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Field development planning using an active surrogate model and optimization algorithms for a Southern Iraqi oil field

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Abstract

Greenfield development planning is a challenging problem due to the complex objective function and the large number of variables. While stochastic algorithms and data-driven offline surrogate models have been used to locate and control wells, these methods often require a large number of runs or fail to reach an accurate optimal solution. For this reason, the current study aimed to develop a dynamic surrogate model updated after each evaluation, referred to as an active learning model. In this study, deepEnsemble and gaussian process (GP) algorithms were applied as an active alternative model. This approach was compared with optimization algorithms directly coupled with real simulations, where algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), complex matrix adaptation evolution strategy (CMA-ES), and differential evolution (DE) were used for comparison. The deepEnsemble active model outperformed the other approaches, achieving a net present value (NPV) of more than 1 E+10 and 17% recovery factor (RF) for a field in southern Iraq for a production scenario. The algorithm suggested shutting in two existing wells and drilling 23 new wells. The algorithm was also tested using a water injection scenario; a stable pressure, NPV of approximately 1.28 E+10, and 25% RF was achieved by suggesting drilling 39 new wells, 17 of which were injection wells. The approach has proven effective in dealing with complex field development problems with a minimum number of runs.

Keywords: DeepEnsemble; Optimization; Proxy Model; Well Placement; Field Development.

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1- Introduction

Petroleum remains a primary source of energy and a raw material for many chemical industries. As a global demand increases, more effective planning is required to ensure the efficient exploitation of these resources.

Determining the number, location, and control of wells is one of the most important aims in field development plans. This task, however, is challenging, as the field development optimization problem is nonlinear and high-dimensional [1]. Many studies have been conducted in an effort to address the problem, with most previous research focused on applying optimization algorithms or developing proxy models [2]. In the area of optimization algorithms, most well placement and control research has applied stochastic algorithms, with less focus on gradient-based algorithms, as these methods are more prone to becoming trapped in local optima [3]. Finite difference gradient (FDG) simulated annealing (SA), and simultaneous perturbation stochastic approximation (SPSA) have been applied to a simplified 2D reservoir model extracted from the Gulf of Mexico considering scenarios with single and seven well placements [4]. The study found that SPSA and SA were more efficient in reaching near-optimal solutions. Genetic algorithms (GA) and particle swarm optimization (PSO) have been widely applied in optimization of field development strategies.

GA was used to determine infill well locations in a tight oil reservoir in the Halfaya field, up to five wells [5]. PSO and GA were also employed to optimize well locations along with flow rates in an Iranian oilfield, the scenario included up to eight wells [6]. The GA was applied to one of the Iraqi fields to find the best locations for up to 7 wells [7]. Other evolutionary algorithms have also been used, such as covariance matrix adaptation – evolution strategy (CMA-ES) and differential evolutionary (DE), which showed higher efficiency in not falling into a local solution, compared to GA [2]. Hybrid algorithms have been employed to accelerate convergence and to enhance robustness and avoid being trapped in local optima. Yazdanpanah et al. [8] developed a hybrid approach that combined the global search of GA and the local search abilities of PSO. The hybrid approach yielded more reliable results than either GA or PSO alone. Mohammad Nezhadali [9] utilized sequential hybridization to solve problems like the number, locations, and drilling schedule of wells for a 2D synthetic reservoir. The results exhibited that the hybrid algorithms together like GA, SA, and stochastic gradient descent (SGD) outperformed in

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finding the optimal solution compared to running each one.

However, even with the use of optimization algorithms, full field development still requires running thousands of simulations to arrive at a good solution. Therefore, many research recently have developed proxy models to speed up the optimization process, replacing traditional physic-based simulations with faster models that maintain acceptable accuracy [10]. Machine learning models like categorical boosting (CatBoost), gradient boosting, light gradient-boosting machine (LightGBM), extreme gradient boosting (XGBoost), and adaptive boost (AdaBoost) are used as proxy models to determine the distance between wells, injection well locations, injection patterns, and injection & production rates [11]. Artificial neural network (ANN) is used as proxy model when input are coordinates of injection wells (x,y) and the outputs are flow rate and pressure [12]. ANN also partially replaced numerical simulation in by creating an ANN of two hidden layers. The ANN was trained on 1,500 days of cumulative oil and water production as inputs, while the output was cumulative production after 10 years, reducing the need for simulation at every future time step. This model was then used to identify the optimal location for injection wells [13]. M. Chu et al. [14] compared ANN with convolutional neural network (CNN) and found that CNN was better at finding the best location for a single well. Davudov et al. [15], developed a hybrid model between fast marching method (FMM) and XGBoost, where the drainage volume is calculated from FMM, serving as an input to XGBoost alongside permeability, and porosity, while net present value (NPV) as the output. The model was then linked with PSO to find the optimal well location.

Data-driven models leverage machine learning and statistical techniques to approximate relationships between inputs and outputs, thus enabling quicker and more straightforward implementation [10]. Nevertheless, their reduced accuracy may introduce risks in critical design decisions, such as well placement, flow rate determination, or selecting the number of wells [2]. In response to these limitations, there has been increasing interest in active surrogate model, such as Bayesian optimization and active learning. This approach has proven effective in numerous studies [16-18] outperforming pre-trained models by concentrating the learning process on the most informative regions, thereby reducing the reliance on extensive random sampling and enhancing the efficiency and intelligence of the optimization process.

By reviewing the literature, several points were identified. First, much of the literature has limited optimization problems to small areas, such as developing a small sector or a few infill wells [2]. This is mainly because high dimensional problems require extensive simulations when coupled with optimization algorithms. Second, many studies have tested their proxy models or optimization approaches on virtual reservoirs rather than real ones. Third, based on my knowledge, no study has been conducted on the simultaneous optimization of well locations, numbers, and operations using active surrogate models.

Compared with previous studies, the current study aims to address several areas. First, it addresses the problem of offline alternative models by proposing an active approach based on a set of neural networks called deepEnsemble. Second, the proposed approach is used for the joint optimization of flow rates, well locations, and well numbers, which is a rare problem in literature due to its difficulty. Third, the current study is the first development study of the Zubair Formation in the Abu Amoud field, and two scenarios will be applied: the first is depletion, and the second is water injection. In addition, the current approach will be compared with optimization algorithms (including GA, PSO, CMA-ES, and DE) and gaussian process (GP) as active model.

2- Area of study

Abu Amood is one of the significant untapped hydrocarbon resources located in Dhi Qar, covering an area extent of 120 km². The field is situated approximately 250 km southeast Baghdad, 16 km north of Qall'at Sukkar, and 17 km southwest of the Dejaila field. The first exploration well was drilled in 1980, then followed by 4 wells. Many studies have concentrated on evaluating and constructing 3D geological models for formations such as Mushrif, Nahr Umr, Zubair, and Yamama [19-22]. The Zubair Formation was selected to develop in this study.

3- Methodology

In the current study, two approaches will be implemented to solve the optimization problem. The first is the regular optimization approach, where the optimizer (GA, PSO, CMA-ES, and DE) is combined with the simulation seeking the optimal parameters. The second approach involves applying an active surrogate, where the optimal point within the surrogate is found, and the model is updated iteratively until the optimal solution is reached, as shown in Fig. 1. However, both approaches cannot be implemented in common software such as Petrel 2018 with Eclipse or CMG 2021 software, as several algorithms used in this research are not supported by standard commercial software (Petrel 2018 supported GA, and CMG 2021 supported PSO and DE only), and some proxy models are also lacking (Petrel 2018 supported surface response models, and CMG 2021 supported polynomial and radial basis function neural networks only). Therefore, it was necessary to combine one of the simulators (Eclipse was selected for this study) with a programming language to be more flexible in dealing with the problem. The Python programming language was chosen because it is a popular language in the scientific community and contains many open-source libraries that can be implemented more easily than applying the code from scratch. Among the libraries that were used in this research are the TensorFlow library to implement the deep learning model, the pandas library to deal with matrices, the Matplotlib library to deal with figures, the Trieste library to deal with optimization, and the res2df library to deal with Eclipse files. In the following subsections, the algorithms used in the research will be explained.

3.1. Genetic algorithm

The genetic algorithm (GA) is a nature-inspired algorithm, first introduced by Holland in 1970 [6]. The algorithm derives its concept from Darwin's theory of evolution, where the strongest and fittest individual ultimately represents the optimal solution [23]. As shown in Fig. 2, the flowchart of GA initiates with random values, where each solution is referred to as a chromosome. The chromosomes are evaluated by employing a fitness function. The best solutions are selected as pairs, and the others are removed to produce new solutions. Various selection methods can be used, including roulette wheels, tournaments, or random selection. Some chromosomes are then chosen for mutation to make the population more diverse. These steps are repeated until the algorithm reaches the desired criteria.

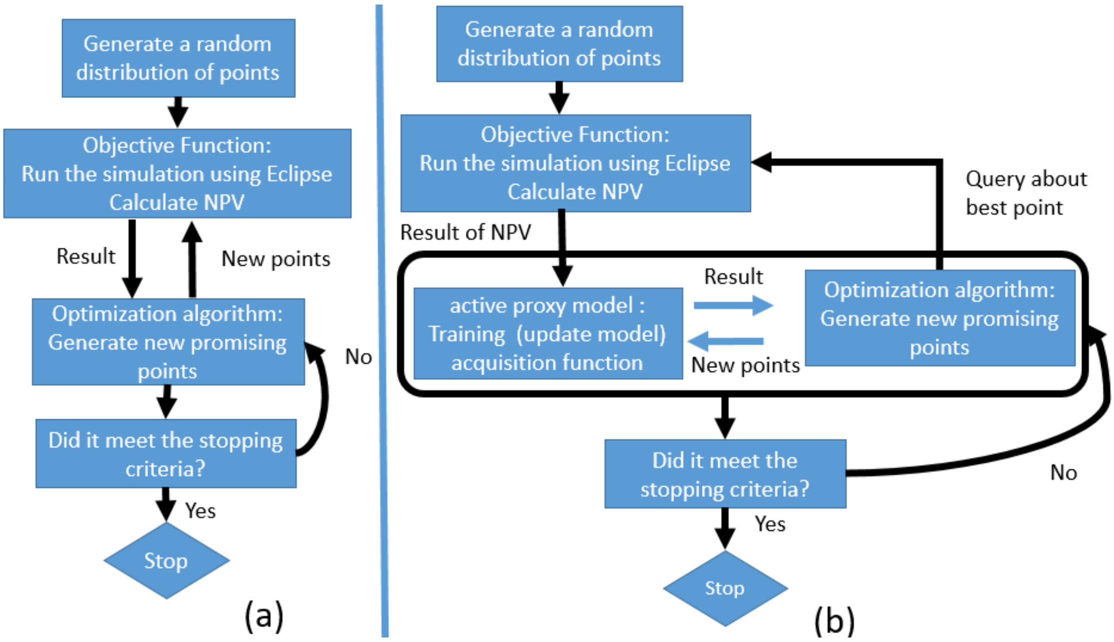

Fig. 1. The two approaches applied in the study

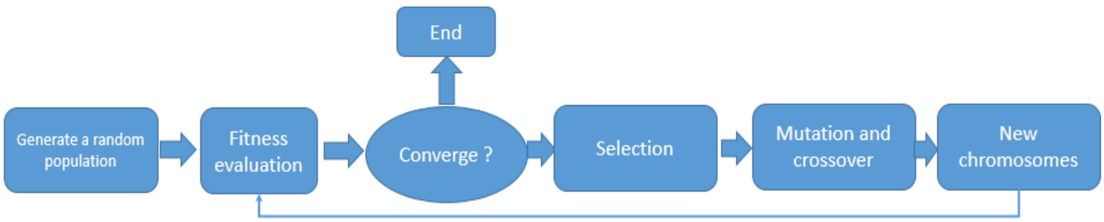

Fig. 2. Flow chart of GA

3.2. Particle swarm optimization

PSO is another type of stochastic algorithm inspired by the behavior of swarms of animals such as birds and fish. It was first introduced in 1995 by Kennedy and Eberhart [3]. Particles begin searching for the solution space with random speeds and positions. An objective function is calculated for each Particle, and the speeds $vit+1$ and positions $xit+1$ are updated using the following equations:

$$v_i^{t+1} = w\, v_i^{t} + c_1 r_1 \left(p_{best_i} - x_i^{t}\right) + c_2 r_2 \left(g_{best_i} - x_i^{t}\right) \quad (1)$$

$$x_i^{t+1} = x_i^{t} + v_i^{t+1} \quad (2)$$

The first term represents the influence of inertia, where w is inertia factor and vit current velocity of particle; the second term represents the effect of the best location obtained by particle, where $pbesti$ is particle best position; the third term represents the effect of the best location obtained by swarm, where $gbesti$ is swarm best position. Additionally, xit is current position of particle, c1-c2 are social constants, and r1-r2 are random numbers in [0, 1]. The steps are repeated until the stopping criterion is met [2].

3.3. Differential evolution

The differential evolution (DE) algorithm shares similarities with the GA, as both contain crossover, mutation, and selection. However, DE starts with mutation, followed by crossover and selection [24]. The algorithm has shown greater robustness and speed than GA. Even in WPO applications, some researchers have stated its superiority over other evolutionary algorithms [2].

3.4. Covariance matrix adaptation evolution strategy

The CMA-ES algorithm is the evolutionary algorithm that combines evolutionary strategies and covariance matrix adaptation [25]. Initially, the algorithm randomly generates a set of points, these points are then evaluated using an objective function, and the best ones are selected. The performance of these selected points is used to update the covariance matrix, which describes the shape and direction of the search distribution. This improved distribution is then used to generate a new generation of solutions. This process is repeated over multiple generations until the algorithm meets a specified termination condition. And the distribution improves over time to focus on more promising regions of the solution space.

3.5. Gaussian process

The gaussian processes (GPs) are non-parametric models that gain their inherent flexibility from not requiring the assumption of a specific functional form (e.g., linear or polynomial) for data. Fundamentally, a GP is conceptualized as a probabilistic distribution over functions, a characteristic that enables its unique capacity for quantifying predictive uncertainty [26]. GP inference operates on the understanding that any unobserved input is mapped not to a single value, but to a complete probability distribution representing the distribution of its potential outcomes [17]. Critically, the epistemic uncertainty associated with these predictions diminishes proportionally to their proximity to observed data points (i.e., simulation outputs). Consequently, predictions for points nearer to the training data exhibit reduced variance and tend to converge more closely to the actual observed values. The similarity between unobserved points and existing data is precisely quantified by a kernel function (also called a covariance function). This kernel is instrumental in defining the underlying functional relationship and dictating the smoothness and characteristics of the learned function that best explains the observed data.

3.6. DeepEnsemble

ANNs are predictive models inspired by the human brain, introduced in 1943, and research in this field has continued to evolve. ANNs are distinguished from other models by their ability to approximate complex non-linear functions any. ANNs are used in many fields, such as medicine, engineering, and science. ANN has also been used extensively in the petroleum industry in areas such as drilling (such as predicting by rate of penetration), production (such as production forecasting), petrophysics (such as estimation of petrophysical properties), and reservoirs (such as proxy models in simulations) [27]. In general, an ANN contains several layers, each with several neurons. Each neuron represents weights multiplied by input variables and summed with biases and activation functions between the layers. Methods such as backpropagation are typically used to find appropriate weights and biases to fit the data. ANNs have three types of layers; the first layer is called the input layer and usually has many inputs. The last layer is called the output layer and usually has one or more outputs. The layers between the output and input layers are called hidden layers.

However, to make an ANN capable of updating, we need to make it predict uncertainty, such as a Gaussian process. To do this, several ANNs with the same number of layers and activation functions are built, called DeepEnsemble [28]. Each one of the models has a different initialization to create multiple predictions for the same point. The mean and variance between the ANN models are estimated, where the mean represents the predicted value and the variance represents the uncertainty value. This means and variance will be used in the acquisition function to find the optimal point or next point for evaluation by the simulation.

3.7. Objective function

The objective function is the primary tool for evaluating solutions in a search space, which in the petroleum industry typically aims to maximize NPV. A common objective equation in the literature [2, 29] is as follows:

$$NPV = \sum_{t=1}^{T} \Delta t \, \frac{Qo * p_o + Qg * p_g - Qw * p_w}{(1+r)^t} - \sum_{n=1}^{N} C \tag{3}$$

Where Qo is cumulative oil production, Qg is cumulative gas production, Qw is cumulative water production, p_o is the oil price ($/STB), p_g is the gas price ($/Mscf), p_w is the water treatment cost ($/STB), r is annual discount rate, Δt is time step, t is cumulative time, C is initial investment for each well. When including water injection, the formula becomes [1, 6, 16, 30]:

$$NPV = \sum_{t=1}^{T} \Delta t \, \frac{Qo * p_o + Qg * p_g - Qw * p_w - Qi * p_i}{(1+r)^t} - \sum_{n=1}^{N} C \tag{4}$$

Where Qi is cumulative fluid injection, pi is fluid injection cost.

4- Results and discussion

In the following sections, the mentioned algorithms and methods will be applied, and then the best methodology will be tested with an injection well development plan.

4.1. Fixed spacing scenarios

In this section, multiple scenarios were applied with different spacing and numbers of wells, which were determined using fixed spacing without optimization algorithms. While the drainage area for wells in fields of southern Iraq is between 400–500 m, in this study, drainage areas from 400 to 1,200 m have been tested, as shown in Fig. 3, Fig. 4, and Fig. 5. Table 1 shows the NPV value was calculated from Eq. 3 for each scenario. The best value was obtained when the spacing was 600 m between wells, which was achieved with 59 new wells.

The spacing of 400 m between wells has a lower NPV than the 600 m and has the highest number of wells, with approximately 114 wells. A large number of wells is not always optimal, especially from an economic perspective, as it increases the number of additional wells and associated costs. Water production is faster with a denser number of wells, and the pressure drop occurs more quickly.

When the number of wells is 34, 22, oil recovery (RF) is better than when the number of wells is 59. However, the NPV is lower due to the annual discount factor in Eq. 3. The larger number of wells (59) extracts more oil in a shorter period but may cause a rapid pressure drop, which results in lower ultimate recovery.

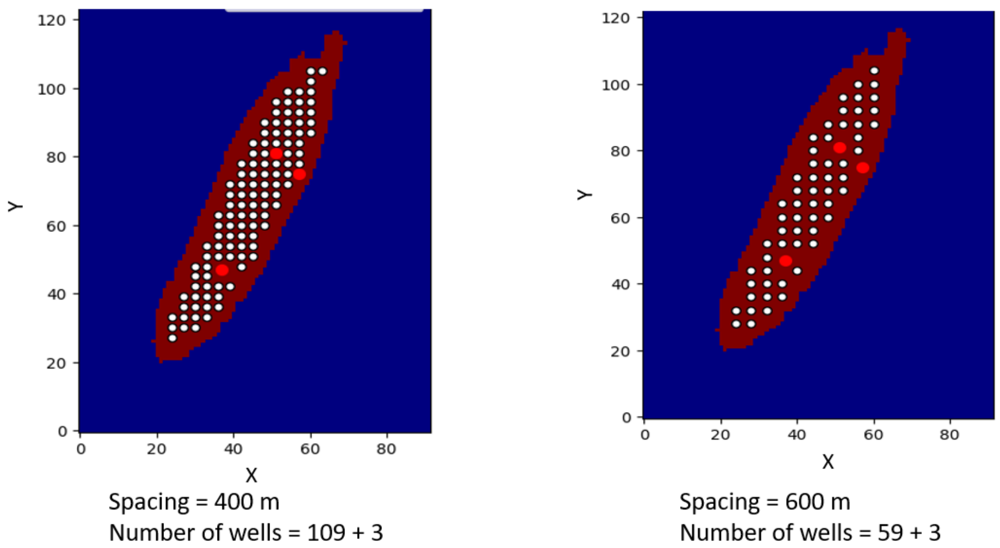

Fig. 3. Scenarios with 400m and 600m spacing

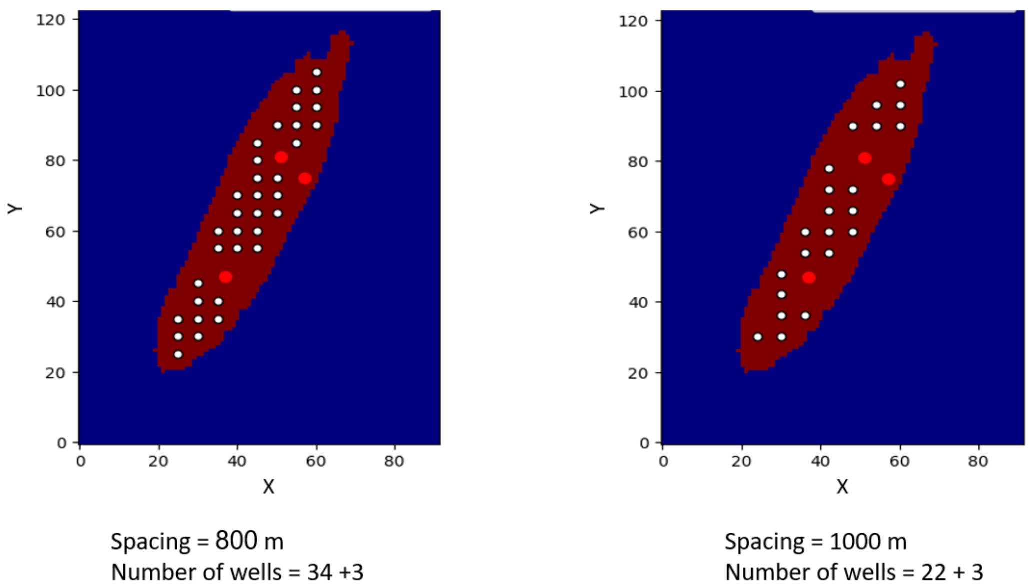

Fig. 4. Scenarios with 800m and 1000m spacing

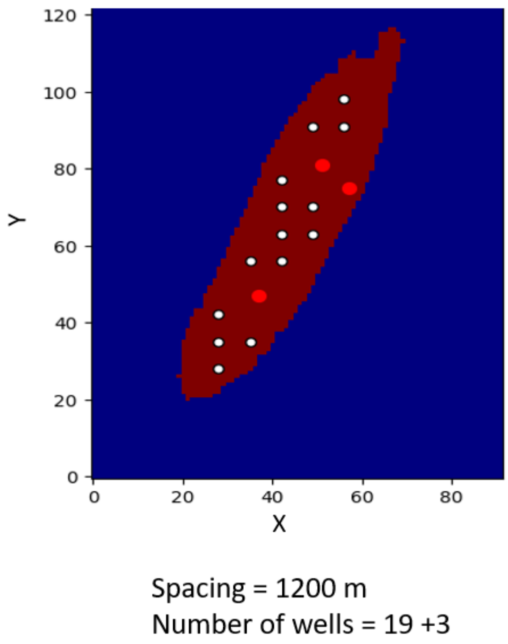

Fig. 5. Scenarios with 800m and 1000m spacing

Table 1. NPV of scenarios with different spacing

Spacing (-)	wells Number (-)	NPV ($)	RF (-)	Water Production (m3)
400	109 + 3	8,639,885,708	13.4 %	1.51e+07
600	59 + 3	9,248,094,794	14.5 %	1.33e+07
800	34 + 3	8,935,294,429	15 %	1.25e+07
1000	22 + 3	8,034,492,598	15.3%	1.19e+07
1200	14 + 3	6,785,258,466	14.5%	9.14e+06

4.2. Optimization cases

Initially, four algorithms (GA, PSO, CMA-ES, and DE) were used directly with simulation to find a good case. A budget of 300 runs was set to determine the best performing algorithm under limited evaluations. Optimization parameters were determined from previous studies in light of the restricted number of runs. Controlled variables included well locations along the x- and y-axes, the number of wells, and flowrate. For drilled wells, only flowrate was considered a controlled variable. Forty new wells were selected as the maximum for optimization by the algorithm. Potential wells were considered “drilled” only if the optimized flow rate exceeded zero; otherwise, they were treated as undrilled, and no drilling cost was included.

The problem involved a total of 125 variables, which defines it as high-dimensional. A final solution was unlikely to be reached given the limited evaluation budget. Fig. 6 shows that despite 300 runs, no algorithm achieved an NPV better or similar to that of the 600 m fixed-spacing scenario. Due to their inherent stochasticity, these algorithms typically need a high number of function evaluations to converge, especially in high-dimensional optimization tasks.

All algorithms started from poor initial points due to random initialization and then proceeded with iterative optimization within the solution space. Fig. 7 shows that PSO and GA performed better than DE and CMA-ES under the specified conditions. Still, this does not confirm their overall superiority, since CMA-ES might perform better with a more extensive evaluation budget. Within 300 runs, the GA algorithm showed the best performance.

The following section, GP or bayesian optimization (BO), and Deep Ensemble will be applied. In these models, the method used to select the next evaluation point by the optimizer relies on generating a set of candidate points through random sampling, followed by parallel gradient-based refinement of the most promising ones. The best-performing candidate is then selected for actual evaluation by simulation. The upper confidence bound (UCB) acquisition function was selected to yield the best performance after many runs.

As shown in Fig. 8 and Fig. 9, both BO and Deep Ensemble achieved better results than the previous algorithms and the fixed-spacing approach, requiring fewer than 300 runs. Furthermore, the Deep Ensemble model outperformed BO primarily during the first 80 evaluations. This indicates that Deep Ensemble was more effective in capturing the relationship between inputs and output, especially in high-dimensional, complex, and non-stationary objective functions [31].

The CMA-ES optimization algorithm was tested to find the next evaluation point within the Deep Ensemble, as shown in Fig. 10. Although it arrived at a good solution with fewer runs than the previous optimization, it required more time to compute each point. It took approximately 8 hours for only 43 runs, compared to approximately 10 hours for conventional parallel optimization with 300 runs in the regular Deep Ensemble.

To ensure that the optimal solution was reached, the Deep Ensemble algorithm was run for up to 1000 evaluation. The solution found improved slightly, as shown in Table 2. Fig. 11 shows the distribution of wells for the two cases.

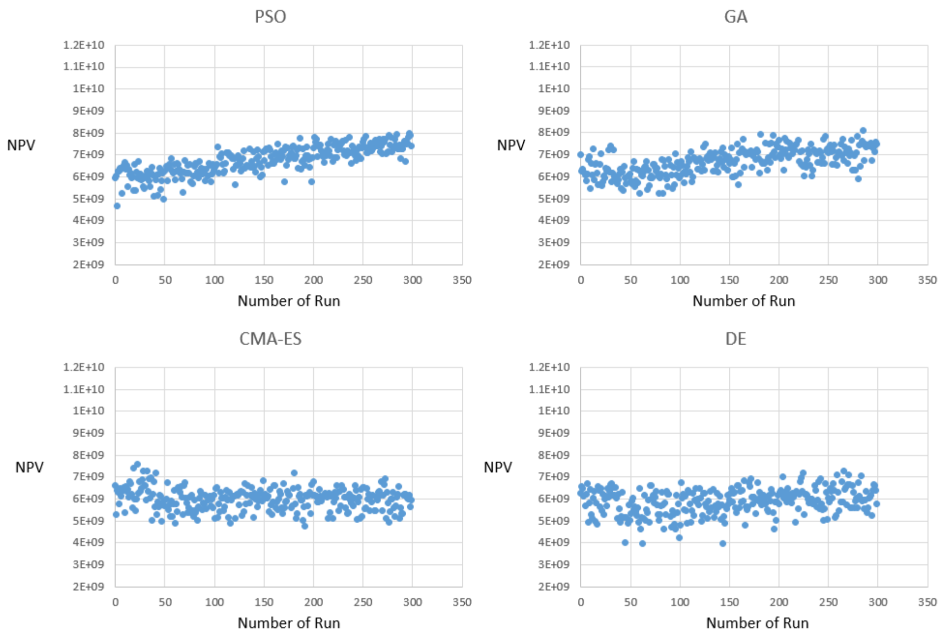

Fig. 6. All runs for each algorithm

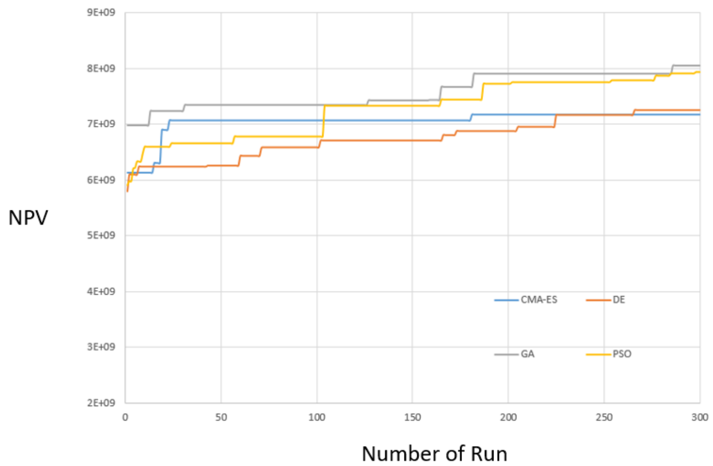

Fig. 7. Comparison of optimization algorithms

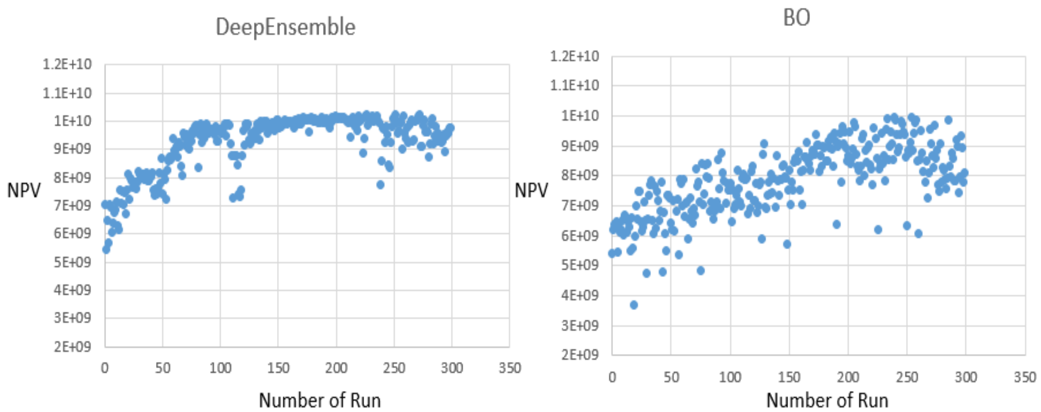

Fig. 8. All runs for each active proxy model

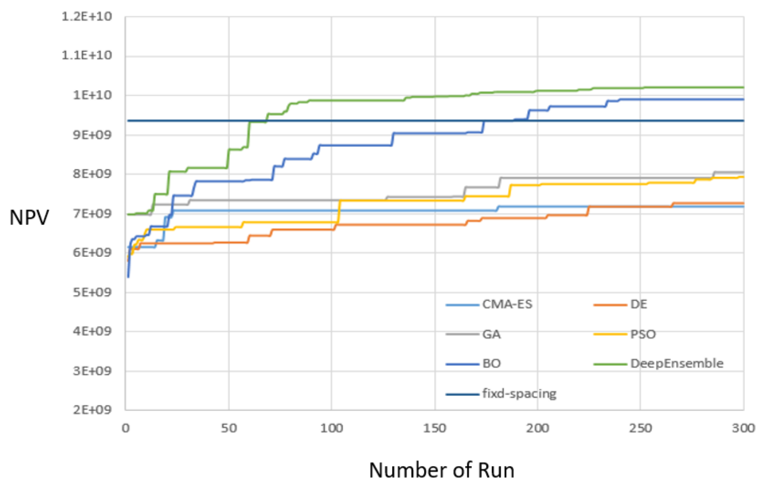

Fig. 9. Comparison of optimization algorithms and proxies model

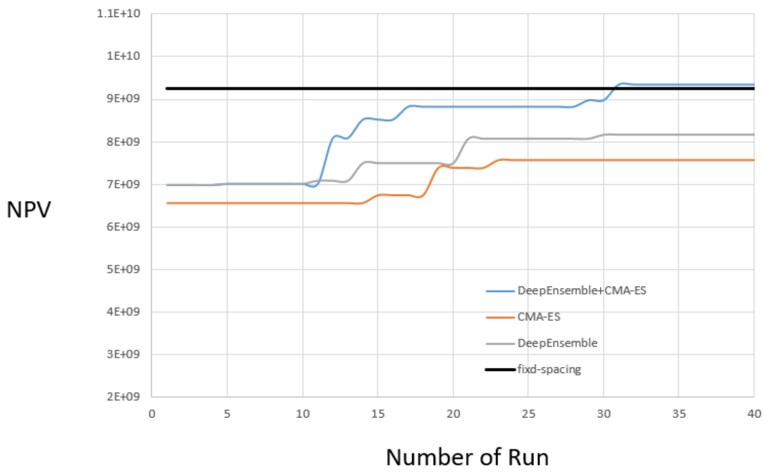

Fig. 10. Comparing CMA-ES and DeepEnsemble

Table 2. NPV of best scenarios

Runs number	wells Number (-)	NPV ($)	RF (-)	Water Production (m3)
300	20 + 3	10,058,028,342	17 %	6.69e+06
1000	23 + 3	10,200,773,404	17.1 %	7.19e+06

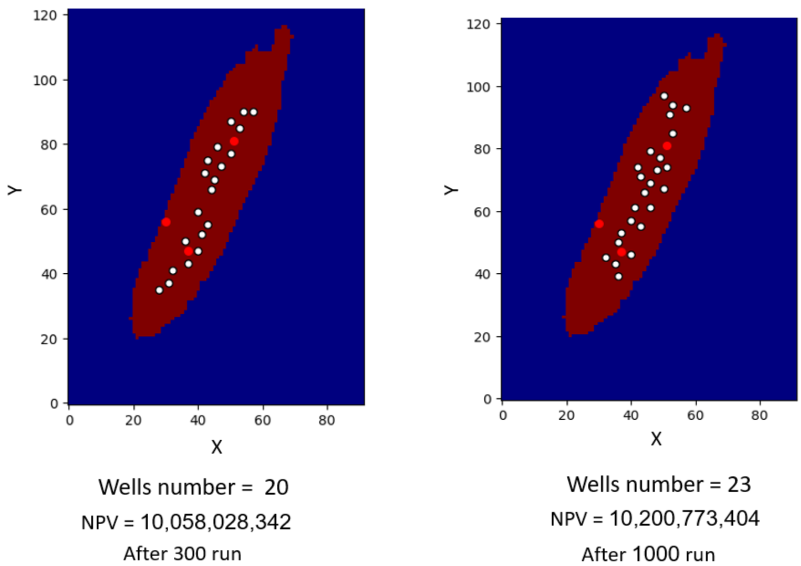

Fig. 11. Best scenarios from DeepEnsemble optimization

4.3. Injection case

In this case, injection wells were included along with the appropriate timing for injection. As the problem size increased, some of the previously obtained production solutions were used to train the active model before starting the optimization process in an effort to find faster solutions. Fig. 12 shows the well distribution, where the algorithm surrounds most of the injection wells with production wells. Based on the applied current approach, approximately 39 new wells were proposed, including 17 injection wells. Additionally, 3 previously drilled wells located near injection wells or field boundaries were shut in. Table 3 shows a clear improvement in NPV, which calculates using Eq. 4, compared to the production-only scenario. An improvement in RF has also been observed. An increase in water production is also noted, which is expected due to the presence of injection wells. Fig. 13 demonstrates that, after loading the production and injection scenarios into the Petrel 2018 software, the x-axis represents the production period from 2025 to 2045. The three y-axes represent the reservoir pressure, total production, and production rate for each scenario. The injection scenario maintained reservoir pressure, in contrast to the continued decline observed in the production-only scenario. An improvement in the production rate was observed, leading to a significant increase in cumulative oil production compared to the production-only case. These results demonstrate the potential of the proposed approach in developing effective injection scenarios. The outcome was achieved after approximately 1,000 algorithm evaluations.

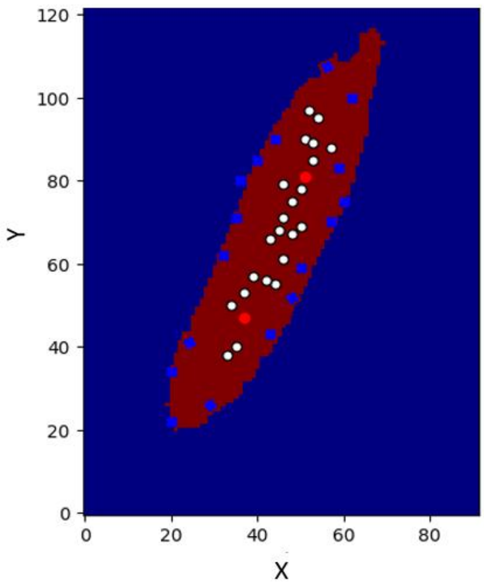

Fig. 12. Distribution of well for best injection scenario

Table 3. NPV of best injection scenario

Production wells	Injection wells	NPV ($)	RF (-)	Water Production (m3)	Water Injection (m3)
22 + 2	17	12,841,101,844	24.95%	2.93e+07	5.15e+07

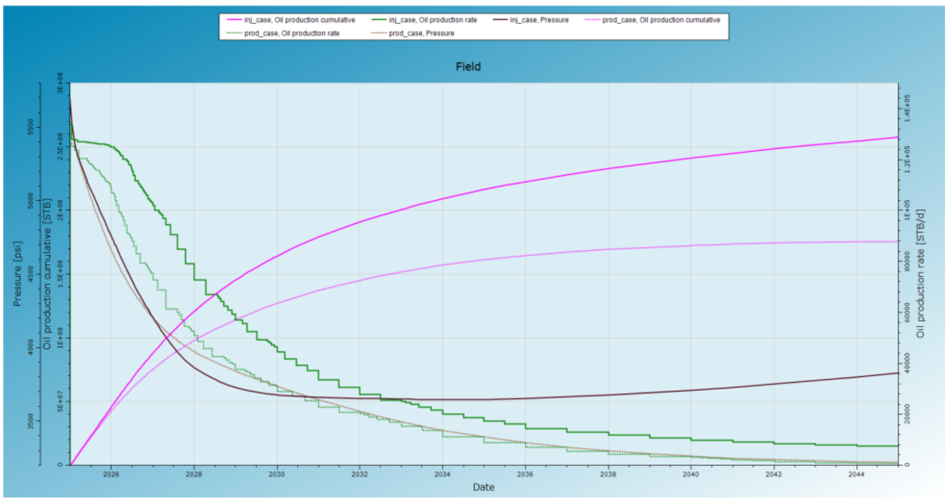

Fig. 13. Oil production rate, cumulative oil, and pressure

5- Conclusion

The current study applied an active model based on a set of neural networks that continuously update the training data (DeepEnsemble). The DeepEnsemble outperformed the CMA-ES, GA, PSO, and DE optimization algorithms under a limited computational budget (300 runs) and a high-dimensional problem (125 variables). DeepEnsemble demonstrated better performance as an active proxy model compared to BO due to its ability to capture non-stationary objective functions. The proposed approach was applied to the Zubair Formation in the Abu Amoud field, where it achieved an NPV of 1.0E+10 and a 17% RF in the depletion scenario. The optimized strategy recommended drilling 23 new wells and shutting in two existing producers. In the water injection scenario, the approach achieved an NPV of approximately 1.28E+10 and a 25% RF, with a proposed drilling plan of 39 new wells, including 17 injection wells. These findings highlight the potential of the proposed DeepEnsemble approach for real-field application, especially in complex joint optimization problems where computational efficiency and decision-making are critical.

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تخطيط تطوير الحقل باستخدام نموذج البديل النشط وخوارزميات التحسين لحقل نفط جنوب العراق

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الخلاصة

يُعد تخطيط تطوير الحقول الجديده مشكلة صعبة نظراً لدالة الهدف المعقدة والعدد الكبير من المتغيرات. في حين يتم استخدام الخوارزميات العشوائية والنماذج البديلة القائمة على البيانات لتحديد مواقع الآبار والتحكم فيها، إلا أن هذه الطرق غالبًا ما تتطلب عددًا كبيراً من التشغيلات أو تفشل في الوصول إلى الحل الأمثل. لهذا السبب، هدف الدراسة الحالية إلى تطوير نموذج بديل يتم تحديثه بعد كل تقييم، والمعروف باسم النموذج النشط. في هذه الدراسة، تم تطبيق خوارزميات مجموعة الشبكة العميقة (deepEnsemble) و العمليات الغاوسية (GP) كنموذج بديل نشط. تمت مقارنة هذا النهج بخوارزميات التحسين المرتبطة مباشرا بالمحاكاة، حيث تم استخدام خوارزميات مثل الخوارزميات الجينية (GA) وتحسين سرب الجسيمات (PSO) واستراتيجية تطور التكيف المصفوفي المعقد (CMA-ES) والتطور التفاضلي (DE) للمقارنة. تفوق نموذج البديل النشط deepEnsemble في الأداء، محققاً صافي القيمة الحالية (NPV) بأكثر من ١٠ مليارات واسترداد (RF) اكثر من ١٧٪ لحقل في جنوب العراق لسيناريو الإنتاج. تم الاقتراح بأستخدام الخوارزمية إغلاق بئرين حُفرتا سابقاً وحفر ٢٣ بئرًا جديدًا. كما اختُبرت الخوارزمية مع سيناريو حقن المياه؛ حيث تم تحقيق ضغط مستقر، وNPV يبلغ حوالي ١٢،٨ مليار، وRF بحوالي ٢٥% من خلال اقتراح حفر ٣٩ بئراً جديداً، منها ١٧ بئراً حقن. وقد أثبت هذا النهج فعاليته في التعامل مع مشاكل تطوير الحقول المعقدة بأقل عدد من تشغيلات للمحاكاة.

الكلمات الدالة: مجموعة الشبكة العميقة، تحسين، نموذج الوكيل، تحديد موقع البئرن، التطوير الحقل.