (2,r_{ij}) \quad (8)$$

where "r_{ij}" is the difference between firefly i and firefly j. A random integer within (2, r_{ij}) is defined as the cycle length. If "n" fireflies at the beginning had been had by us, after an iteration, there will be (n*M) number of fireflies and the best n among (n*M) will be selected for the next iteration. This strategy helps the algorithm converge faster to the optimal solution. Moreover, seeing the studies of Shams [62] for a detailed description of the mechanism and applications of FFO is constructive and helpful.

Bee Colony Optimization (BCO)

The BCO optimization technique, which is another algorithm for stochastic optimization was introduced by Pham et al [63]. BCO is inspired by the behavior of honey bee in searching for their food. In nature, the honey bees begin searching for promising flower patches by sending scout bees (global search). If a flower patch is found out by a scout bee, the bee randomly looks further in the vicinity of the promising flower (local search) in an attempt to find a better one. The scout bee informs other bees waiting in the nest by depositing nectar and dance in front of the nest (waggle dance). Waggling dance is a movement performed by a scout bee at the nest to show the direction and distance of the food source to the other bees. Scout bees use waggle dance to communicate information about the food source to the rest of the colony by providing the following information:

1. The direction of the food source: scout bee runs in a straight line indicating the direction of the food relative to the sun azimuth to the nest.
2. The distance between the food source and the nest: scout bee circles in alternating left and right return path. The duration of the dance indicates the duration taken to the food source.
3. The quality of the food source: scout bee deposits nectar indicating the quality of the food. The higher food quality, the higher the deposited nectar will be. The algorithm of the BCO technique is summarized in Figure 2. Scout bees are randomly sent to food source sites (n). The fitness values of each site (objective function) are calculated and sorted from the lowest to the highest (a minimization problem).

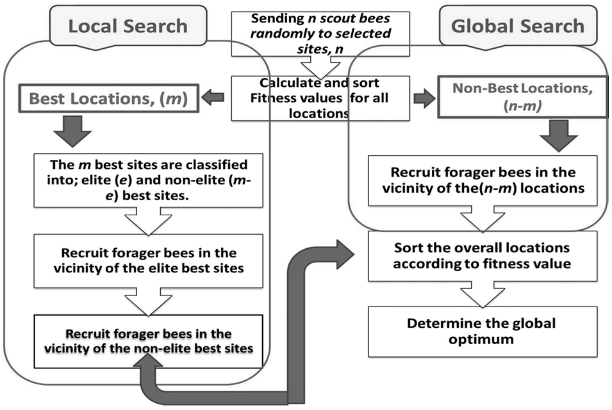

Figure 2: Flow chart of BCO pseudo code.

All encountered locations are classified into (m) best locations and (n-m) non-best locations. The m best sites are also classified into two sub-groups: elite and non-elite best sites. All best locations are covered by local search step of the algorithm by recruiting separate forager bees in the neighborhood vicinity of the elite and non-elite sites. The global search process covers the (n-m) sites by random search. The overall locations are then sorted based on their fitness values, and the global optimum is determined. Reviewing the studies of Shams et al. [64] for a detailed description of the mechanism and applications of BCO is useful.

Harmony Search Optimization (HSO)

HSO is a stochastic optimization algorithm developed by Geem et al [65] and inspired by harmony improvisation of musicians searching for the best harmonious performance. The harmony improvisation is the process that happens when a musician searches for a better state of harmony guided by an aesthetic standard. The musicians meet several times to practice. Perfect harmony is not achieved in the early rehearsals because the rhythm and pitch of each instrument cannot be immediately tuned. Continued practice and rehearsals enable the musicians to memorize the specific rhythm and pitch of each instrument leading to "better harmony". The sets of "better harmony" are memorized, and the worse sets are discarded once better sets are found. Updating the harmony sets continues until the best harmony is achieved. HSO algorithm mimics the process of harmony enhancement, and the sets of better solutions are saved to the harmony memory. In comparison with other evolutionary based optimization algorithms, harmony memory is a unique feature of HSO algorithm. In harmony search optimization, an optimal solution is generated by the following three rules:

1. Random search: is the process that involves generating random solutions bounded by predefined constraints. The main objective of this rule is to escape from local optima of the new solution by using sketchy search within the whole search space of each studied variable, and certainly find newer and more precise solution by doing global search. This rule represents the global search, the exploration part, of the algorithm mechanism.
2. Considering the harmony memory (CHM): is the process that involves selecting solution values for each variable from the memory of the conducted random search. The probability of selecting is given a value between zero and one. High probability between 0.75 and 0.95 usually gives better solutions. This rule represents a mean of exploiting the local searches.
3. Pitch adjusting (PA): is the process that involves normalizing the selected solutions by bounding them between their lower and upper values. The objective of this rule is to prevent conflicting between different order of magnitudes of different studied optimization variables and help in escaping

from local optima and finding an optimal solution. Standard harmony search optimization algorithm can be presented by the flow chart shown in Figure 3.

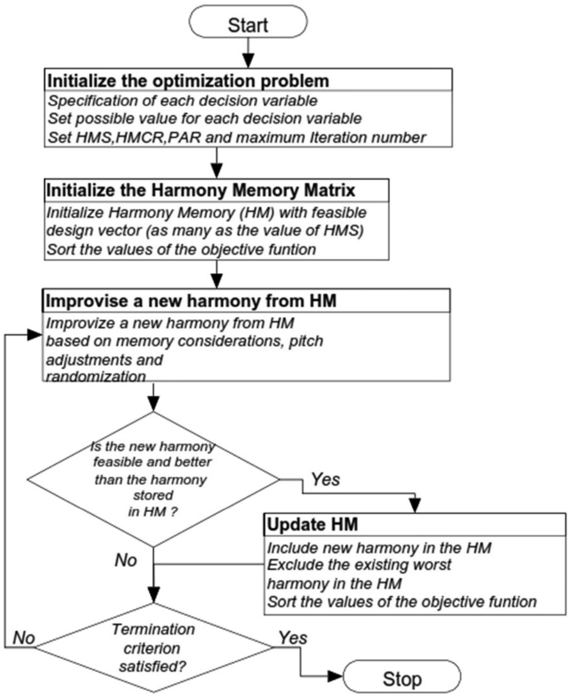

Figure 3: Flow chart of the HSO pseudo code.

An important feature that distinguishes HSO algorithm is that all solutions are contemplated during generating a new solution by considering harmony memory. Each studied variable is independently examined, and a harmony vector is produced every time by a set of new optimization parameters in the harmony memory. According to Alia [66], HSO has captured attention and been successfully applied in various engineering applications. The good balance between exploration and exploitation techniques during the search for finding optimal solutions makes the HSO algorithm robust and efficient. The rule of pitch adjusting can be considered as a key factor for the balance in the harmony search algorithm. Moreover, a detailed discussion of the reasons for HSO superiority is presented in Shams [67].

Methodology

Three synthetic history matching problems of different reservoir engineering applications with variable complexity are used as test problems. Two different scale material balance and one reservoir simulation assisted history matching problems are used to prove the superiority of the newly proposed technique(s) in each sub-step of the three main steps of the assisted history matching procedure. The objective of using different test problems is to validate the results and check if the conclusions can be generalized. The performance of the proposed workflow (with the recommended algorithms in each step) is compared with the performance of other recent assisted history matching algorithms. A performance indicator is developed to quantify the relative error between the estimated values of history matching parameters using the studied algorithms and their exact solutions. For fairness in comparing the different algorithms, the search space of the uncertain parameters and the number of experimentally designed samples of each test problem are kept the same. Detailed descriptions of the test problems and the strategy followed in the comparative studies are presented in the following sections.

Single Tank Material Balance Test Problem

Simple single tank material balance problem with a Hurst-van Everdingen-modified aquifer model was constructed. Three uncertain parameters (oil in place, aquifer encroachment angle, and aquifer permeability) are selected as history matching parameters to test the studied optimization techniques.

Multiple Tanks Material Balance Test Problem

In Figure 4, the schematic of a multiple-tanks material balance test problem is shown. The model consists of three fault blocks, and each fault block has two layers. Each fault block and layer are modeled with their own material balance model, which gives a total of six compartments. Production from the layers is commingled (i.e. communicating only through the wellbore). The fault blocks are communicating with some transmissibility across the faults. The total number of wells is eight, each well (producer/ injector) is controlled by a productivity index value and flowing bottom-hole pressure. Twenty uncertain parameters (oil in place, layer reservoir thickness, aquifer encroachment angle, initial gas cap volume, transmissibility among different tanks) of the different fault blocks are selected as history matching parameters.

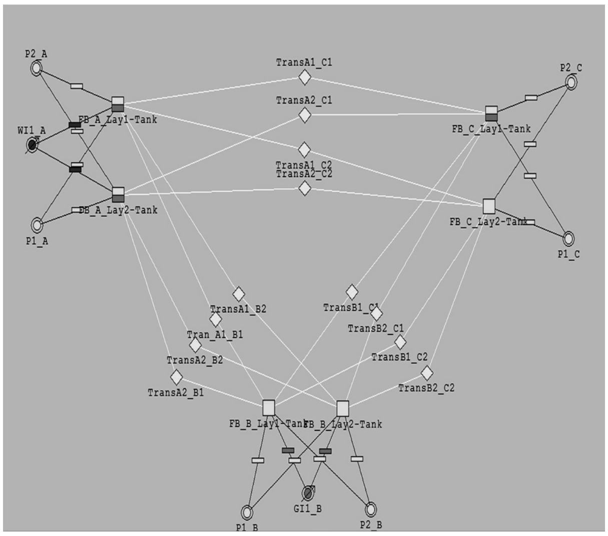

Figure 4: Multiple tanks material balance test problem.

Reservoir Simulation Test Problem

A reservoir simulation model with actual structure data, shown in Figure 5, is used as the history matching test problem in this comparative study. The model dimensions are (50 x 49 x 199) in I, J, and K directions respectively. The model's total number of cells is 487,750. The model contains three fault blocks having different initial oil-water contacts and gas-oil contacts. A North East aquifer is modeled analytically by a Carter Tracy aquifer model. The model contains twenty-three wells (twenty producers and three injectors).

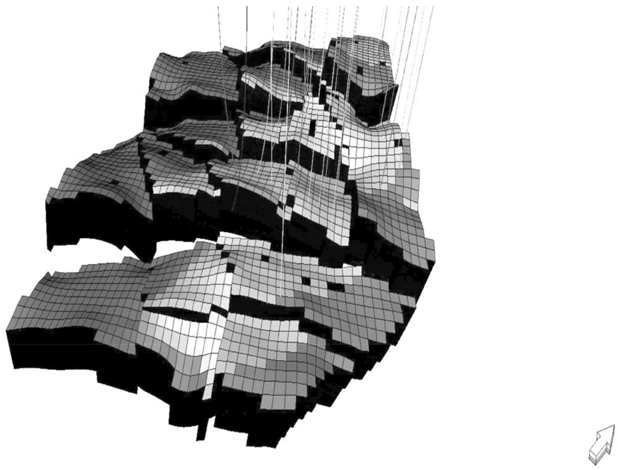

Figure 5: 3D model of the reservoir simulation test problem.

In Figure 6, the pressure and production data performances on a field basis are shown.

To apply the assisted history matching procedure, fifty history matching parameters are selected. The selected history matching parameters are oil-water contact and gas-oil contacts of the different compartments, permeability multipliers, aquifer porosity, aquifer permeability, aquifer thickness, aquifer angle of influence, fault transmissibility multipliers, Corey exponents of the different rock types, critical water saturations of the different rock types, and skin values of wells.

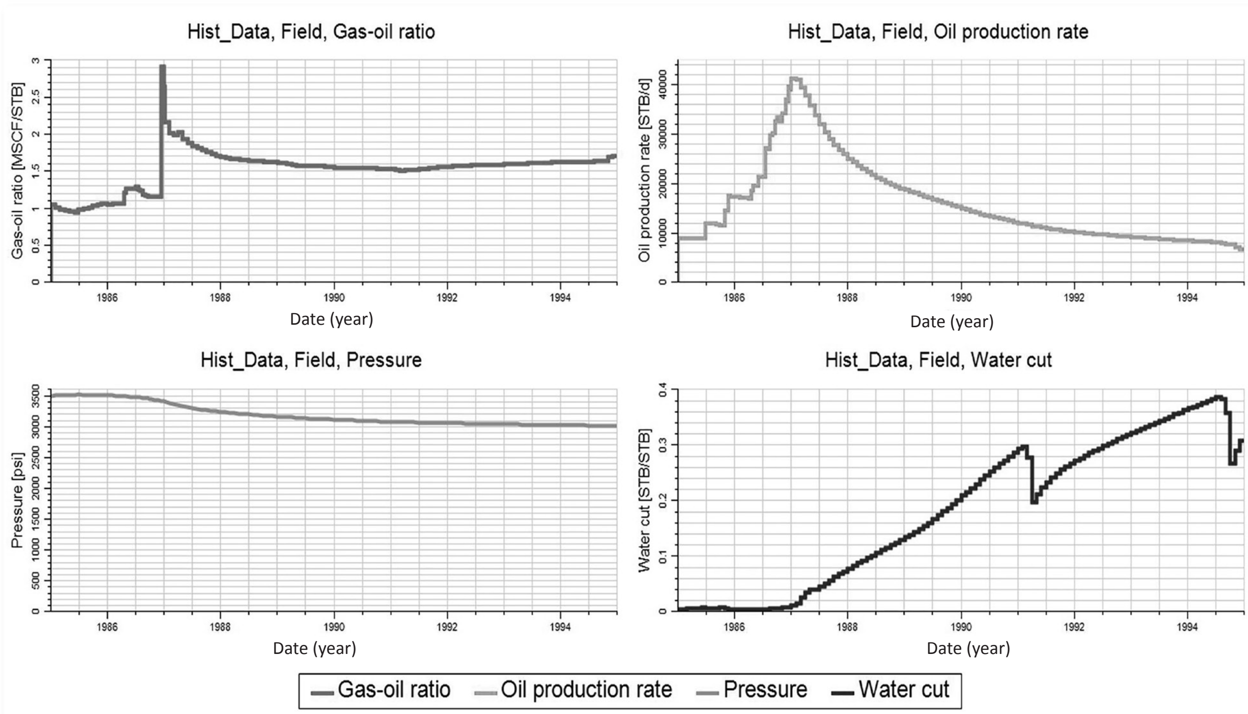

Figure 6: Historical field pressure and production data.

RESULTS AND DISCUSSION

The studied assisted history matching newly proposed techniques are applied to the three test problems and the results of each assisted history matching aspect are presented in this section. The assisted history matching test problems are constructed according to the following strategy:

- Use MBAL® and (ECLIPSE® and Petrel®) software tools to generate pressure and production performance using known reservoir parameters for 10 years. MBAL is used to generate material balance problems, and ECLIPSE and Petrel are used to generate a reservoir simulation test case.
- Use the generated pressure and production data as known historical data in the test problems.
- Alter the original reservoir parameter to obtain unmatched pressure and production performances.
- Use the studied experimental design technique to select the samples of the history matching parameters. The selected samples are used to build the scoping runs.
- Perform the scoping runs and calculate the objective function of each scoping run using the following formula (Equation 9):

$$f(x)=\sum\frac{1}{n}\left\{\begin{array}{l}\sum_i[w_i(y^*_i-y_i)^2]_{\mathrm{WC}}+\sum_i[w_i(y^*_i-y_i)^2]_{\mathrm{GOR}}\\+\sum_i[w_i(y^*_i-y_i)^2]_{\mathrm{Pressure}}\end{array}\right\} \tag{9}$$

where n is the number of the observed data points, $y_i^*(x)$ represents the simulated data obtained using the set of parameters x's, y_i is the observed data, and w_i is the weight assigned to each set of data in the objective function.

- Build a proxy model which interpolates the objective function with the experimentally designed reservoir parameter samples.
- Minimize the created proxy model using the studied optimization algorithms. This minimization process is run five times to take a more representative solution. Consistency was

maintained in running the studied optimization algorithms.

- Use the following performance indicator to quantify the error between the estimated and exact solutions of the reservoir uncertain parameters. Performance indicator is calculated using Equation 10.

$$\text{Performance Indicator}, \% =$$
$$Avg.\left[Abs.\left(\frac{\text{Estimated solution} - \text{Exact solution}}{\text{Exact solution}} x100\right)\right] \quad (10)$$

Results of Experimental Design Comparative Studies

The three studied experimental design techniques (LHC, Sobol, and Halton sequences) are applied to the three test problems, and the results are presented in this section. ANN proxy models are built and minimized using GA. The proxy modeling and optimization techniques used in the assisted history matching procedure are maintained the same to ensure that the only factor responsible for enhancing the assisted history matching process is the experimental design technique. The average value of the performance indicator for each test problem comparative study is calculated and presented in Table 1.

Table 1: Average values of the performance indicator calculated for the three test problems, the experimental design comparative study.

Aspect	Technique	Average Performance Indicator, %		
		Single Tank Material Balance	Multiple Tanks Material Balance	Reservoir Simulation
Experimental Design	LHC	31.14	44.12	39.47
	Halton	14.03	37.56	31.83
	Sobol	8.15	30.18	28.88

As shown in Table 1, the Sobol sequence experimental design method has a lower value of the average error than both Latin hypercube and Halton sequence techniques. This observation is the same for all three test problems.

Results of Proxy Modeling Techniques Comparative Studies

The three test problems are used to provide three comparative studies between four powerful proxy modeling techniques (ANN, Kriging, TPS, and RBF). In the case of ANN as the proxy modeling technique, a two-layer feed-forward network using (1) sigmoid transfer function for the hidden neurons and (2) linear transfer function for the output neurons is used to fit the multi-dimensional data.

The network is trained with Levenberg-Marquardt backpropagation algorithm. Training automatically stops when generalization stops improving. This can be indicated by an increase in the mean square error of the validation samples. Input and target vectors are randomly divided into three sets as follows: 70% to train the network, 15% to validate the network, and 15% to test the network generalization.

In the case of using Kriging as a proxy modeling technique, the Gaussian correlation function is used to assume that the data represents a smooth continuous domain. The pseudo-likelihood function is used to optimize the hyper-parameters instead of the standard marginal likelihood to make sure that the prediction variance is zero at the samples.

In the case of using TPS as a proxy modeling method, the smoothing spline (f) is used to minimize the following weighted sum:

$$pE(f)+(1-p)R(f) \quad (11)$$

where E(f) and R(f) are the error and roughness measures respectively, p is the smoothing parameter (a number between 0 and 1). As the smoothing parameter varies from 0 to 1, the smoothing spline varies from the least-squares approximation to the data by a linear polynomial when p is 0, to the thin-plate spline interpolant to the data when p is 1. The convergence speed of each iteration increased as p decreased while losing the splines interpolant. In these test problems, p = 1 was used.

In the case of using radial basis function as a proxy modeling method, the proxy function approximations are represented by a sum of N radial basis functions (Equation 12). Each associated with a different center x_i, and weighted by appropriate coefficients w_i which are estimated using the matrix methods of linear least squares.

$$y(x)=\sum^{N}_{(i=1)} w_i \, \Phi (||x - x_i||) \quad (12)$$

To be fair in comparing the four studied proxy modeling techniques, the experimental design method used to select the sample points, the design search space size of the history matching parameters, and the optimization routine that used in the minimization process are kept the same. The Sobol sequence and GA are used as the experimental design and optimization technique respectively. The average value of the performance indicators for each test problem comparative study is calculated and presented in Table 2.

Table 2: Average values of the performance indicator calculated for the three test problems, the proxy modeling comparative study.

Aspect	Technique	Average Performance Indicator, %		
		Single Tank Material Balance	Multiple Tanks Material Balance	Reservoir Simulation
Proxy Modeling	ANN	29.31	31.33	28.88
	Kriging	27.51	30.9	25.38
	TPS	39.77	42.16	38.09
	RBF	37.36	47.79	35.85

The results show that both Kriging and ANN techniques are remarkably superior to TPS and RBF proxy methods. Kriging and ANN proxies give solutions closer to the exact solution, and consequently improve the assisted history matching process.

Results of Optimization Techniques Comparative Studies

The studied optimization algorithms (GA, PSO, FFO, BCO, and HSO) are applied to the proxies of the three different test problems, and the results are presented in this section. This work focuses on standard versions of the selected/studied algorithms. To keep the likeness of all algorithms, individuals in a population, the number of iterations in a run and number of runs were kept constant. The fundamental GA was implemented. Also, fitness is taken as (1 / tour length). Roulette wheel selection, partially matched cross over operator with a probability of 95%, and reciprocal exchange mutation operator with a probability of 0.1% was used. Appropriate settings of PSO with the same fitness criteria is used. To be fair in comparing the studied optimization algorithms, the experimental design method used to select the sample points, the design search space size of the history matching parameters, and the proxy model are kept the same to make sure that the only factor affecting the assisted history matching process is the optimization method. In all comparisons, the Sobol sequence is used as the experimental design technique, and Kriging interpolation is used as the proxy modeling technique. The average values of the performance indicators are reported in Table 3. The results show that FFO, BCO, and HSO consistently provide lower values of average error indicator than GA and

PSO. This observation is valid for all the three test problems.

Based on the previous findings, a new assisted history matching workflow integrating the superior techniques presented in this work is proposed by us. The Sobol sequence and Kriging are used as experimental design technique and proxy modeling techniques respectively. The firefly, bee colony, and harmony search optimization algorithms are used as optimization techniques.

Table 3: Average values of the performance indicator calculated for the three test problems, the optimization techniques comparative study

Aspect	Technique	Average Performance Indicator, %		
		Single Tank Material Balance	Multiple Tanks Material Balance	Reservoir Simulation
Optimization Algorithm	GA	26.828	30.9	25.38
	PSO	40.98	29.41	35.18
	BCO	18.29	22.67	22.49
	HSO	12.86	20.29	22.06
	FFO	10.88	21.68	21.08

The following sections (the second part of this work) presents the application of the proposed assisted history matching workflow in a full field reservoir simulation model for a mature gas-cap reservoir with 28 years of history.

Assisting the History Matching of Reservoir "X" Simulation Model

Reservoir "X" is a mature gas-cap reservoir that commenced production in December 1988. A strong gas-cap drive mechanism with weak bottom water aquifer is encountered during the production lifetime of the reservoir. Structurally, the reservoir consists of three fault blocks which are fully communicating through six conductive faults. Three out of the six faults block in the reservoir have the same initial oil-water contact and gas-oil contact and follow the same pressure depletion trend. Reservoir "X" is penetrated by 23 wells and currently producing from nine wells. In Figure 7, the 3D simulation model of the reservoir is presented. The model dimensions are (44 x 119 x 72) in I, J, and K directions respectively (376,992 total number of cells including 116,676 active cells).

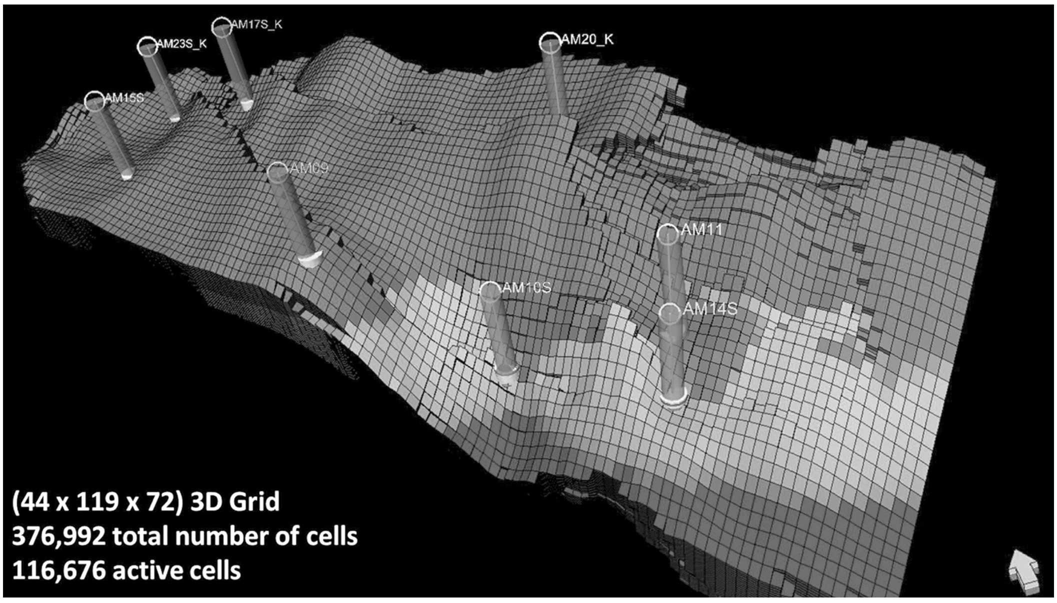

Figure 7: 3D reservoir simulation model of reservoir "X".

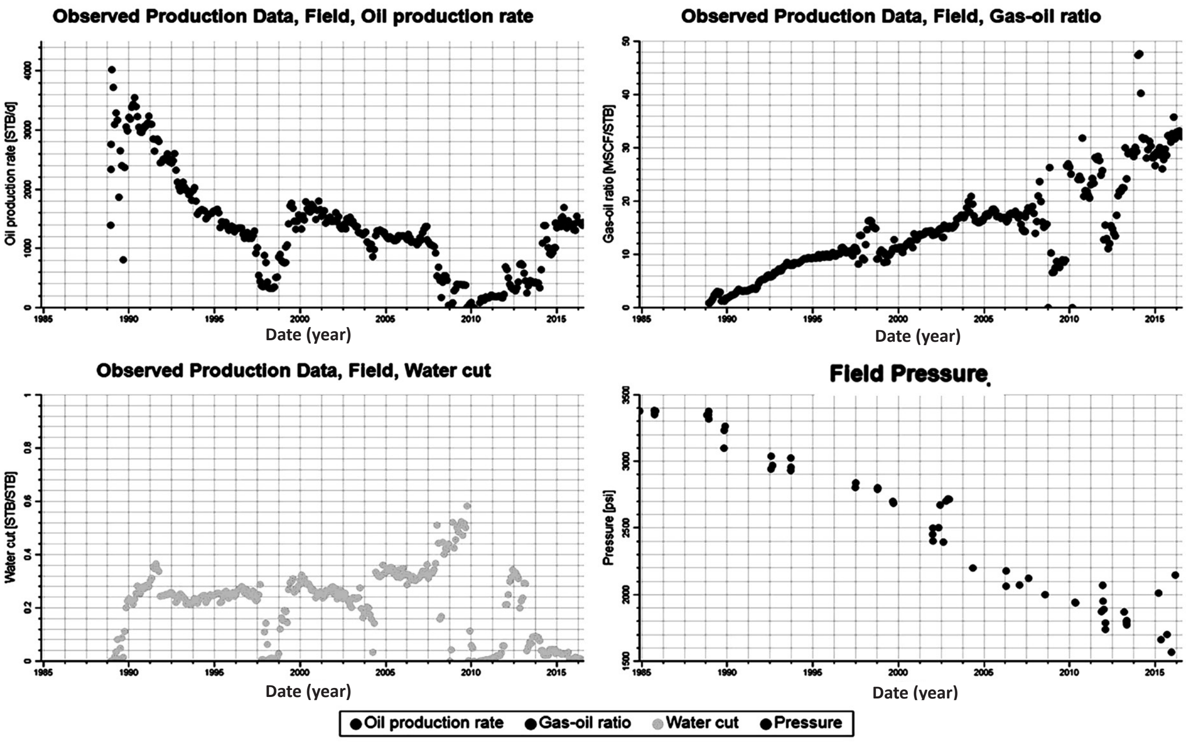

Figure 8: Historical field pressure and production data performance of reservoir "X".

Figure 8 shows the pressure and production data performances on the field basis.

The latest reservoir simulation study conducted on reservoir "X" succeeded in manually matching the 28 years historical data. The integrated reservoir study took about five months including 90 days for the manual history match. This work presents the attempt of assisting the history matching of the reservoir "X" using workflow discussed here. Moreover, the results obtained using our workflow are compared with those obtained with the manual history match. The comparison is based on match quality and process duration. In addition, our results are also compared with those obtained using the most widely applied assisted history matching workflows implemented in the most commercial assisted history matching software tools. The assisted history matching workflows are employed on the same 15 history matching parameters which were initially identified and used in the manual history match, presented in Table 4. Selected assisted history matching workflows are executed according to the following methodology:

- Use the Sobol sequence (proposed) and LHC (most widely used) experimental design techniques separately to select 25 samples out of the uncertainty range of the assigned history matching parameters.
- Build two sets of scoping runs. Each set containing 26 runs (25 selected by each experimental design method and an additional run that represents the most likely values of the history matching parameters) following Goodwin's rule of thumb [68] that states that the number of scoping runs should not be less than (2*No. of variables +1) with an upper limit of 26 runs.
- Run the scoping runs over the first half of the historical data (first 14 years). For each scoping run, a multiple objective function (static reservoir pressure, water cut, and gas oil ratio) is

calculated according to the following formula:

$$f(x)=\sum\frac{1}{n}\left\{\begin{array}{c}\sum_i[w_i(y*_i-y_i)^2]_{\mathrm{WC}}+\\ \sum_i[w_i(y*_i-y_i)^2]_{\mathrm{GOR}}+\sum_i[w_i(y*_i-y_i)^2]_{\mathrm{Pressure}}\end{array}\right\} \tag{13}$$

where n is the number of the observed data points, $y_i*(x)$ represents the simulated data obtained using the set of parameters x's, and y_i is the observed data, and w_i is the weight assigned to each set of data in the objective function.

- Use Kriging (proposed) and ANN (most widely used) to build two proxy models that interpolate the objective function with the experimentally designed reservoir parameter samples. Kriging represents our recommended proxy modeling technique, and ANN represents the most widely used one.
- Minimize the Kriging proxy model using any of the proposed optimization algorithms (FFO, BCO, and HSO). Minimize the ANN proxy model using GA. Each minimization process is run five times to take a more representative solution. Consistency is maintained in running the studied optimization algorithms.
- Use the values of the history matching parameters obtained with the two workflows as input for running the next half of the history (last 14 years) in prediction mode.
- Compare between the simulated and observed data of both workflows over the second 14 years of history that were run in prediction mode using the following error indicator (Equation 14):

$$Error\ Indicator=\sum\left\{\begin{array}{c}Avg.\left[\frac{(y*_i-y_i)}{y_i}\right]_{\mathrm{WC}}+Avg.\left[\frac{(y*_i-y_i)}{y_i}\right]_{\mathrm{GOR}}+\\ Avg.\left[\frac{(y*_i-y_i)}{y_i}\right]_{\mathrm{Pressure}}\end{array}\right\} \tag{14}$$

Results of Assisting the History Matching of Reservoir "X" simulation Model

Our proposed workflow in assisting the history matching of reservoir "X" is applied versus the most widely used workflow, and the results are compared with the manually history-matched model as shown in Figure 9. To make a quantitative comparison, an error indicator is calculated for each history matched model (Equation 14). In Table 4, the final values of the history matching parameters resultant from different studied workflows are presented. As shown in Table 4, the values of the history matching parameters obtained using the proposed workflows are close to that obtained using manual history matching.

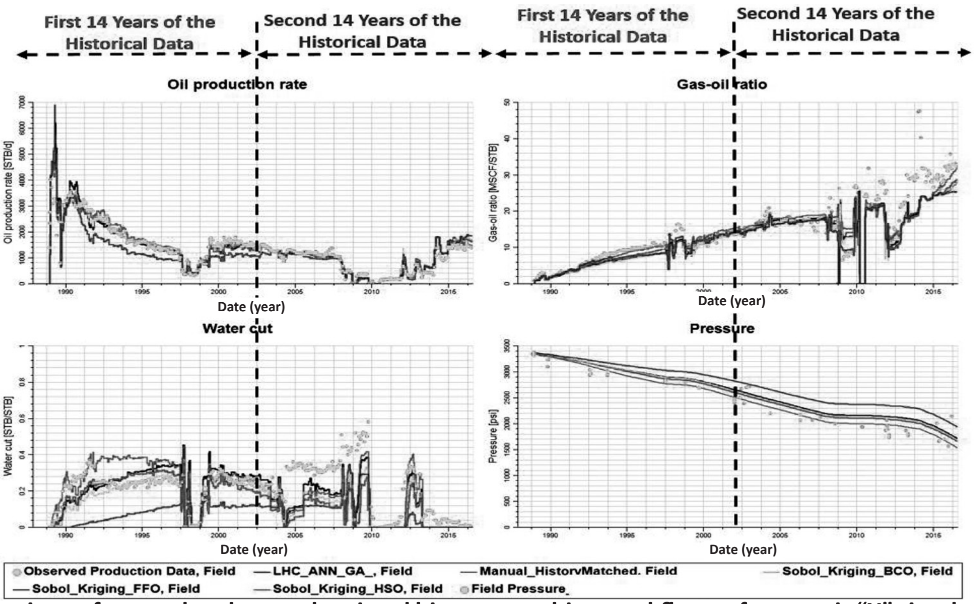

Figure 9: Comparison of manual and several assisted history matching workflows of reservoir "X" simulation model.

Table 4: Values of history matching parameters that give the matched model based on different workflows.

HM Parameter	History Matching Technique				
	Manual HM	LHC-ANN-GA	Sobol-Kriging-FFO	Sobol-Kriging-HSO	Sobol-Kriging-BCO
OWC (ft)	7189	7211	7192	7176	7200
GOC (ft)	6780	6799	6781	6779	6780
Perm X,Y Multiplier	5.06	4.21	4.59	3.62	6.95
Perm Z Multiplier	5.24	2.23	2.82	6.08	6.83
Critical Water Saturation, fr	0.32	0.34	0.30	0.33	0.33
Corey Exponent of Water (Krow)	3.80	3.06	3.26	4.44	3.70
Krw@Sorw, fr	0.48	0.48	0.45	0.54	0.46
Corey Exponent of Oil (Krow)	3.71	3.91	4.09	3.63	3.42
Corey Exponent of Oil (Krog)	3.84	3.09	3.81	4.30	3.40
Kro@Somax, fr	0.63	0.63	0.64	0.64	0.61
Corey Exponent of Gas (Krog)	2.31	3.06	2.64	1.86	2.44
Krg@Swmin, fr	0.85	0.87	0.84	0.85	0.87
Krg@Sorg, fr	0.62	0.60	0.56	0.64	0.66
R_V (vs.) Depth, MSCF/STB	0.08	0.09	0.08	0.08	0.09
Rs (vs.) Depth, STB/MSCF	1.08	1.04	1.05	1.14	1.05

In Figure 10, the number of runs conducted to obtain the match, duration taken in days for every workflow, and the value of the error indicator for each history-matched model is shown.

Figure 10: Number of runs conducted to obtain the match, duration taken in days, and value of the error indicator for each history matched model.

As shown in Figure 10, the manually history-matched model is obtained after running 200 runs within 90 working days whereas all assisted history-matched models are obtained using 26 scoping runs and conducted within only two working days. Regarding the match quality, our proposed workflows have the lowest values of the error indicator. On the other side, the conventional assisted history matching workflow (LHC-ANN-GA) has the highest value of the error indicator. In Figure 11, a map comparing the history match of both the conventional approach (LHC-ANN-GA) and the proposed approach (Sobol-Kriging-FFO) is shown.

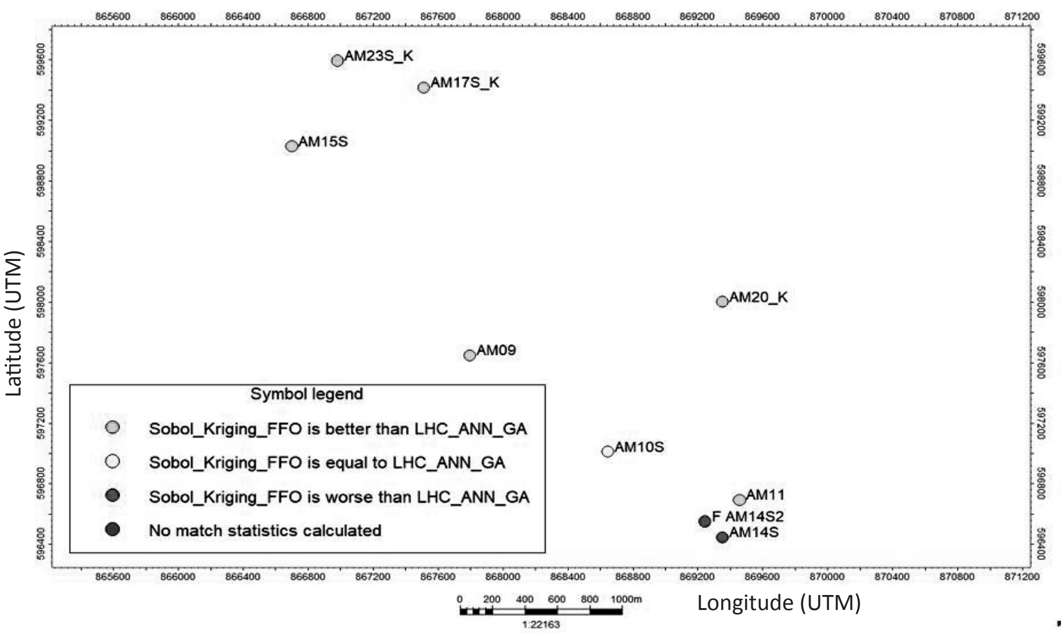

Figure 11: Comparing the map between calculated objective function on a well basis for (Sobol-Kriging-FFO) and (LHC-ANN-GA) workflows.

As shown in Figure 11, the objective function on a well basis is calculated, and the color of each well is indicative of the relative quality of wells match. The proposed workflow (Sobol-Kriging-FFO) yields a better match for six wells, equal match of one well, and worse match for two wells compared with the match obtained using LHC-ANN-GA. Moreover, similar results are obtained for other proposed workflows (Sobol-Kriging-BCO) and (Sobol-Kriging-HSO).

RESULTS AND DISCUSSION

Assisted history matching is different from regression-based history matching (automatic history matching) which depends only on linear/nonlinear regression techniques. Due to the deterministic nature, the regression based optimization algorithms search for stationary points in the search space. As a consequence, the resultant solution could be a local optimum and not the global optimum. Recent assisted history matching workflows employ experimental design, proxy modeling, and stochastic optimization methods. In addition, experimental design techniques enhance the process of selecting sample values within the uncertainty ranges defined for the history matching parameters. Proxy models are then constructed to represent the objective function (error) between actual and estimated performance values. Proxy modeling saves the time of running actual simulations during the history matching process. In addition, stochastic optimization algorithms avoid being trapped in local minima, and consequently find better solutions.

This work presents a new three-step assisted history matching workflow that relies on recent algorithms imported from computer science applications. It also presents the application of the new workflow in a field case. The proposed technique(s) in each element of the assisted history matching workflow is compared with those techniques which are commonly used in the literature and commercial software tools. Three test problems of different levels of complexity are used to validate the results. In the experimental design step, the proposed technique (Sobol sequence) shows better performance than the most widely used technique (LHC). The proxy modeling comparative study concludes that both Kriging and ANN techniques are superior to TPS and RBF proxy methods. In addition, kriging is selected to be the proxy modeling method in the proposed workflow. Based on the superiority shown by the three proposed optimization algorithms (FFO, BCO, and HSO) compared with GA and PSO, any of the three techniques can be used in the proposed workflow. The three proposed optimization algorithms give similar results with no significant difference. It is worth mentioning here that the performance of any optimization algorithm varies with a different selection of the algorithm parameter values, the operators which are used by them, and the tuning of their parameters etc. Moreover, the mechanism and the superiority/distinguishing features of each proposed optimization algorithm are presented earlier.

The process of assisted history matching is not new; however, the choice of algorithms to use in the process is what makes this work different from any other previous work. Finally, the proposed assisted history matching algorithms and workflow have never been used before in reservoir engineering assisted history matching problems.

CONCLUSIONS

Based on the results of the comparative work using three synthetic test problems and comparing a history-matched model of reservoir "X" obtained using a proposed assisted history matching workflow (The Sobol sequence experimental design technique, Kriging proxy modeling, and FFO/BCO/HSO optimization algorithms) with those obtained manually or obtained using a conventional workflow (LHC, ANN, and GA), the following conclusions may be derived:

- The proposed assisted history matching workflow gives results of the similar quality to that of the manual history matching by saving a significant amount of time.
- The proposed assisted history matching workflow is superior to the most commonly used conventional assisted history matching workflows.

NOMENCLATURES

LHC	: Latin hypercube
TPS	: Thin plate splines
RBF	: Radial basis function
ANN	: Artificial neural network
GA	: Genetic algorithm
EnKF	: Ensemble Kalman Filters
PSOF	: Particle swarm optimization
FFOF	: Firefly optimization
BCOF	: Bee colony optimization
HSO	: Harmony Search Optimization
WC	: Water cut
GOR	: Gas oil ratio
OWC	: Oil water contact
GOC	: Gas oil contact
Krow	: Oil relative permeability
Krg	: Gas relative permeability
Krw@ Sorw	:Water relative permeability value at residual oil saturation
Krg@ Swmin	: Gas relative permeability value at connate water saturation
R_V	: Vaporized oil in the vapor phase
R_s	: Solution gas oil ratio

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