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Optimization Techniques for History Matching and Production Forecasting

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Abstract*: Reservoir modelling and production forecasting can provide vital inputs to the efficient management of petroleum. Since the reservoirs are highly heterogeneous and nonlinear in nature, it is often difficult to obtain accurate estimates of the spatial distribution of reservoir properties representing the reservoir and corresponding production profiles. If an accurate model of a reservoir is built, it can lead to efficient management of the reservoir. This paper describes the mathematical modelling of oil reservoirs along with various optimization techniques applicable for history matching and production forecasting. Gradient based and non-gradient based optimization techniques viz. Simulated Annealing (SA), Scatter Search (SS), Neighborhood algorithm (NA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Ensemble Kalman Filters (EnKF) and Genetic Algorithm (GA) and their application to reservoir production history matching and performance are presented. The recent advancements and variants of these techniques applied for the purpose are also presented.

***Keywords*: Reservoir modelling, History matching, Ensemble Kalman Filter, Genetic Algorithm**

I. INTRODUCTION

Reservoir modelling and Production forecasting are crucial inputs to the efficient management of petroleum. Developing reliable numerical reservoir models which integrate all the geological, geochemical, geophysical, and petrophysical data of the reservoir available through the petroleum exploration process, can help alleviate this problem. Since the reservoirs are highly heterogeneous and nonlinear in nature, obtaining accurate estimates of the spatial distribution of reservoir properties representing the reservoir is pretty difficult which influence corresponding production profiles. Petroleum engineers always pursue to construct reservoir models which are able to produce consistent production forecasts so that further reservoir development in terms of recovery strategies (primary, secondary and tertiary) to be employed, locating new wells and surface facilities can be optimally designed.

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Wells occupy a minute percentage of the total area of the reservoir and this doesn't give us any clue about the reservoir properties at all. Hence, the available reservoir models cannot be directly used. To overcome this difficulty, petroleum engineers usually define an inverse problem, where one quests for a few parameters that can be fed as inputs to the reservoir simulator and will yield the same production history as actually recorded in the field. The input parameters with uncertainties are many, namely rock properties – porosity, permeability and thickness; rock fluid interaction properties – saturations, relative permeabilities, depth of oil/water and oil/gas interfaces; laboratory measured data – fluid PVT behavior, compressibility, capillary pressure data, viscosities and formation volume factors; water influx if aquifers are present. Out of these, the most sensitive and most uncertain parameters are the porosity and permeability. Moreover, it is neither desirable nor necessary to include all other variables in optimization. Barring porosity and permeability, the rest can be tweaked manually. This is a very tedious exercise and the solution will never be unique since a large number of distributions can be found which will result in similar production histories. This process is called history-matching and was traditionally carried out manually and is a very sluggish process. Although some reservoir engineers still use it, more often, optimization-based automated history-matching has now become popular.

II. HISTORY MATCHING AND OPTIMIZATION TECHNIQUES

All history-matching techniques proposed in the literature are based on the inverse modelling problem [1]. Although the main aim of history-matching is minimization of the square of data mismatch, the methods that are used for minimization as well as for evaluating uncertainty vary broadly. After manual history-matching, evolutionary algorithms were developed to automate the history-matching. The automated approach is iterative and links optimization techniques to statistical analysis and obtains the suitable best parameter combination that results in good reservoir history matching [2]. These algorithms are population-based optimization algorithms, enthused by processes happening in biological evolution. The optimization algorithm for minimizing objective function for history-matching can be broadly divided into two categories viz. gradient and non-gradient methods.

A. Gradient based Methods

These methods make use of the conventional optimization approach which has been taken up from optimal control theory to calculate solution which will be closer to local optimum [3].

These methods will initially calculate the objective functions' gradients, and then, find in which direction the optimization search should go on, in order to get the problem solved [4].

In the framework of history-matching algorithm, the production responses' gradients with respect to changes in reservoir parameters are forwarded to evaluate the magnitude and direction of the changes to be made to the parameters [5].

Various optimization algorithms that are reported ([6] & [7]) in literature are Steepest descent method, Gradual deformation approach, Levenberg-Marquardt method, Gauss-Newton method, Singular value decomposition method, Limited Memory Broyden, Conjugate Gradient technique, Fletcher-Goldfarb Shanno and Quasi-Newton methods.

These gradient methods require the objective function's first derivative (Jacobian) or second derivative (Jacobian and Hessian) of static properties of the reservoir. They also demand an estimate of sensitivity coefficient, which is a partial derivative of certain dynamic parameters like pressure and saturation with respect to static ones like permeability, azimuth of geospatial variogram and porosity [8]. The normal attainment is through the finite difference approximation for the partial derivative.

Kruger introduced the automation of history matching where he proposed the procedure for determining areal permeability distribution of 2-dimensional reservoir in cycling or flooding projects. He then compared the obtained results where he calculated pressure distributions with the field measurements and concluded the reservoir model to be trained for production data for trustworthy prediction of reservoir performance [9]. Two researchers, Jacquard and Jains, proposed a technique of evaluating sensitivity coefficients to solve history matching problems. Here, modified steepest descent method was used for lessening the deviation between simulated and measured pressure arrived at with certain changes in a few parameters for a 2-dimensional transient flow, single-phase reservoir model. The reservoir model was described analogous with electrical parameters like resistance, inductance and capacitance to permeability, production rates and porosity of the reservoir model respectively. Authors reported a successful implementation of the history-matching problem though restricted to the zonation of permeability [10].

Jacquard and Jains (1965)' description of a nonlinear regression approach was used by Jahns to match the reservoir pressure that was obtained interference test. The properties like transmissibility and storage term of each reservoir zone are varied with the help of regression analysis. This method was suggested non-suitable for multiphase flow with change in fluid saturation but with single phase flow, it could easily be applicable [11]. Coats et al. introduced method that is a union of linear programming and least squares, which could help assessing a linear relationship of error with the reservoir properties. The methodology of zonation was used as a method of parameterization with lower and upper boundary constraints on reservoir parameters like permeability and porosity. The reservoir description was developed with random generator of number of runs with the help of reservoir simulator and within the given constraints. It was used on three 2-dimensional reservoirs (one reservoir with single phase gas, another reservoir with single phase oil and the third with two phase) flows [12]. Although the method provided satisfactory matching, the validity of assumptions remained doubtful, thus limiting the application of these methodologies. Slater and Durrer (1971) applied linear programming and a gradient-based method as a search technique to attain a finest history-matched model [13]. The modification of the gradient method of Jacquard and Jain helped find the step size and search direction for modifying the sensitivity coefficient that minimizes the objective function. It was reported that finding the step size by gradient methods in less porous and permeable regions was difficult because of objective function's strong non-linear relationship with lower permeability values and their highly sensitive nature. Thomas et al. applied a classical Gauss-Newton method that automatically varies the reservoir parameters that fetches the better history matched reservoir model. The method used implementation of box-type constraints on reservoir parameters. Authors reported that their method not only gave equivalent history match on less simulation runs in comparison with the work of previous researchers, but also can handle non-linear cases better [14].

Carter et al. and Hirasaki proposed sensitivity coefficient method based calculation of gradients. In this method, the derivatives of pressure as well as saturation with respect to sensitive coefficients (model parameters) are calculated ([15] & [16]). These are later used in calculating the Hessian matrix for second order, gradient-based optimization algorithms [17]. Carter et al. (1974) proposed two new iterations based non-linear programming methods, applicable to minimize the objective function of a compressible, single phase flow reservoir. For calculating sensitivity coefficient, these techniques, however, utilized the Jacquard and Jain's method. The authors claimed that the method proved to be equally efficient to produce a good match of calculated and observed pressure when compared with previous works, for predefined constraint intervals. However, the method is limited to cases with single phase flow and needed more computational time for calculating sensitivity coefficient with less efficiency near optimum solution. Hiraski (1975) proposed a semi-automatic procedure of history matching that matches oil production data only, but, was not suitable to complex reservoirs. The author's method was used to calculate the reservoir parameters by deducing a relation between dimensionless cumulative injection and the derivative of cumulative oil production with respect to reservoir parameters.

Chen et al. (1974) & Chavent et al. (1975) showcased history matching problem as a control problem, in which observed data like pressure is considered as a state variable and reservoir parameters like permeability as forcing variables ([18], [19]). The adjoint method was applied to calculate the objective function gradient, which initially computes the derivative of the objective function and later uses first order gradient-based optimization algorithm. This work is demonstrated on a synthetic and a real Saudi Arabian reservoir (both being single phase) considering the reservoir parameters as continuous functions of space and showed that the time of computation for optimization was lesser than that taken by conventional constant-zone gradient optimization methods, by Chen et al. Chavent et al. tested the technique on semi-realistic single phase reservoir model.

Steepest descent method and adjoint method was used to minimize a non-quadratic objective function and compute the gradients respectively, during which the generation of impractical values of transmissivities was avoided during computation. However, this methodology needs many iterations for non-linear problems and hence is more suitable for linear problems. Watson et al. (1980) applied both the earlier methods by using optimal control approach and could successfully evaluate porosity, spatially varying permeability and relative permeabilities [20].

Yang & Watson (1988) applied variable-metric method coupled with optimal control theory, another optimization technique, for automated history matching [21]. The authors, after testing their methodology on two 2-phase, 1-dimensional and 2-dimensional synthetic reservoir models, reported that variable-metric methods viz. self-scaling variable metric (SSVM) method and the Broyden/Fletcher/Goldfarb/Shanno (BFGS) method were more appealing in comparison with the steepest descent method and other conjugate-gradient methods, except for those cases where performance metrics are quadratic in nature. They henceforth concluded that their method was effective in both ways viz. handling the inequality constraints and bettering the convergence rate.

Gavalas et al. (1976) & Shah et al. (1978) introduced the Bayesian framework for history matching which delivers better guesses of true porosity and permeability distributions in reservoir as compared to the routine zone-gradient optimization methods. This probabilistic approach requires prior statistical information (viz. co-variance and mean) on unknown parameters and then integrates it with the geographical information in the objective function so as to minimize the statistical uncertainty in estimating reservoir parameters [22], [23]. The results of this study are compared with those results obtained from sensitivity coefficient method and reparameterization by zonation by Shah et al. (1978). Both the research groups, however, testified that the accuracy of the estimates noticeably depend on the accurate prior statistical and geological information.

de Marsily et al. (1984) proposed a method which combined pilot point method and optimal control theory and the technique was applied to parameterize groundwater hydrology [24]. The concept was first applied to the field of petroleum engineering by Fasanino et al. (1986) in which reservoir parameters like permeability and porosity values at predetermined pilot points were disturbed for history-matching of a single phase gas reservoir [25]. The parameters, at locations other than the predetermined pilot points, were found out by interpolation using conditional simulation or kriging by using the parameter values at pilot points. Hence, the technique does calculate gradient at pilot points and avoids at all the other grid blocks thereby reducing the unknown parameters that one has to estimate. This method offers rough solution for the inverse problem of history matching coupled with an uncertainty about the location and the quantity of pilot points to be specified. The further extension of work on pilot points method and its application to history matching can be seen in others' studies [26]; [27]; [28]; [29]; [30]. The pilot point method was successfully applied for estimation of porosity values, which, later helped in history-matching, as done by Bissell et al. (1997) on a synthetic reservoir. Using sensitivity information figured out by a direct method which assumed that the high sensitivity regions are prejudiced by location of pilot points, optimum locations of the pilot points were established. The query of choosing number and optimal locations of pilot points was discussed by Cuypers et al. [31]. Xue et al. (1997) and Liu and Oliver (2004) reported certain drawbacks of pilot point technique like slower convergence, undershooting or overshooting of reservoir parameters at the pilot points that result in massive variations of objective functions as iterations advance [32].

The technique suggested by Carter et al. (1974) and Chavent et al. (1975) was extended further to multiphase flow case study by Anterion et al. (1989). The method was tested on a synthetic, fully implicit, 3-phase, 3-dimensional reservoir and reported an enhanced precision of history matched models with fewer simulation runs and lesser computing time [33]. For calculating sensitivity matrix, applications of gradient simulator are extensively studied by few researchers ([34]; [35]; [36]; [37]; [38]; [39]). Nevertheless, their expertise suggested avoiding using direct methods, as reservoir models with large number of grid blocks are too complex to be solved and consume much computation time and larger memory size. Killough et al. (1995) introduced multiple right hand side iterative linear equation solvers (MRHS) for adjoint equations system, which enhanced the gradient solver performance. Their methodology was tested on upto 10,000 grid blocks reservoir models and the results obtained from the MRHS iterative solver were compared with those obtained from the standard red-black line successive over-relaxation and direct solvers [40].

A modified Gauss-Newton method was used for solving history-matching problem of a 3-dimensional synthetic reservoir for estimating porosity and permeability was applied by Tan and Kalogerakis, (1992). The authors executed the methodology successfully to completely automate the procedure of history matching that helped in attaining genuine values of porosity and permeability. They have also reported that the Guass-Newton method is capable of decreasing the number of sensitive coefficients to be evaluated [41]. Chu et al. (1995) employed this technique for history matching a single phase reservoir and attempted to condition the well-test pressure information with the porosity and permeability distributions of the reservoir grid block, with modified generalized pulse-spectrum technique. The authors reported that the technique accomplished a reasonable evaluation of the permeability distribution but not the porosity distribution [42]. Reynolds et al. (1996) used this Gauss-Newton methodology for multi-well pressure data history matching to assess reservoir parameters, where a subspace method was applied, to reduce the size of Hessian matrix, as parametrization technique. They affirmed that there was a notable reduction in computation time taken for producing realizations [43]. He et al. (1997) used the method of Chu et al. (1995) for a single phase flow reservoir and generated sensitivity coefficients related to porosity fields [44]. They have extended the method of Carter et al. (1974) after they found that they could not attain better guesses of sensitivity coefficients associated to porosity fields. It was further extended to a synthetic 2 phase, 2-dimensional flow of oil & water reservoir history matching problem by Wu et al. (1999), who have arrived at a history-matched model by fine-tuning the average log-permeability of every layer.

Li et al. (2003) extended it further to a 3-dimensional, three phase reservoir problem. But the drawbacks as reported by those who used Guass-Newton method and its variants are adverse well-test pressure data match, when bad initial guess was made and the leisurely convergence for huge production data [45].

Levenberg-Marquardt method, a variant of Gauss-Newton method, was used by Bi et al. (2000), where Hessian matrix was modified for better convergence rate. The authors have employed the technique to condition 3-dimensional stochastic channels to well observations and well-test pressure data [46]. Zhang et al. (2003) presented a randomized maximum likelihood (RML) that gave a good initial population for the algorithm and used Levenberg-Marquardt method to condition 2-dimensional stochastic channels to well observations and pressure data [47]. This method was later used by Vefring et al. (2006) for estimation of properties of reservoir by minimizing the variance between the reservoir simulation model states and corresponding measurements from the drilling process. The algorithm showed slower convergence rate and also brought instability for reservoir models with large number of parameters and huge production data [48].

The higher efficiency of Conjugate gradient or quasi-Newton method can be attributed to the fact that this method needs gradients of objective function to be calculated thus reducing the computational time. Makhlouf et al. (1993) used this approach for estimating permeability values of grid blocks of a reservoir with 2-phase and 3-phase flows [49]. For complex history-matching problems, limited memory BFGS (LBFGS), another variant of quasi-Newton method, was employed. This proposed method uses objective function and gradient values, from the preceding iteration that constructs the Hessian approximation. The authors reported extensively on several gradient optimizers viz. preconditioned conjugate gradient, LBFGS, BFGS and Levenberg-Marquardt for real and synthetic reservoirs and concluded that LBGFS is relatively efficient than the rest [4]. Liu & Oliver (2004) tested the use of adjoint equation for calculation of gradient and the quasi-Newton method as minimizing algorithm on a 5-spot water injection problem that has around 70,000 model parameters [32]. Eydinov et al. (2009) described the application of LBFGS algorithm for evaluating the relative permeability curves and porosity and permeability distribution for a 3-phase synthetic reservoir [50].

Parish et al. (1993) formulated a knowledge based system (KBS) for reservoir engineers that acts as a decision support tool. The KBS uses instructions like IF THEN, ELSE, statements to make appropriate history matching decisions [51]. Roggero and Hu, (1998), proposed a stochastic optimization method called as Gradual Deformation method as a substitute to conventional gradient optimization method for conditioning a stochastic 3-dimensional reservoir model to the production and well-test data. The problem is formulated as a linear combination of two Gaussian realizations with expected covariance and mean to create new realizations that matches better than the initial generations. The matches are further enhanced by integrating them with other equi-probable realizations. The process is continued till an acceptable match is accomplished [52]. Hu (2000) extended this research and studied local gradual deformation, multi-dimensional gradual deformation and gradual deformation with regard to structural parameters [53].

Hu et al. (2001) established the efficiency of this method generated by sequential simulator for constraining reservoir facies model to the production data [54]. Another constraint was added to the objective function that earlier had only data mismatch in it by Ravalec-Dupin & Noetinger (2002), when they comprehended that proper samples of posterior probability density function were not achieved with the help of gradual deformation algorithm [55]. Caers (2003) applied gradual deformation method with multi-point geostatistics for a streamline simulation model to generate initial realizations for history matching [56]. A conclusion was drawn by Liu & Oliver (2004) that gradual deformation method achieved much better results than those obtained by Markov Chain Monte Carlo method [32].

The primary advantage of using these types of gradient-based techniques is their quick convergence to optimal solution. Although these methods are found effective and are widely used, they still have certain shortcomings viz. converging at the local optimum solution and calculating first and higher order derivatives of highly nonlinear objective functions. Hence, researchers had to divert their focus onto non-gradient based stochastic methods to overcome these drawbacks.

B. Non-Gradient based Methods

Non-Gradient based methods (stochastic algorithms) have certain advantages over gradient based methods. These methods are helpful in approaching global optima rather than being restricted to local optima compared to gradient method and do not involve rigorous calculations for minimizing objective function. They involve large computation time and large no of simulation runs, so that solution converges to a global optimum. These do not require initial guess in the vicinity of the optimum solution, which make them applicable for non-unique history matching. In non-gradient based methods, with the help of certain operators, a number of equi-probable reservoir models evolve progressively, until global optimum is reached. Various algorithms based on non-gradient based methods are now in use viz. Simulated Annealing (SA), Scatter Search (SS), Neighborhood Algorithm (NA), Particle swarm optimization (PSO), Ant colony optimization (ACO), Kalman filters (KF) and Genetic Algorithms (GA).

B.1 *Simulated Annealing (SA)*

Simulated annealing (SA) is a probabilistic technique that approximates the global optimum of a given function, which is introduced by Kirkpatrick et al. (1983) and Cerny (1985). In a large search space, it is a metaheuristic to approximate global optimization and is used often for the cases with more discrete search space [57] & [58]. The methodology has been applied for estimating of petrophysical properties of a reservoir and conditioning concurrently [59]. The authors used the technique for estimating capillary pressure for gas/water and relative permeability curves simultaneously.

Sultan et al. (1993) applied SA on a black oil reservoir which was experiencing waterflooding for automatic history matching and reported the values predicted are in good match with the observed field production data [60].

Ouenes and Saad (1993) suggested a naval SA algorithm that helps in reducing computation time and applicable for large scale reservoirs for minimizing the objective function [61]. Ouenes et al. (1994) applied the SA algorithm for a fractured reservoir and estimated the reservoir wettability, pore volume, permeability and wellbore properties [62].

Sagar et al. (1995) applied the SA technique and minimized an objective function that comprised of average permeability data besides the spatial statistics of the reservoir obtained from well log/core data [63]. A heat-bath algorithm was proposed for SA by Sen et al. (1995) and was applied for predicting permeability fields [64]. Abdassah et al. (1996) integrated acoustic impedance data with the conventional SA method and achieved a better reservoir simulation [65]. Portella and Frais, (1999), used the technique of SA integrated with pilot point method to solve automatic history matching problem [66].

B.2 *Scatter Search (SS)*

The technique of Scatter Search is unique, in that it stores given information about the global optima in a diverse and elite set of solutions and later exploiting this to recombine samples. It is an iterative process, in which initial population is partitioned into subsets and the subsets are combined linearly with certain weights. The outcomes of recombination are fine-tuned with the help of an embedded heuristic and are evaluated for the condition whether or not they should be retained.

Sousa et al. (2006) applied SS technique and history matched heterogeneous and homogeneous synthetic reservoirs. The problem was framed as an optimization problem with uncertainties in parameters to be discretized. This resulted in enhancing the accuracy of the outcomes which increased the possible solutions in number [67].

B.3 *Neighborhood Algorithm (NA)*

It is a global optimization, non-derivative search algorithm in a Bayesian framework which is used for sampling the multi-dimensional parameter space. Random model sets are generated initially and are then ranked according to the data match. Geometrically constructed spatial properties, called as Voronoi cells, are utilized to build up new models from the previous best matched models.

NA algorithm is used to develop history matched models. NA was introduced to reservoir applications for highly non-linear problems such as seismic data waveform inversion by Sambridge (1999). The author claimed that the technique was consistent with the distributed systems [68]. Later, few other researchers, Subbey et al. (2004) and Christie et al. (2006) used a Bayesian framework for quantifying uncertain parameters in flows through porous media and developed history matched models applying NA [69] & [70]. Rotondi et al. (2006) used the technique of NA for an offshore gas field that has 7 wells and for which 6 years production data was available. The authors reported that the uncertainty quantification done using Bayesian inference and forecasts of production of hydrocarbons matched accurately with data, in comparison to other history matching algorithms [71]. Erbaş and Christie' (2007) studies was more focused on determining the inaccuracies that are associated with various sampling algorithms for quantification of uncertainties in parameter estimation and reservoir performance predictions. The authors scrutinized the efficiency of NA for generating history-matched models of a real field from North Sea reservoir [72]. Suzuki et al. (2008) pooled NA with 'similarity distance' measure in order to make it applicable for large reservoir realizations [73].

B.4 *Particle Swarm Optimization (PSO)*

It is a population based stochastic optimization technique, which is developed by Kennedy and Eberhart in 1995. It is a bio-inspired technique and is used for continuous and discrete optimization problems. In PSO, the possible solution sets are called 'particles' which are mobile throughout the search space and the site of a particle represents a solution for the problem [74].

Kathrada (2009) has applied PSO methodology on a synthetic reservoir, when he evaluated the technique in conjunction with hierarchal clustering algorithm and generated history matched models [75]. PSO was applied by Fernandez Martinez et al. (2009) for seismic history matching where the subsurface facies model is conditioned to match seismic data with time-lapse and production history. The authors claimed that the methodology is as competitive as other optimization techniques with respect to uncertainty quantification and convergence [76]. Ali Ahmadi et al. (2012) combined PSO with Artificial Neural Network-based soft-sensor and genetic algorithm and applied the same to a real field for optimization [77]. It is reported in the studies of various researchers that PSO methodology is also helpful in determining the optimum well locations ([78], [79] & [80]). Awotunde, (2012) upgraded the basic PSO technique and developed multiple history-matched models of permeability distributions [81].

B.5 *Ant-Colony Optimization (ACO)*

ACO, an evolutionary approach and applicable to continuous as well as discrete variable optimization problems, is introduced by Dorigo et al. (1996). It is a population based stochastic optimization method which exploits the swarm intelligence and is evolved from social behavior of ants [82]. As proposed by Fatemeh and Farhang (2008), ACO technique can be used to predict well flow pressure, fluid injection rates and optimal well locations for injection and production [83]. Rutkowski et al. (2008) applied a multidimensional, continuous ACO for evaluating the optimum number of phase separators required in an oil industry [84]. Oil-bearing zones of a reservoir are also recognized by applying a hybrid particle swarm – ACO algorithm (PS – ACO) [85].

Hajizadeh (2011) and Hajizadeh et al. (2011) extensively studied differential evolution (DE) algorithm and ACO on two reservoirs and achieved a few history-matched reservoir models. The authors claimed that ACO provided a better quality multiple history-matched models and took fewer simulation runs in comparison to DE algorithm ([86] & [87]). The ACO combined with back-propagation algorithm, was proposed by Irani and Nasimi (2012) and Amir et al. (2013). They tested the algorithm for predicting permeability distributions from well log data and proved that the algorithm was more effective than the conventional BP algorithm. ACO was applied for analyzing waterflood for an oil reservoir with high porosity, low permeability and high oil saturation ([88] & [89]).

B.6 *Ensemble Kalman Filters (EnKF)*

The EnKF has originated as another version of the Kalman filter for complex problems where the sample covariance replaces the covariance matrix [90].

It is a recursive filter, where in, when new data arrives, it computes the next step instead of running full optimization over the horizon, which makes it suitable for problems with huge number of variables. EnKF is utilized to update not only static parameters, but also dynamic variables of the reservoir model. The EnKF calculations generally rely on an ensemble of realizations of the reservoir model.

The model predictions are combined with new measurements, when available, and the realizations get updated.

Naevdal et al. (2002) applied EnKF for updating static parameters by fine-tuning the permeability fields [91]. Gu and Oliver (2005) used EnKF and continuously updated permeability, porosity, saturation fields and pressure of a 3-dimensional reservoir history matching problem. They claimed a fairly good history match with reduced computational cost by using small ensemble size. However, issues related to porosity and permeability fields overshooting were pointed out [92]. EnKF was used in conditioning lithofacies realizations generated by pluri-Gaussian model of Liu and Oliver (2005). They have compared the EnKF performance with that of gradient-based minimization method for estimating the facies boundaries. It was reported that EnKF was found to be more effective for history matching the production data [93]. EnKF with confirming option was used by Wen and Chen (2005) for matching production history of a real reservoir. The authors reported that an ensemble size of 200 would be sufficient and anything less than the size would be too small to predict uncertainties in the model [94].

Gao et al. (2006) compared the results of uncertainty quantification obtained by EnKF with those obtained by using Bayesian setting with randomized maximum likelihood (RML) and reported that the results are matching [95]. Skjervheim et al. (2007) applied EnKF to update model continuously by integrating production data and 4-dimensional seismic data, resulting in better estimation of permeability field [96].

Haugen et al. (2008) applied EnKF for history matching of a reservoir by predicting gas-oil contact and water-oil contact. However, few concerns related to prediction of structural parameters and non-Gaussian facies distributions were raised by the investigators [97]. Chen et al. (2008) suggested a closed-loop optimization technique which incorporates a new ensemble based optimization scheme with EnKF (EnOpt)that needs no adjoints [98]. Agbalaka and Oliver (2008) applied EnKF for automating history-matching of production data and facies distribution. They have reported satisfactory results wherein they used a sub-space methodology in a case with synthetic pressure data for one phase flow of 2-dimensional and 3-dimensional cases [99].

EnKF was applied for history matching and characterization of an unconventional 3-dimenstional steam assisted gravity drainage oil reservoir by Chitralekha et al. (2010). The quality of ensemble realizations was assessed in terms of R-square values and their weighted mean square error (WMSE) for distance dependent covariance globalization and localization methods that were used for updating the values of permeabilities. It is observed that least error permeability values are obtained by localization method. EnKF algorithm estimated permeability distribution which are compared to those of a 3-dimensional synthetic reservoir and gave lower root mean square error (RMSE) for localized EnKF algorithm than with global EnKF algorithm [100].

Emerick and Reynolds (2011) significantly improved history matching and performance prediction by applying half-iteration EnKF (H-EnKF) combined with covariance localization method. The authors reported performance comparison of a real reservoir between H-EnKF with covariance localization and without covariance localization, and claimed that the former method provided better history matching and performance prediction [101]. Another variant of EnKF method, constrained EnKF (CEnKF) was proposed by Phale and Oliver (2011), which also accounts for constraints on credible values of certain state variables while data assimilation. The authors claimed that the technique attained better prediction of reservoir properties by enforcing bound constraints on saturations and non-negativity constraints on molar densities [102]. Zhang and Oliver (2011) studied uncertainties related with geological structures and proposed a technique that updates multiple scales of heterogeneity in Ensemble Kalman filter. The authors reported that the results obtained have shown better history matching and water cut match [103].

In order to minimize sampling error that is occurring at single update step of EnKF, Kovalenko et al. (2012) derived Euclidean norm distribution of the sampling error evolving at single step update assuming normality of forecast distributions and negligible observation error. The methodology was applied on few synthetic reservoir models and the propagation of error at single step update was illustrated [104]. A parallel data assimilation framework for quantifying uncertainty and characterization of reservoir was introduced by Tavakoli et al. (2013), who disbursed multiple realizations among various computers for computations. A network was built and the communication among these computers was done at data assimilation step. The technique was tested on a synthetic reservoir for Ensemble Smoother (ES) method besides EnKF. The authors concluded that the computation time was reduced and a parallel efficiency of 50% was attained for ES in comparison with 35% attained for EnKF [105].

B.7 *Genetic Algorithm (GA)*

It is a mathematical modelling algorithm which is based on Darwin's 'survival of the fittest'. It is computer-based search procedure inspired from genetics, which has widespread application. This process utilizes initial population of individuals, known as chromosomes, which are further processed where they undergo inheritance, crossover and mutation for several generations that obtains potential solutions. The new generation chromosomes are evaluated based on a fitness function.

The methodology of GA has been applied widely in innumerous engineering as well as real world problems viz. learning robotic behavior [106], prediction of protein structure [107], inverse problems in the field of electromagnetics [108], designing an optimal neural architecture for developing online soft-sensor [109] and many more.

GA is proved to be an efficient method for inverse history-matching problems and reservoir parametrization. Sen et al. (1995) introduced the application of GA for reservoir modelling and generated permeability distributions from tracer flow data and a set of reservoir outcrops, followed with quantifying uncertainties in production forecasts.

With a population size of 200, they could achieve global optimum solution with values of 0.60, 0.01 and 0.9 as crossover probability, mutation probability and update probability respectively. The authors also reported that the choice of these probabilities and population size largely affects the performance of GA [64].

A modified GA for estimating fault throw, shale permeability and sand permeability was proposed by Bush and Carter (1996), that used steady state genetic algorithm with modified rank selection operator. The authors claimed that this modified GA when tested on a synthetic PUNQ-S3 reservoir outclassed the standard GA [110]. Guerreiro et al. (1998) tested GA to determine properties of a reservoir by systematically matching tracer breakthrough profiles utilizing parameters such as porosity outside and inside the insertion and geometry of insertion. With a population size of 200 and using three different crossover operators, in their studies, viz. single point operator, two point operator and uniform cross over operator with values of probabilities as 0.08, 0.48, 0.24 respectively and bit-flip mutation probability as 0.02. The authors used a rank-based elite selection that is helpful in selecting the best realization as per the fitness value and reported that the methodology achieved satisfactory results [111].

A neural-genetic model for estimating permeability from well log data was developed by Huang et al. (1998) that utilized GA for optimizing connection weights used for training neural networks. They reported that, though GA consistently reduced the performance error as compared to neural networks, convergence was slower [112]. However, by integrating a fuzzy reasoning, the neural-genetic model was modified to hybrid neural-fuzzy-genetic methodology that gave faster convergence [113]. Soleng (1999) used steady state GA for conditioning petrophysical properties such as porosities and permeabilities, of PUNQ S3 synthetic reservoir to field observations. The author claimed the methodology was reasonably fast at achieving near-optimal solutions in the vicinity of realistic reservoir conditions, with a population size of 50. He also suggested the use of a 3-dimensional crossover operation to nullify the disturbing effect of crossover. He applied the technique successfully to a small reservoir, taking few parameters into account for conditioning the field observations, but doubted its efficiency for a large scale reservoir [114].

GA optimizer was tested extensively on PUNQ S3 complex synthetic reservoir for history matching and its results are compared with those obtained from SA and GA with hill climbing by Romero & Carter (2001). Various parameters like V-shale, permeability and porosity were encoded in a complex 3-dimensional chromosome structure for which a bit-flip crossover operation is used. All other parameters like well-skin factors, relative permeability end points were encoded in 1-dimensional chromosome for which k-point crossover operator is used. The authors claimed that they achieved better results with GA optimizer than SA and manual history matching [115].

A novel concept, top down reservoir modelling (TDRM), was proposed by Williams et al. (2004) for history matching of production data and quantifying uncertainties. The TDRM is currently trademarked technology of British Petroleum. This approach utilizes GA optimizer in combination with reservoir simulation model to determine sensible multiple history-matched models. The tool has been successfully applied to 18 oil and gas reservoirs. They have reported that a 20% increase in the predicted net present value (NPV) of projects is resulted through TDRM approach [116]. The TDRM workflow was successfully applied in British Petroleum Trinidad and Tobago assets to determine ideal well locations in an oil field with production history available for 30 years from 13 wells [117]. Apart from TDRM, GA is also used in MEPO® and ENABLE®, commercial softwares that are helpful in improving quality of history matched models. Choudhary et al. (2007) attempted for quantifying subsurface uncertainty, automatic history matching and infill well optimization, using MEPO® for two West African mature fields [118].

The modelling of a fractured reservoir using available field data is often difficult and levies large computational cost. Lange (2009) used discrete fracture network flow simulator (DFN) coupled with GA based inversion methodology for characterizing such reservoir models [119]. Han et al. (2011) proposed multi-objective optimization (MOO) utilizing an altered GA optimizer for production history matching of water-flooding projects. The methodology was tested on a 2-dimensional heterogeneous reservoir with 1 injection well and 3 production wells, divided into 400 grid blocks. The authors reported better prediction with small performance error and a better estimate of reservoir parameters with their method [120].

Monfared et al. (2012) combined subsurface response modelling with GA for inverse history matching. The authors constructed proxy reservoir models which constitute as simulator response, with the help of available measurements. They then built a reservoir model which is based on minimized proxy model generated by GA, which took fewer runs and less time at lesser cost in comparison with other techniques. The same has been tested on a field whose production history is known for 41 years and history-matched models were achieved which were fairly consistent with water cut, shut-in pressure, observed oil rate and repeated formation test pressure [121]. Murgante et al. (2012) tested GA and differential evolution (DE) on four case studies each with varying number of parameters, for history matching [122]. Ali Ahmadi et al. (2012) designed a soft sensor to predict permeabilities of a real reservoir, based on a feed-forward neural network. The authors used PSO and a hybrid GA for optimizing the soft sensor. The optimal values of weights of the reservoir parameters were obtained using GA. They reported and compared the results obtained from conventional neural network and the developed soft sensor to illustrate the effectiveness of the proposed methodology [77].

The application of Adaptive Genetic Algorithm for reservoir history matching coupled with higher order neural networks for oil production forecasting was explored by Chakra [123]. However, the author reported that the grid block size used in her studies must have introduced some error as coarse grid block size was chosen.

Baehyun et al. (2014) proposed a vigorous pareto-based history matching model that accounts for complex relationships among well performances.

The methodology, integrated with Successive Linear Objective Reduction (SLOR) and Dynamic Goal Programming (DGP) for dimension-reduction and preference-ordering respectively, named as DS-MOGA (DGP and SLOR with Multi-objective Genetic Algorithm), was applied to a heavy oil reservoir for history matching and production forecasting. The authors have reported that multiple qualified trade-off solutions can be obtained using this methodology when compared to traditional MOO techniques [124].

While solving history matching and optimization problems, there is a possibility to come across several potentially conflicting objectives. The objective functions involving multiphase production history, differences in reservoir pressure and 4-dimensional time-lapse seismic data are few examples that are potentially conflicting. Park et al. (2015) proposed a pareto-based multi-objective evolutionary algorithm (MOEA) that directly uses the dominance relation for fitness function. The authors have applied the proposed pareto-based MOEA to 2-dimensional synthetic and 3-dimensional real reservoirs and reported that their methodology outperforms conventional GA that is used for history matching [125].

Dongjae et al. (2017) have demonstrated the utility of a multiscale approach by combining MOGA for global history-matching with a streamline-based joint inversion for local calibration. The authors history-matched three-phase production data and bottomhole pressure. The method was tested on Norne field in the North Sea [126]. A geostatistical multi-objective history matching method was successfully evaluated to the benchmark PUNQ-S3 reservoir problem where 12 objectives were targeted by Joao et al. [127]. The authors claimed that purpose of history matching was achieved, without suffering significant computational costs, the credit of which is due to the selection criteria used in the cascading selection step.

III. CONCLUSION

The importance of history matching, production forecasting and the need of optimization enabled many researchers to develop and apply various optimization techniques to the reservoir, that included gradient-based and non-gradient-based methods. In this paper, the application of these optimization techniques and their variants to oil fields is presented. Though the application of these techniques could solve the purpose of history matching which helps in characterizing the reservoir and evaluating uncertainties, each of them have their own limitations and are specific to certain case studies. Hence the research on developing of or the evolution of newer techniques is still in progress that is not case-specific and also achieves better convergence with minimum computational time.

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