Well Placement Optimization: A Survey with Special Focus on Application for Gas/Gas-Condensate Reservoirs

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Abstract

Well placement within a reservoir is a challenging step in the reservoir development process. Determining the optimal well location is a complex problem involving many factors including geological uncertainty, reservoir and fluid properties, economic costs, and technical ability. Often, broad possibilities and constraints on computational resources limit the scenarios that can be considered. The use of engineering judgment to solve this complex and nonlinear problem may not be sufficient. The use of automatic well placement optimization as an aiding tool has recently gained interest in the petroleum industry and in academia. This paper surveys the literature dealing with well placement optimization. The areas considered include: optimization algorithm, reservoir response model, approach to handle uncertainty, and a special section on well placement optimization in gas/gas-condensate fields. Major drawbacks of current methods and areas of possible future work are identified.
1. Introduction

Optimum well placement (determining optimum number, type and location of wells) is a crucial step in field development. This problem has recently gained more attention due to the increase in the world’s energy demand and increasing pressure to obtain maximum recovery with minimum investments in gas and oil fields. With easy onshore fields becoming rare and many of the world’s major producing regions reaching maturity, new costly offshore developments are becoming more attractive. This makes the need for optimized reservoir performance more important every day.

The well placement problem is a highly nonlinear problem that depends on many continuous or discrete decision variables. Additional constraints such as subsurface geomechanics, well drilling and construction, and surface facilities as well as geological and economic uncertainty can add to the complexity of the problem. This problem gets even more complicated where non-conventional (horizontal, deviated or multilateral) wells are considered.

The number of possible solution combinations to the well placement variables raises exponentially with the increase of decision variables. Finding the optimum solution for this problem by running a few case studies is not possible. Using intuitive engineering judgment alone also may not be sufficient. For almost three decades, many researchers have attempted to solve this problem through automatic optimization procedures. Automatic well placement optimization is the main subject of this review paper. Automatic well-placement optimization is an iterative procedure that can be divided into two main parts: (a) an optimization engine based on user-defined decision variables suggests possible optimum well locations and (b) a reservoir response model that reports to the optimization engine the performance of the proposed well locations. The iteration between these two parts continues until stopping criteria (set by user) are met. To solve this complex problem, a variety of approaches have been investigated in the past. These approaches differ mainly in the optimization algorithm, reservoir response modeling technique, and available decision variables and constraints. Some investigators have included the effect of uncertainty in their well placement method using a variety of techniques.

In this paper, we will present a survey of well placement optimization methods available in the literature with a special focus on well placement techniques for natural gas reservoirs. We have divided the survey into the following sections: first, we present various optimization methods used to solve the optimum well placement problem; next, a survey of reservoir response models (used in the context of well placement optimization) is presented; then, a review of methods to handle uncertainty in well placement optimization follows and finally, we present a survey on well placement optimization in gas/gas-condensate fields. The citations made here do not reflect any judgment on the scientific importance of a paper. Instead, they were chosen as representative of the work in the subject area, particularly emphasizing the most recent work.

2. Optimization methods

Various optimization methods have been used in well placement optimization. In all these methods, the well placement problem is translated into optimization of an objective function (NPV or cumulative hydrocarbon production). In the following section, we will provide a brief review of the optimization methods used to find the optimum of the objective function:

2.1 Mixed integer programming

This approach was the first method used in well placement optimization. Mixed integer programming is a special form of linear programming. Linear programming is an optimization method to maximize (or minimize) an objective function in a given mathematical model with a set of requirements represented as linear relationships. Linear programs are problems that can be expressed as:
maximize \( f(\mathbf{x}) = \mathbf{c}^T \mathbf{x} \)  
subject to \( A\mathbf{x} \leq \mathbf{b} \)  

where \( \mathbf{x} = (x_1, x_2, \cdots, x_n) \) is the solution vector (initially unknown), \( \mathbf{c} \) and \( \mathbf{b} \) are known coefficient vectors and \( A \) is a known matrix of coefficients. If only some of the \( x_i \)s are required to be integers, the problem is called a mixed integer programming. Nemhauser and Wolsey (1988) provide a good introduction on this method.

Mixed integer programming was applied by Rosenwald and Green (1974) to the well placement optimization problem. They used a branch-and-bound mixed integer program as the optimization engine in combination with a mathematical reservoir model to select optimum well locations with specified production schedules from designated possible locations. Their work was limited to oil reservoirs.

The mixed integer programming method has not been popular for well placement optimization. This may be due to some limitations in handling nonlinear reservoir response, uncertainty, and economic evaluations (Cullick et al. 2003).

However, several researchers used this method in order to optimize development of offshore oil and gas fields. This includes finding the optimum platform locations, the number of wells drilled from each platform, the pipeline-network design, and production constraints (Devine and Lesso 1972; Sullivan 1982; Dogru 1987; Watson Jr. et al. 1989; Hansen et al. 1992; Garcia-Diaz et al. 1996; Eeg and Herring 1997; Iyer et al. 1998; van den Heever and Grossmann 2000).

2.2 Gradient-based optimization

Gradient-based optimization methods look for a maximum (or minimum) of \( f(\mathbf{x}) \) (an n-dimensional objective function of \( \mathbf{x} = (x_1, x_2, \cdots, x_n) \)) through its approximation by a Taylor series expansion:

\[
f(\mathbf{x} + \Delta \mathbf{x}) \approx f(\mathbf{x}) + (\nabla f(\mathbf{x}))^T \Delta \mathbf{x} + \frac{1}{2} \mathbf{x}^T \nabla^2 f(\mathbf{x}) \Delta \mathbf{x}
\]

After an initial value of \( \mathbf{x}_{i=0} \) is selected, the optimization is performed iteratively in the following steps:

1. Determine a direction \( \mathbf{d}_i \) and a step size \( \alpha_i \).
2. Evaluate \( f(\mathbf{x}_{i+1}) \) where \( \mathbf{x}_{i+1} = \mathbf{x}_i + \alpha_i \mathbf{d}_i \).
3. Check the convergence criterion for \( f(\mathbf{x}_{i+1}) \); if the stopping criterion is met, terminate the optimization; otherwise, go to step 1.

There are various techniques to calculate the parameters \( \mathbf{d}_i \) and \( \alpha_i \). The Newton method is a classical example of a gradient-based optimization method where \( \mathbf{d}_i = -[\nabla^2 f(\mathbf{x}_i)]^{-1} \nabla f(\mathbf{x}_i) \) and \( \alpha_i = 1 \).

One challenge in well-placement optimization using gradient-based methods is the calculation of the gradients of the objective function. Bangerth et al. (2006) used the finite difference method to calculate the gradients. Handels et al. (2007) and Zandvliet et al. (2008) addressed this problem using an adjoint-based technique. They applied their technique to the problem of placing one vertical well in a two-dimensional reservoir model with a number of grid blocks in \( x \) and \( y \) coordinates. The basic idea of their work is to place eight ‘pseudo-wells’ in the neighboring wells around each actual well. A pseudo-well is a well with a very low rate with negligible effect on the reservoir’s overall performance. They used an adjoint model to calculate the gradient of the objective function (NPV) using the rates at each pseudo-well.
Wang et al. (2007) presented an alternate adjoint-based approach. At the initial step, they suggested to place an injection well at each grid block that does not contain a producer. All the injectors will inject at the same rate (equal to total injection rate divided by number of injectors). The optimization objective is to maximize NPV which takes into account the drilling cost for each well and revenue through hydrocarbon production. A steepest ascent algorithm is then used to adjust injection rates towards maximizing NPV over a specified reservoir lifetime. In the following optimization steps, some injector rates may reduce to zero. In this case that injector will be removed from the model.

Another example of adjoint-based methods is presented by Sarma and Chen (2008). They proposed a continuous approximation to the well placement problem in order to ease the application of the gradient-based optimization technique. This approximation is implemented by using spatial integrals of a Gaussian function to introduce pseudo-wells around the original wells.

Castineira and Alpak (2009) used an adjoint-based well placement optimization (similar to Handels et al.) with the addition of a sequential optimization step to provide an initial guess. Vlemmix et al. (2009) applied the adjoint-based optimization to finding optimum well trajectory for a single horizontal/deviated well. Their method includes creating ‘pseudo side tracks’ from each trajectory point. These ‘pseudo side tracks’ are assigned a very small perforation length that makes their effect on overall reservoir performance negligible. These side tracks are then used to find the gradient direction and then optimize the well path.

In a recent study, Forouzanfar et al. (2010) applied an adjoint-based technique to optimize the well locations and rates in a waterflooding project. They solved the problem in two stages: (1) calculation of the optimum total injection rate and/or production rate for the specified life of the project, and (2) estimation of optimum number of injectors and producers, their optimum locations, and their optimum rates.

The performance of gradient-based methods is highly dependent on the initial guess and can sometimes lead to a local optimum, and not the global one. However, in the well placement optimization application, these methods could be easily used to improve an initial well placement plan based on reservoir engineering judgment. This method will provide an improved objective function with each iteration, resulting in a better well placement scenario, close to the original selection, within a few iterations.

2.3 Genetic algorithms

This method is one of the most popular methods in the well placement optimization. The idea of a genetic algorithm is first introduced by Holland (1975). Genetic algorithms can be thought of as self-adapting systems. Self-adaptation is present in everyday life, from simple insects adapting to an ever increasing human environment by changing their diet and behavioral patterns, to the flu virus adapting and mutating every year, creating different strains. The cultivation of certain vegetables that leads to selective breeding, is a prime example of Genetic Algorithms in play.

A Genetic Algorithm (GA), in its purest form, will try to replicate the concepts of natural evolution, in a controlled and mathematical environment. In a well placement optimization problem, the different individuals in a generation are replaced with well location data, and their cumulative production or NPV is a measure of their fitness that will affect their chance of survival. Once the limits of the reservoir are established, the domain can be represented by a binary code. This binary code will contain data pertaining to well location in a 3-D environment. The first step is to generate an initial population (randomly selected well locations). The next step will be to evaluate each well and rate their individual performance by calling a reservoir simulator and evaluating the objective function (cumulative production or NPV). Then, the individuals can be compared and rated for the reproduction step. During reproduction, for each
new solution, two individuals will be selected as ‘parents’ with the probability of selection being proportional to their fitness compared to the overall fitness of the group.

The mutation step ensues after the reproduction. Akin to nature, there are two types of mutation. The first type, *creep mutation*, will change a whole section of the binary code at once. The creep mutation will produce smaller variations, usually causing the well to move one grid at a time. This is the equivalent of the small gradual changes species undergo to adapt to the environment. The second type, *jump mutation*, changes a single binary digit from 0 to 1 or vice versa and will cause a radical change, comparable to the genetic jumps observed occasionally in certain species to significantly improve their chance of survival.

Once the mutation is completed, the new generation of wells is subjected to the same procedure described above resulting in agglomeration around some local maximums. With sufficient time and generations, most of the wells should converge on the global maximum, with only the occasional jump mutation sending a well out of the global maximum region. **Fig. 1** presents how a well optimization problem can be approached using a Genetic Algorithm. The red dots represent well locations in a square homogenous reservoir. It is shown that by the second generation, the well locations begin to converge towards the center of the reservoir (the optimum location).

For the first time, Bittencourt and Horne (1997) applied genetic algorithms for well placement optimization. They used a hybrid optimization method based on genetic algorithm, the polytope method.
and tabu search for placement of a fixed number of wells. Guyaguler and Horne (2000) used the polytope search and ordinary kriging to aid the GA in well placement optimization and reduce the number of necessary simulations.

Montes et al. (2001) studied the effect of several GA parameters such as initial population, population size, and mutation rate. Their results show that the initial population distribution does not have a significant effect on the results. They also conclude that the general rule in GA literature for the optimum population size (twice the number of bits used in a chromosome) applies here also. Their results are not conclusive about the mutation rate, but they recommend the general rule of the GA literature; using a variable mutation rate that increases with the number of generations.

GA application was extended to placement optimization of nonconventional (horizontal/deviated or multilateral) wells by Yeten et al. (2003). They introduced an optimization technique based on GA in combination with artificial neural networks, a hill climber and near-well upscaling as acceleration techniques. They applied their method to optimize the number, type, trajectory, and location of wells.

A hybrid GA (GA with polytope and kriging) was used by Ozdogan et al. (2005) in a new Fixed Pattern Approach (FPA) for well placement optimization in waterflooding projects. In this method the waterflooding pattern is fixed by the user. Using FPA, they reduced the parameters in the search space to two: 1) distance from the reservoir boundary and 2) well spacing that resulted in faster convergence to optimum solution. They compared the performance of the optimization algorithm applied to a deepwater oil field with and without FPA. In this application, FPA reduced the number of necessary simulations by 50%.

Larionov et al. (2006) used a combination of GA, Gold section method and ant colony method for well placement optimization. Zarei et al. (2008) combined GA with a neuro-fuzzy proxy model to reduce the number of necessary flow simulations.

Emerick et al. (2009) improved the previous GA implementations by introducing a new technique to handle linear and nonlinear constraints. These constraints include maximum well length, minimum distance between wells, inactive grid cells, and user-defined undesirable regions for well placement. They used the Genocop III technique (introduced by Michalewicz and Nazhiyath (1995)) to handle these constraints.

Nogueira and Schiozer (2009) applied GA for placement optimization of multiple (vertical or horizontal) injection or production wells where the number and type of wells are not fixed. To reduce the number of necessary flow simulations, they suggested a two-stage procedure: 1) optimal quantity and 2) optimal location of the wells and iteration through this procedure until no further improvement could be achieved. Lee et al. (2009) used GA to optimize the number, location and trajectory of horizontal wells using a 2D node-based configuration. In their method, they allow for multiple kick-off points.

In a recent study, Bukhamsin et al. (2010) applied a continuous GA algorithm for optimization and concluded that it is more robust than binary GA for the problem they studied.

The overall experience with well placement optimization using GA identifies it as a reliable method to find the global optimum. A major drawback of this method especially for field application is the excessive number of reservoir simulations needed. This is mainly due to the requirement of a minimum population size (twice as the number of bits in the binary code) to ensure convergence. The population size rapidly increases with number of grids and complexity of the optimization (e.g. multi-well and non-conventional well optimization). Due to this limitation, in field application, the use of some acceleration methods to reduce the number of simulations (as in hybrid GA introduced by Yeten et al. (2003) and
Ozdogan et al. (2005)) becomes a necessity. However, this may come with the possible cost of some reduction in the method’s reliability.

2.4 Other methods

Besides linear programming, gradient-based optimization and genetic algorithms, other optimization methods have been investigated for well placement optimization. In the following paragraphs, we present an overview of these methods:

Beckner and Song (1995) and Norrena and Deutsch (2002) used simulated annealing as the well placement optimization method. Simulated annealing (introduced by Kirkpatrick et al. (1983)) is a probabilistic method for finding global optimum of a function with several local optima. This method mimics the thermodynamic process of annealing in which a solid is slowly cooled from its recrystallization temperature to a ‘frozen’ structure that corresponds to minimum energy configuration. A good introduction to this optimization method is provided by Aarts and Korst (1989).

Santellani et al. (1998) suggested a ‘survival of the fittest’ method to optimize the location of a pre-defined number of vertical wells. In their method, they first consider vertical wells in all the possible locations and use a reservoir simulator to calculate the fitness function for each well. The fitness function is defined as the well’s cumulative hydrocarbon production. They rank the wells based on their fitness function and in each iteration remove a pre-defined number of wells with the lowest fitness value. The procedure stops when a given number of wells remain. They reported satisfactory results from application of their method to Ekofisk and Smarbukk oil fields in the North Sea.

A back propagation neural network was used by Centilmen et al. (1999) to reduce the number of simulations necessary for well placement optimization. In their method, they first applied the reservoir simulator to train the neural network and after a certain number of trainings, the neural network is used to predict the remaining simulations and predict the best well location.

Bangerth et al. (2006) applied two new methods: simultaneous perturbation stochastic approximation (SPSA) and very fast simulated annealing (VFSA) to the well placement optimization problem. They compared the performance of these methods with the finite difference gradient (FDG) method, GA and Nelder-Mead simplex method. They compared the performance of SPSA, VFSA, GA and Nelder-Mead simplex methods for placement optimization of one vertical well in a 2D reservoir model. Their results showed that both SPSA and VFSA performed better than other methods. However, they report a faster convergence (with less function evaluations) for SPSA while VFSA obtained better solutions with more function evaluations. They also compared the performance of SPSA, VFSA, and FDG in placement optimization of seven wells in a 2D reservoir model. In this more complicated example, they observed similar characteristics of performance by the SPSA and VFSA methods, as in their one-well example. FDG performed worse than the SPSA and VFSA methods due to high dimensionality of the problem and the need for an excessive number of function evaluations.

Ding (2008) applied a new evolutionary method for placement of non-conventional wells. This method is called Covariance Matrix Adaptation Evolution Strategy (CMAES) that was introduced by Hansen and Ostermeier (2001). The CMA-ES method is a stochastic optimization method that uses a covariance matrix of the design space over previous generations to create a new generation of design parameters. In this approach, the new generation is taken from a multivariate normal distribution with a covariance equal to the approximated covariance matrix.

Particle swarm optimization was applied to well placement optimization in pattern waterflooding by Onwunalu and Durlofsky (2009). The particle swarm optimization was first introduced by Kennedy and
Eberhart (1995). This method is a population-based method (similar to GA) that mimics the cooperative search behavior observed in animal groups such as a group of fish and birds. In this method, the individual solutions or ‘particles’ form a ‘swarm’ that move in the search space towards the optimum. The particles interact with each other and the movement direction of the particles is affected by the collective experience of the swarm. Engelbrecht (2005) provides more details on this method. Onwunalu and Durlofsky (2009) reduced the decision variables in their well placement optimization to pattern type (e.g. five-spot, seven-spot), and pattern operators (e.g. rotating, stretching). This reduction in search space in combination with the particle swarm optimization resulted in an efficient technique for well placement optimization in pattern waterfloods.

3. Reservoir response models

To evaluate the objective function in the well placement optimization, a reservoir response model is needed. The majority of the studies presented in this field use conventional finite difference simulation to evaluate the reservoir response. Although this is a reliable technique, an excessive number of simulations needed in some of the optimization techniques (e.g. genetic algorithm) can make them too computationally expensive for application in large-scale fields. Some researchers suggested the use of parallel computing to distribute the simulations on a network of computers (e.g. Cullick et al. (2005), Bangerth et al. (2005), Parashar et al. (2005)). Many researchers have focused on addressing this problem by studying alternative methods to evaluate the reservoir response. A brief review of these studies is presented in the following:

Rian and Hage (1994) suggested a front tracking method to speed up the reservoir response modeling and, therefore, well placement optimization. In their method, user-specified saturation fronts are tracked as discrete lines of constant saturation in a 2D reservoir model. Pan and Horne (1998) investigated using the least squares and kriging methods to approximate function evaluations using fewer simulations. They pointed out that both methods need adequate sample data and require validation by simulations after optimum solutions are obtained.

The use of an analytical reservoir simulator was first suggested by Beecroft and Shtern (1999) which resulted in very efficient well placement optimization. Their method is based on geometrical and fluid mechanics approximation steps. Pallister and Ponting (2000) investigated the use of streamline vs. finite difference simulation for performing the simulations in well placement optimization. At the conclusion of their study, streamline simulation did not perform as well as the finite difference method in well placement optimization of a large number of wells.

Cruz et al. (1999; 2004) introduced the concept of ‘quality map’ to approximate the reservoir response in well placement optimization and to speed up the process. The quality map is defined as a two-dimensional representation of the the reservoir responses. To obtain the quality map, they used a flow simulator to model the reservoir with a single well. Then, they varied the location of the well to other possible well locations. The quality of each location was defined as cumulative oil production after a long period of production.

Nakajima and Schiozer (2003) used the quality map concept in horizontal well placement optimization. The quality map in their work represents the regions with best production potential in a reservoir. They applied their method to a reservoir model based on Campos Basin in Brazil. They used numerical simulation, fuzzy logic and analytical solutions to build the quality map. Their results showed a similar performance obtained by numerical and fuzzy maps while the analytical approach did not provide reliable information.
A production proxy model was used by Kharghoria et al. (2003) to speed up the optimization of a horizontal well path. In their model the production potential of each grid block is equal to \( \phi (S_o)^n k \) where \( \phi, S_o, \) and \( k \) represent the grid block’s porosity, oil saturation, and permeability, respectively. \( n \) is a correlation parameter. The production potential of a horizontal well was defined as a weighted-average of the production potentials of the grid blocks surrounding the horizontal well based on their distance to the path of the horizontal well.

Hazlett and Babu (2005) presented a well placement method where they used a semi analytical reservoir simulation model to calculate the reservoir feedback. Their simulator was based on the boundary element method (BEM). Using the BEM method, they calculated flow potential in 2D and 3D closed-box domains for single-phase, pseudo-steady state fluid flow. They allowed inclusion of different heterogeneities in the domain: permeability, porosity, permeability anisotropy and unstructured grids. They applied their method for multi-well and horizontal well optimization. Maschio et al. (2008) used the quality map concept in combination with GA to speed up the well placement optimization. Their quality map is based on static reservoir properties (permeability, thickness, porosity and initial oil saturation). They proposed using this quality map to reduce the number of initial well locations (initial population) included in the GA optimization process to decrease the computational effort.

Onwunalu et al. (2008) used statistical proxy (in combination with GA as optimization engine) to approximate the reservoir response. Using semi-analytical reservoir simulation in combination with a gradient-based optimization technique, Tilke et al. (2010) could reduce the computational time necessary for the well placement optimization to ‘minutes’ using desktop software and hardware. They considered possibility of having multiple wells (vertical, horizontal or deviated) in a reservoir with rectangular geometry.

4. Effect of uncertainty

There is a significant amount of uncertainty in field development planning. This is mainly due to the uncertainty of the geological model used for the estimation of the reservoir response. This uncertainty can affect the economics of a field development plan and, therefore, cannot be ignored in the optimization process. Many researchers have developed well placement optimization techniques that included the effect of uncertainty. A survey of their work is presented in the following:

The first study in well placement optimization that included the uncertainty effects was published by Aanonsen et al. (1995). They included the effect of uncertainty in reservoir description using response surface methodology. For each geological realization, they performed reservoir simulations for various well locations to build a response surface. These response surfaces were then used to guide well placement. They did not combine this technique with any optimization algorithm. They applied their method to two field examples from the North Sea.

Vincent et al. (1998) addressed the problem of finding the best well location in a reservoir with structural uncertainty. They used the D-optimality experimental design technique (Fedorov 1972) to determine the best location with a minimum number of simulations. Guyaguler and Horne (2004) presented a utility framework to address the well placement problem under uncertainty. They used the utility framework to quantify the risk attitudes of the decision makers using utility functions. These functions transform the uncertain well placement problem into a deterministic one suitable for application of optimization techniques. They applied their method to the PUNQ-S3 problem (Barker et al. 2000). They also presented an alternative approach using a random function formulation. They reported satisfactory results using the random function formulation with less computation effort than the utility formulation method, although the results are less accurate.
Cullick *et al.* (2003; 2005) proposed the use of Monte Carlo or quasi-Monte Carlo algorithms combined with an optimization method based on artificial intelligence and tabu search to well placement optimization under uncertainty.

The quality map method was applied by Loureiro and Fresky (2005) to well placement optimization in a reservoir under uncertainty using the multiple realizations approach. They applied their method to the Maureen Field, UK. Only vertical producers are included in this study. They used the quality map as a guiding tool to reduce the number of trial and errors using reservoir simulation.

Artus *et al.* (2006) addressed the problem of optimized placement of nonconventional (horizontal, deviated and multilateral) wells under geological uncertainty. They proposed using a statistical proxy method to reduce the number of necessary reservoir simulations. This proxy method is based on the cluster analysis approach and approximates the Cumulative Distribution Function (CDF) of the objective function. They combined this proxy method with GA for optimization. They demonstrated an effective performance of this method, especially for monobore and dual-lateral wells, with a 90% reduction in the number of reservoir simulations.

Time-dependent uncertainty in well placement optimization was addressed by Ozdogan and Horne (2006). The previous studies, including the effect of uncertainty, assumed a static uncertainty while in reality, if the wells are not drilled all at the same time, the amount of geological uncertainty should decrease with time as more production data becomes available. Ozdogan and Horne addressed this problem in their work by introducing the concept of ‘pseudohistory’ that is the P50 (median) of probable production of a future well based on possible geological realizations. They included the effect of time on uncertainty by performing a history match on the ‘pseudohistroy’ of a future well.

In a recent study, ensemble optimization was applied by Leeuwenburgh *et al.* (2010) to well placement under uncertainty to a synthetic example under fixed production constraints.

### 5. Gas/gas-condensate applications

There have been several studies on the application of various well placement optimization techniques in several oil fields (e.g. a UKCS field by Gutteridge and Gawith (1996) including, the Pompano field in the Gulf of Mexico by Guyaguler *et al.* (2002), a giant oil field in Azerbaijan and a mature oil field in the North Sea by Litvak *et al.*(2007a; 2007b), and a giant Siberian fluivial sandston oil reservoir by Litvak and Angert (2009)). Well placement optimization in gas fields has received less attention. In this section, we present a survey of application of various well placement optimization techniques in gas or gas-condensate fields:

Seifert *et al.* (1996) presented the first well placement application in a gas field (the Frobisher complex in UKCS blocks in the North Sea). In this study, they determined optimum horizontal well trajectories in terms of azimuth, location, inclination and well length. Their optimization were based on a ‘quantitative but partially subjective ranking’ of 956 numerically ‘drilled’ wells. Their optimization technique was not fully automatic and some manual analysis was involved.

Levey and Sippel (1997) studied the problem of finding optimum well spacing in a giant compartmentalized gas field in Texas. They considered the effect of geological uncertainty in the problem. They found the optimum well spacing (required to meet the target recovery factor of 80%) through an exhaustive search for different realizations of the field (especially based on compartment size).
Gas-condensate fields have been studied for well placement optimization. Optimum placement of horizontal wells in these reservoirs has gained more attention in these studies. This is due to the vulnerability of vertical wells to condensate blockage. In a gas-condensate reservoir, as pressure decreases condensate accumulates around the wellbore, leading to significant reduction in gas production in vertical wells. Horizontal wells can effectively reduce the condensate blockage problem (Miller et al. 2010).

Schulze-Riegert et al. (2010) studied the problem of horizontal well placement under static geological uncertainty in a real North Sea gas condensate field. They parameterized the search space using angular coordinates. The only design parameters in this work were the start and end point of the well trajectory. In this work, they use a Monte Carlo based sampling algorithm for screening purposes and a genetic algorithm for the optimization. Schulze-Riegert et al. (2011) extended their previous study to the optimization of two horizontal well paths using a different optimization method (CMA-ES). In this work, they assumed three possible geological realizations with different weights.

Morales et al. (2010a) studied the well placement optimization problem in a synthetic gas reservoir and in a gas-condensate reservoir model based on published data from Qatar’s North Field. This study focused on optimization of a single horizontal well with user-defined length. The GA was used as the optimization method in this study. The objective of this study was to maximize cumulative gas production.

The authors first presented the application of their method for a synthetic field example with heterogeneous permeability distribution (Fig. 2a). The optimum well locations using the GA is then compared with the results of an exhaustive search. As expected, GA successfully finds the optimum well location. Using the exhaustive search results, variation of Cumulative Gas Production (CGP) with horizontal well location is demonstrated in Fig. 2b.

![Fig. 2.](image-url) (a) permeability (in md) distribution of a synthetic gas reservoir model and (b) cumulative gas production vs. heel coordinates of a single horizontal well (adapted from Morales et al. (2010a)). The length of the horizontal well is fixed at 800 ft. Dimensions in figure (a) are in ft.
The results show that:

(a) The sensitivity of cumulative gas production to well location is not significant (4.8%) compared to oil reservoirs. However, even this relatively small improvement can lead to a significant increase in NPV, especially for giant gas fields such as Qatar’s North Field.
(b) The well location with global maximum is surrounded by multiple local maximums (Fig. 2b). This feature that can be common in heterogeneous gas fields, can make achieving convergence to global maximum difficult for gradient-based optimization methods.

The application of the GA optimization technique is then presented for a reservoir model based on Qatar’s North Field. The North Field is the largest non-associated gas field in the world that holds more than 900 Tcf of proven natural gas reserves. Fig. 3 shows a map of the North Field. The North Field covers over 6,000 square kilometers.

![Fig. 3. Map of North Field, Qatar](image)

Published data for the Qatar’s North Field is limited. Whitson and Kuntadi (2005) published some data about this gigantic natural gas reservoir. The reservoir is an extension of the Khuff formation, and it is widely accepted that the reservoir is composed of four main layers called K1, K2, K3 and K4. Whitson and Kuntadi (2005) reported that each of these layers contains a highly permeable layer sandwiched between two low permeability sections (Fig. 4). In this figure, the thick black lines represent the high permeability area in each zone.
Morales et al. (2010a) applied the genetic algorithm to find the optimum horizontal well location in a reservoir model based on K1 layer. The effect of condensate formation was included through compositional simulation using an equation of state. The genetic algorithm could provide a location with an increase of 3.4% in cumulative gas production after only ten simulation runs compared from the initial location based on engineering judgment. The optimum well location after 200 generations (4000 simulations) provided a 5% increase in cumulative gas production (Fig. 5).

Based on the observation that the variation in cumulative production in gas or gas condensate fields is not very sensitive to well location, Morales et al. (2010b) implemented a modification in the genetic algorithm that resulted in faster convergence to the optimum location compared to a conventional genetic algorithm.

This modification was implemented in the reproduction step of the genetic algorithm. The main objective in this modification is to magnify small variations in fitness values (NPV or cumulative gas production).
usually observed in gas fields. This modification (called ‘MiniVar’ by the authors) includes the following steps:

1. Obtain the fitness values for the entire generation.
2. Calculate the mean and variance of the fitness values
3. Map the original fitness distribution to a standard normal distribution:
   \[ y(i) = \frac{x(i) - \mu}{\sigma}, \quad i = 1, 2, \ldots, n, \]  
   where \( x(i), y(i), \mu, \) and \( \sigma \) represent original fitness value of the \( i \)th individual, fitness value of the \( i \)th individual in a normal distribution, mean of the original distribution, and standard deviation of the original distribution, respectively. \( n \) is the population size.
4. Apply a cumulative distribution function based on the new standard deviation population:
   \[ y'(i) = \frac{1}{2} \left[ 1 + erf \left( \frac{y(i) - \mu_0}{\sqrt{2}\sigma_0} \right) \right], \quad i = 1, 2, \ldots, n, \]  
   where \( \mu_0 \) is the mean and \( \sigma_0 \) is the standard deviation of the new standard deviation distribution.
5. Use \( y'(i) \) instead of \( x(i) \) as the fitness value for the \( i \)th individual in the reproduction step to generate the new generation. If the stopping criteria are not met, go to step 1.

This modification ensures that the small differences in fitness values are magnified. After this modification, the slightly better individuals have a much higher chance for mating and reproduction than they would have without the modification. **Fig. 6** demonstrates this modification through an example.

**Fig. 6.** Comparison of (a) conventional probability and (b) MiniVar method that are applied for a population with a small standard deviation in their fitness value. Fitness Values are 100 for Individual #1, 95 for Individual #2, 102 for Individual #3, 98 for Individual #4 and 99 for Individual #5, with a Mean of 98.8 and Standard Deviation of 2.59(adapted from Morales et al.(2010b)).

They applied their modification to the North Field example and could speed up the GA convergence by approximately twenty times. In their study, besides permeability heterogeneity, they also considered the
effect of initial compositional variation with a trend similar to the one observed in the North Field (Whitson and Kuntadi 2005).

6. Conclusions
A review of the literature on the subject of well placement optimization is presented. This review shows significant advances in the reliability, efficiency, and applicability of well placement optimization methods over three decades. Current technology in well placement optimization can handle the number, type (vertical, horizontal, deviated, multilateral), trajectory (for horizontal, deviated, multilateral wells), and location of wells in oil and gas fields. This includes both primary depletion and waterflooding stages of the field development. Although many optimization methods have been developed for well placement in oil fields, less attention has been given to well placement optimization in gas fields. This might be due to the recent increase in importance and demand for natural gas as a cleaner energy resource. It also can be based on a general assumption that oil field well placement optimization methods can be applied to gas fields. While this statement is generally true, some research studies show that well placement optimization in gas fields can have unique challenges and opportunities for future research. The problem of condensate blockage in gas-condensate fields (that form a significant portion of the world’s natural gas reserves) is one example of these challenges. Based on this review, a few shortcomings in current well placement optimization methods and possible future areas of research in this area include:

1. Optimization method: Current optimization methods do not have both reliability and efficiency features simultaneously. Gradient-based methods are very efficient but cannot guarantee finding a global optimum. More reliable methods, such as genetic algorithms, need an excessive number of reservoir simulations which makes their field application very expensive (in terms of required CPU time or computational hardware).
2. Reservoir response model: The main computational power in well placement optimization is spent on reservoir response modeling. The conventional finite-difference technique is not an efficient reservoir response modeling tool in well placement optimization. Fast and accurate reservoir response models can provide a major boost in the efficiency of well placement optimization.
3. Gas field application: There is a need for specialized optimization methods and reservoir response models that are tuned for application in gas/gas-condensate reservoirs.
4. Oil field application: Current well placement optimization methods are mainly concerned with two stages of oil field development: primary depletion and waterflooding. Specialized well placement optimization techniques are required to handle tertiary oil recovery methods (e.g. gas injection).

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