



Optimization of well locations in tight oil reservoir based on genetic algorithm

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Abstract

In recent years, energy demand has constantly grown worldwide, promoting the oil and gas sector to develop innovative solutions for improving productivity from unconventional reservoirs such as tight oil reservoirs. One of the significant issues in this area is determining the optimal well locations to maximize net present value (NPV). This procedure involves analysing several factors such as reservoir geometry, permeability, porosity distribution or fluids contact, and other factors that affect locations and number of infill wells. The difficulty of these considerations, combined with economic concerns and reservoir related risks, makes it even more challenging to identify the optimum development program for a given field. In this context, this study provides a useful optimization approach for identifying the optimal well location in the Halfaya oil field, a southern Iraqi tight oil field. This approach aims to overcome the issues related to optimizing reservoir development. This study employed the Genetic Algorithm as the main optimization engine due to its effectiveness in solving multidimensional and nonlinear problems. Multiple scenarios were developed with specified well configurations to identify the best scenario for maximizing NPV. This involves conducting multiple optimization runs using the Petrel/Eclipse software to develop a reliable field plan. Consequently, cumulative production for this oilfield has been comprehensively defined and reviewed. The results showed that the genetic algorithm gives acceptable values in optimization problems with relatively few decision variables. This led to an increase in NPV by 5.63%, 19.63 % and 29.30% for scenarios of one, three and five infill wells, respectively.

Keywords: Well placement optimization; Genetic algorithm; Reservoir simulation; Tight reservoirs; Infill oil wells.

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1- Introduction

As the global energy demand continues to increase, the energy sector has shifted its focus toward optimizing hydrocarbon recovery from unconventional resources [1, 2]. Among these, tight oil reservoirs have gained growing attention recently, particularly after the success of gas production from shale [3]. Tight oil, characterized by extremely low permeability (< 1 mD) and low porosity (< 10%), exhibits unique challenges for enhancing and development. Tight reservoirs reveal high laterally and vertically complexity, further complicating recovery efforts [4, 5].

Achieving economically viable production levels in tight reservoirs requires stimulation technologies such as hydraulic fracturing [6-8], horizontal drilling [9, 10], or water flooding [11, 12]. Recently, the well placement method, also known as infill drilling, has emerged as an efficient method for enhancing oil recovery and evaluating reservoirs [13-16]. This unique approach involves strategically drilling new wells or groups of wells within existing reservoirs, targeting previously untapped hydrocarbon zones [17, 18]. Consequently, increasing connectivity with the most productive layers and maximizing NPV or cumulative oil production [19].

On the other hand, determining the optimal placement of infill wells is a complex process that requires the evaluation of several scenarios during the optimization program [4]. The positions of injection and production wells within the reservoir are a major factor affecting hydrocarbon recovery and, consequently, the revenues generated. Thus, establishing the best-case scenario for well locations is vital. Reservoir heterogeneity and hydrocarbon connectivity, in-place, fluid, and petrophysical properties, operational and drilling costs, and time constraints can impact well placement and development processes. Therefore, reservoir simulators and computational algorithms have progressively emerged as innovative approaches to address the challenges related to well placement determination. Optimization algorithms, in particular, have been utilized to find optimal solutions for single-objective problems on specific reservoir models [18].

Additionally, they demonstrated a significant performance in solving petroleum engineering issues[19]. Optimization algorithms can automatically suggest the candidate's well-placement locations. Through the optimization process, professional petroleum engineers rely on their intuition to define different well locations



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and configurations. Then, they analysed the economic feasibility and simulated reservoir models to identify the most favourable options. Next, the field performance will be determined under the new well placement. In the end, optimized well placement locations and distribution can be obtained until the optimization process reaches its stop condition. However, due to the reservoir's intricate and nonlinear characteristics, the intuitive approach may not always yield the optimal solution. This uncertainty necessitates the use of the correct optimization technique.

The utilization of intelligence algorithms in automatic well-location optimization has been extensively explored in the literature [15]. These algorithms, such as generalized differential evolution (GDE), genetic algorithms (GA), cat swarm algorithm (CSA), simulated annealing algorithms (SAN), covariance matrix adaptation evolution strategy, particle swarm optimization algorithm, and others, have been employed to optimize well locations. Among these different optimization algorithms, the genetic algorithm has emerged as a promising tool due to its efficiency and high performance in this area [20].

Therefore, considering the success of GA in addressing problems characterized by high complexity, nonlinearity, and extensive dimensionality, it was employed as a main optimization engine for a tight oil field located in Southern Iraq to determine the optimum well locations that result in maximizing the NPV of this field.

2- Area of study

The Halfaya oil field, located in southern Iraq, serves as the case study of this research. The Halfaya oil field is one the most important oil fields in Iraq [21]. It was initially discovered in 1976, about approximately 35km south of Amarah city – the capital of the Missan governorate. Within the late Turonian-early Campanian Sequence, the Sadi formation arose as the most recent, thickest, and extensively distributed formation layer. In 1958, Owen and Nasr determined the formation's thickness and correlation to Kuwait's Almaque formation [22]. However, the description and age of this formation were reevaluated by Chatton and Hart, Ditmar, and others over more than two consecutive years [23-25]

The Halfaya oil field exhibits an anticline structure, stretching over 10 km in width and 30 km in length. This study mainly focuses on the Sadi oil reservoir, which serves as the primary tight oil-producing zone within the Halfaya oil field [21].

3- Methodology

3.1. Reservoir characteristics and optimization

The initial stage of optimizing well placement involves gaining a comprehensive understanding of the geological and reservoir properties. These properties include porosity, permeability, fluid characteristics, and reservoir boundaries. Acquiring this information is vital to construct precise reservoir models [26]. The next vital stage in this process is the construction of a dynamic model for the reservoir simulator that will include geological and reservoir data. This stage of the simulation has relevance in the reproduction of the reservoir and understanding the pressure and temperature evolution. In the study of Jassam and Al-Fatlawi, a 3D geological model was developed through the comprehensive computation of the well data logging and mapping to come up with the characteristics of the Sadi reservoir at the Halfaya oil field. This approach became the basis for computer simulations allowing us to show dynamical functions in the reservoir, reveal petrophysical parameters to research, and include the porosity, permeability, and water saturation in the research process. The model also considered the structural elements within the reservoir. consisting of four sublayers: Sadi A, Sadi B1, Sadi B2, and Sadi B3. However, sublayer Sadi A does not contain hydrocarbon and was therefore excluded from the geological model. Table 1 provides information on the thickness and number of layers within each zone [27].

Table 1.	Layers	of Sadi	reservoir	zones	[27]
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ZONE	Thickness (m)	No. of layers
SADI-B1	26.1	30
SADI-B2	31.8	35
SADI-B3	20	20

3.2. Optimization

The optimization process comprises of several sections, which begin with defining the decision variables, objective function, workflow, and constraints of the optimization problem.

3.2.1. Objective function

The target of the petroleum industry is to maximize the cumulative oil production which leads to an increase in net present value (NPV). In this study, NPV has been chosen as the objective function to determine the optimal well placement through an optimization method. The best performance is defined by identifying the best location and number of infill wells. The NPV provides economic effects caused by the location of the wells, which are presented based on the production data of the fluid that are obtained from the reservoir numerical simulators. The cumulative oil production (Np) from the reservoir should be maximized to achieve the highest value, as shown in Eq. 1. Furthermore, an increase in NP is accompanied by an increase in the rate of oil production (qt); thus, the highest Np value can be expressed using Eq. 2.

Maximum NPV = f(Np, capital costs, operating costs) (1)

Eq. 1 involves calculating investments and earnings in terms of their present value. NPV is influenced by various economic variables, including costs and income. The economic variables that are used to calculate NPV in this study are listed in Table 2.

(2)

Maximum Np = Maximum $\sum_{i=1}^{m} \int_{0}^{tp} q(t) dt$

Where q(t) is the total oil flow rate, *i* is the time steps, and *m* is the total number of time steps.

Table 2.	Costs	used	to	cal	cu	late	NP	V

Cost	Value \$
Oil price	75
Gas price	3
Discount rate	0.06

3.2.2. Decision variables

To improve reservoir performance through optimal well placement, this study has assigned well coordinates (X, Y) as the key decision variables in the optimization process. These coordinates are essential in determining the potential production from the reservoir.

3.2.3. Optimization process

The optimization process involves the generation of an initial value for the variable decision, which represents the coordinate of the infill well. Subsequently, the reservoir simulator model calculates the net present value and incorporates it into the reservoir simulator to obtain updated results. This iterative process continues until a satisfactory match is achieved as illustrated in Fig. 1. However, there are several challenges associated with integrating optimization methods and reservoir simulator. These challenges include the number of decision variables, the number of simulations runs, the required runtime, and the complexity of the problems. All these factors significantly influence the application approaches used to generate optimal solutions. To overcome these challenges, genetic algorithm optimization has been employed technique to streamline the process, reduce computational time and at the same time to manage the complexity of reservoir models achieving improved accuracy of production capacity predictions. The ultimate goal is to provide practical and reliable solutions for optimizing infill well location in Al Sadi formation, thereby maximizing its performance and profitability.

3.2.4. Genetic algorithm

The Genetic Algorithm is a robust optimization technique inspired by natural selection and genetics [28]. It combines the principle of survival of the fittest and random information exchange. In 1975, John Holand [29], presented the first GA application to solve complicated issues, demonstrating that bit chains can effectively represent these issues and be improved through simple transformations [30]. The GA modelling process involves encoding potential solutions of a problem into structures called chromosomes. These chromosomes (population) consist of variables called genes. Initialization of these chromosomes is an essential step in the GA process. A new group of chromosomes is then generated based on their fitness values, also known as the objective function [31]. This objective function should be first evaluated accurately to avoid local optimum solutions. Additionally, it is important to run GA applications for various radii of evaluation to ensure a proper radius of evaluation. Performing the GA application requires selecting a group of individuals, or a population, to undergo an evolutionary process. This process normally occurs in cycles called which represent the level generations of the optimization's iterations. Chromosomes with higher fitness values have a greater chance of being selected. Reproduction in the GA process occurs through crossover, mutation, and recombination procedures, continuously conducted by setting random values to genes [32] as shown in Fig. 2. This process is repeated until the best possible solution is reached [33, 34].



Fig. 1. Flow chart for optimization of the well placement using GA



Fig. 2. Mutation process

3.3. Base study case

The base study case used in this study serves as a baseline for evaluating the current field performance before the introduction of infill wells to determine the cumulative production and NPV. This allows for comparison before and after adding infill wells. The base case is illustrated in Fig. 3, showing the locations of wells produced from the Sadi formation within the Halfaya oil field. The development strategy was established for the period spanning from 30/9/2022 to 1/1/2035, achieving results listed in Table 3 along with Fig. 4. Three key conditions were considered in this case:

- Water cut must not exceed 50% in any well; if it does, the well will be shut down.
- Well pressure must remain above the bubble point pressure of 215 bar; if the pressure drops below this value, the well will be close.

The PETREL / ECLIPSE simulator software is recognized as the industry standard and widely used in the petroleum industry. In this study, the simulator was employed to calculate the original oil-in-place (OOIP) of 4277 MM STB based on the geological model [27]. Table 4 presents the data generated for each unit in the Sadi formation within the Halfaya oil field.



Fig. 3. Base reservoir case before added infill wells for unit B2, black dots represent the current well locations

Table 3. Cumulative production and NPV according to the base case



Fig. 4. Results of oil production rates and pressure for the base case

Table 4. OOIP for each unit in the Sadi formation-Halfava oil field

Layer	OOIP, MM STB	Percentage, %
Sadi-B1	1792	41.89
Sadi-B2	1950	45.5
Sadi-B3	535	12.5
Total	4277	100

To achieve the aims of this study, three scenarios were developed to explore the impact of different numbers of infill wells within the simulation model. These scenarios are listed in Table 5.

 Table 5. Optimization infill wells scenarios proposed in this study

Scenario	Number of infill wells	Decision variables
Scenario one	One infill well	2
Scenario two	Three infill well	6
Scenario three	Five infill well	10

4- Results and discussion

4.1. Scenario 1

In this scenario, one infill well has been added and initially placed in a random location. Table 6 lists the GA parameters used for this scenario. This well will serve as a representation of a machine learning algorithm, and it has been systematically moved and assessed its performance until it reaches the optimal location, as shown in Fig. 5 and Fig. 6. Determining the coordinates of the reservoir boundaries helps prevent the infill well from existing outside the reservoir boundaries. Therefore, a workflow has been developed to verify whether the well remains within the reservoir boundaries or not.

 Table 6. Optimization algorithm parameters for one infill well

Parameters	Value
Optimizer	Genetic algorithm
Max number of iterations	120
Population size	60
Max number of generations	8
Selection operator	Roulette Wheel
Mutation probability	0.5



Fig. 5. Reservoir after adding one infill well for unit B2, red dot is the infill well



Fig. 6. Distribution of one infill well according to reservoir permeability for unit B2

Fig. 7 illustrates the reservoir production rates over 13 years after applying one infill drilling scenario in comparison to the base reservoir case. The simulation results showed a slight increase in oil production and net

present value by 7.05% and 5.62% compared to the base case, as shown in Table 7.



Fig. 7. Predicated results of oil production rates and pressure for Scenario I

Table 7. O	ptimization	results for	or one i	nfill v	well Scenario
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Case	Well Coordinates (X,Y)	Cumulative Production sm ³	Different from basic case %	Net present value \$	Different from basic case %	Period Years
One infill well	727, 3510	11,147,401	7.7%	4,929,350,501	5.63%	13

4.2. Scenario 2

This scenario includes adding three infill wells for the development strategy of the selected oilfield The wells' coordinates were selected randomly at the first trial and GA application was used then to determine their optimal coordinates and location according to the statistical parameters listed in Table 8. The optimal locations of these wells are illustrated in Fig. 8 and Fig. 9. The three infill wells are labelled in the red colour.

Table 9 describes optimal well locations and optimization results within the reservoir resulting from GA optimization of three infill well scenarios. The history-matching results of this case compared to the base case in 13 years are illustrated in Fig. 10. An increase of 19.66 % and 19.65 % in field oil production and NPV respectively, have been achieved after applying three infill wells, as shown in Table 8.

 Table 8. Optimization algorithm parameters for three infill wells

Parameters	Value	
Optimizer	Genetic algorithm	
Max number of iterations	138	
Population size	60	
Max number of generations	8	
Selection operator	Roulette Wheel	
Mutation probability	0.500	



Fig. 8. Optimal locations of three infill wells for unit B2



Fig. 9. Distribution of the three infill wells according to reservoir permeability for unit B2

Table 9. Optimization Results for Three Infill Wells Scenario					
Optimal Well Locations (X,Y)	Cumulative Production sm ³	Different from basic case %	Net present value \$	Different from basic case %	Period Year
Infill well 1: (723, 3515) Infill well 2: (731, 3506) Infill well 3: (733, 3500)	12,488,318	20.65 %	5,582,831,515	19.63 %	13



Fig. 10. Predicted results of oil production rates after applying Scenario II

4.3. Scenario 3

The scenario case of adding five infill wells was applied using the GA optimization depending on the optimization parameters that are described in Table 10. The optimization results including the optimal locations of the five infill wells are listed in Table 11 and illustrated in Fig. 11 and Fig. 12.

 Table 10. Optimization parameters used for five infill wells cases

Parameters	Vales
Population size	50
Maximum number of generations	8
Selection method	Roulette wheel
Mutation probability	0.100
Maximum number of iterations	223

Table 11.Optimal well coordinates for five infill well results					
Optimal	Cumulative	Different from	Net present value \$	Different from basic case	Period
Well Locations (X,Y)	Production sm3	basic case %		%	Year
Infill well 1: 723, 3517					
Infill well 2: 728, 3511					
Infill well 3: 732, 3509	13,505,050	30.48%	6,034,090,100	29.30%	13
Infill well 4: 733, 3503					
Infill well 5: 738, 3504					

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Fig. 13 shows the history-matching results of the reservoir after adding five infill wells scenario compared to the base case over a 13-year production period. Maximum improving percentage of production (29.36%) and NPV (29.34%) have been achieved by this scenario as illustrated in Table 11.



Fig. 11. Optimal locations of five infill wells for unit B2



Fig. 12. Distribution of five infill wells according to reservoir permeability for unit B2

Based on the above simulation results (Fig. 7, Fig. 10, and Fig. 13), it can be concluded that infill drilling has the potential to enhance the reservoir oil production and thus the NPV. Among the three scenarios, the five infill well drilling cases showed the best oil production results.



Fig. 13. Predicted results of oil production rates after applying Scenario III

5- Conclusion

The results obtained from the optimization process, after applying artificial intelligence techniques (Genetic Algorithm) to calculate the optimal locations for infill wells showed the following outcomes:

- Because of heterogeneity, tight oil reservoirs suffer from a high decline in flow rates and instability of production rates.
- Optimization of well locations contributes to increasing production and reaching places that current wells cannot reach.

- Suitable levels of oil production rates above bubble point pressure were obtained from approximately the beginning of production until the end of 2034.
- After adding five wells, the increase was about 29.36% over the basic case, which indicates the extent of the impact of the number of wells, considering the economic aspect.
- Because the same number of reservoir simulation runs are necessary regardless of the number of choice factors, GA is unaffected by the number of decision variables.
- Optimal number of infill wells and their locations are not arbitrary because it depends on several factors such as recovery process, production and injection rates and the project lifestyle.
- The number of iterations various with the addition of new wells, as the number of runs in the genetic algorithm was set at about 300 runs, while it took a while (120, 138, and 223) to reach the optimal state for the first, second, and third scenarios, respectively.

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تحسين مواقع الآبار – بناءً على الخوارزمية الجينية في خزانات النفط قليلة النفاذية

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ا قسم هندسة النفط ، كلية الهندسة، جامعة بغداد، بغداد، العراق ۲ SLB ، مدير الذكاء الاصطناعي، جامعة نيويورك، الولايات المتحدة الأمريكية

الخلاصة

في السنوات الأخيرة، شهد الطلب على الطاقة نموًا مستمرًا في جميع أنحاء العالم، مما شجع قطاع النفط والغاز على تطوير حلول مبتكرة لتحسين الإنتاجية من الخزانات غير التقليدية مثل خزانات النفط قليلة النفاذية. تتمثل إحدى القضايا الرئيسية في هذا المجال في تحديد مواقع الآبار المثلى لتعظيم القيمة الحالية الصافية(NPV). يتضمن هذا الإجراء تحليل العديد من المتغيرات الجيولوجية والإنتاجية مثل جيولوجيا المكمن النفطي، والنفاذية، وتوزيع المسام، وملامسات السوائل وعوامل أخرى تؤثر على مواقع وعدد آبار التعبئة. إن تعقيد هذه الاعتبارات، جنبًا إلى جنب مع المخاوف الاقتصادية والمخاطر المرتبطة بالمكمن، تجعل من الصعب تحديد برنامج التطوير الأمثل لحقل معين في هذا السياق، تقدم هذه الدراسة نهجًا مفيدًا لتحسين تحديد مواقع الآبار المثلى في حقل حلفايا النفطي، وهو حقل نفط صخري جنوب العراق. يهدف هذا النهج إلى التغلب على القضايا المتعلقة بتحسين تطوير المكامن النفطية. استخدمت هذه الدراسة الخوارزمية الجينية (GA) كمحرك تحسين رئيسي نظرًا لفعاليتها في حل المشكلات متعددة الأبعاد وغير الخطية. تم تطوير سلسلة من السيناربوهات المحتملة مع تكوينات الآبار المحددة لتحديد أفضل سيناربو لتعظيم القيمة الحالية الصافية (NPV). يتضمن ذلك تطبيق طرق تحسين متعددة باستخدام برنامج petrel/Eclipse لتطوير خطة حقل موثوقة. وبالتالي تم تحديد الانتاج التراكمي لهذا الحقل النفطي و مراجعته بشكل شامل. أظهرت النتائج أن الخوارزمية الجينية تعطى قيمًا مقبولة في مشاكل التحسين مع عدد قليل نسبيًا من متغيرات القرار . أدى هذا إلى زبادة القيمة الحالية الصافية بنسبة ٥,٦٣٪ و ١٩,٦٣٪ و ٢٩,٣٠٪ لسيناربوهات بئر واحد وثلاثة وخمسة آبار تعبئة على التوالي.

الكلمات الدالة: الوضع الامثل للبئر، الخوارزمية الجينية، المحاكاة المكمنية، المكامن قليلة النفاذية، اضافة آبار جديدة.