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Optimization sequence of infill well-drilling using Latin hypercube plus radial basis function network

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Abstract

Infill drilling is the first choice to increase the recovery factor, but the mission of selecting the best well location is considered a major challenge with the huge area of the reservoir and the time consumption to conducting the simulation runs that may reach hundreds to thousands. This paper adopted the design of an experiment plus a proxy optimization technique to solve this problem. Where the Latin Hypercube represents the DoE while the radial basis function network represents the artificial intelligence proxy model. The proxy model mimics the reservoir model to reduce the computation time and speed up the well-placement optimization process. The Latin Hypercube approach is used to generate data to train the proxy model to construct a reliable artificial intelligence model to predict the best wells locations. The results are very optimistic and encouraging to rely on using the art-of-state to construct a proxy model to conduct the infill wells drilling optimization. Where the increase in cumulative oil production for the optimized case is more than the un-optimized case by 6.45% and the decrease in the field cumulative water production for the optimized case is less than the un-optimized case by 16.11% from 2020 to 2040.

Keywords: Infill wells, Radial basis function, Proxy model, Latin hypercube sampling, Reservoir optimization
2020 MSC: 37N40, 65K10

1 Introduction

The objective function of any reservoir study is to maximize the oil recovery factor and net present value with minimum cost. Infill well drilling is considered the way to achieve this objective function in the field development plan (FDP). The location of infill well drilling is an essential challenge task in FDP due to the huge number of simulation run requirements which make the process expensive in time-consuming. Also, the objective function of the well-placement process is complex and usually composed of several local minima [3].

Several authors applied different optimization methods to get the optimal solution of the objective function. A Genetic Algorithm (GA) is considered a tool of computer-assisted optimization is employed for the simultaneous optimization of the location, number, and trajectory of producer and injector wells. The results showed when there isn't enough time to complete the whole optimization or when the problem is complex, the GA may be used as an

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initial solution [5]. Utilizing some of the developed restrictions, the Particle Swarm Optimization (PSO) algorithm was utilized to iterate on the well locations for two production situations. The restrictions are including maintaining a minimum inter-well distance, a minimum and maximum well length, a general orientation of the wells with respect to a predetermined platform location, and keeping the wells within designated reservoir regions [10]. [6] used the CMA-ES to optimize the well-placement and the control parameters sequentially or simultaneously for a deterministic geological model. [1] worked on five different optimization instances to examine the Evolution Strategy (ES) Algorithm and the results of these studies show that the effectiveness and performance of the ES Algorithm are better than the Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Covariance Matrix Adaptation Evolution Strategy (CMA-ES) due to the results, in most instances, of using ES as the optimization approach yields promising outcomes more than the others optimization methods. Wells placement optimization was achieved by using the mean-standard deviation formulation, coupled with an artificial neural network as a substitute for the reservoir simulator. The ANN provides the average NPV and standard deviation of the NPV of an ensemble of geological realization for a given wells configuration. The CMA-ES optimizer is coupled with the ANN to speed up the optimization processes for many objective function formulations [3].

In this paper, we apply and examine a new methodology which is the Design of experiment plus Proxy Optimization technique to perform the objective function of infill well drilling. The main goal of this paper is to construct a fully completely optimized strategy for the field development plan by applying sequence optimization processes at each plan to be the case base for the next optimization plan. The proxy type will be represented by a radial basis function network (RBFN), which is a powerful tool to construct an accurate model to predict and find the optimal solution for the objective function.

2 Area of study

This study was executed on West Qurna 2 which is considered one of the giant Iraqi oilfields. It locates in Basra city in southern Iraqas shown in Fig. 1. The West Qurna oilfield is located within the ancient platform where the sedimentary cover includes the deposits from the Paleozoic to the Tertiary periods [7]. The main oil-bearing formations are Yamama and Mishrif. The Mishrif formations belong to the upper cretaceous system. This study targets the Mishrif formation. The Mishrif formation comprises the major producing reservoir of the West Qurna-2 field [19]. This field is considered a green oil field because the exploitation began at the end of 2014. The number of wells is 55 production wells and 10 water injection wells. All the future strategies will be conducted for 20 years through the duration of 2020-2040. The strategies will undergo for the optimization process to compare the results with their base case.

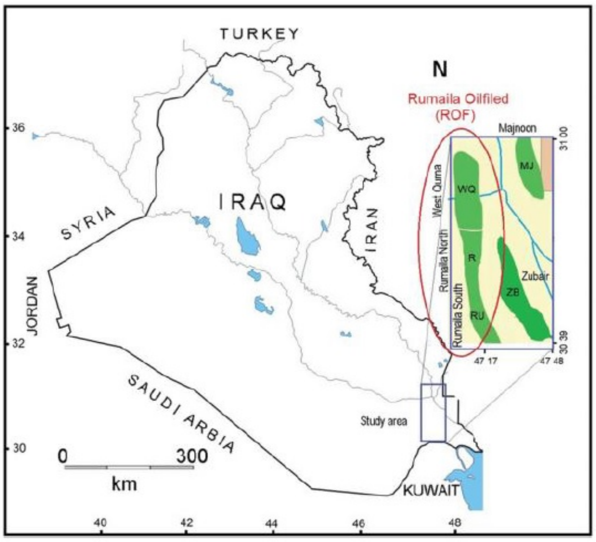

Figure 1: West Qurna oil field location

3 Optimization Algorithms Methods

The optimization algorithm which is used to perform the objective function of the infill drilling is the design of experiments (DoE) plus proxy optimization. The Latin Hypercube is the DoE while the proxy model is the radial basis function network (RBFN) with radial basis function as activation function (RBF).

3.1 Design of Experiments (DoE)

Design of Experiments are techniques that have gained popularity throughout time and continue to be widely used [13, 17]. These methods are used to determine and show the effect of the various variables on the response surface through adapt itself to learn the search space with a minimum number of experiments [8]. Also, with the use of these DoE methodologies, it is possible to evaluate how certain components are related to one another and determine which functions they play in combination [11].

3.1.1 Latin Hypercube Design sampling

The LHD, introduced by Mckay et al., 1979, is a statistical sampling tool used to generate samples from the input parameters to develop multiple computer experiments from a multi-dimensional distribution [12]. After identifying several uncertain parameters, by using Latin hypercube design, the initial simulation scenarios are produced. The idea behind Latin hypercube sampling (LHS) is to divide the domain into squares or cubes depending on how many parameters are being sampled. The same concept might be applied to any higher dimension [16]. As shown in Fig. 2, the LHS samples point uniformly across the domain, as opposed to Monte Carlo sampling, which samples randomly across the domain.

The Latin Hypercube Sampling approach's strength is represented in selecting the random level of each variable based on the space-filling design and then uniformly distributing all points to capture the entire variation. LHS can achieve an accurate random distribution with a minimum number of experiments. The Latin hypercube design is characterized by creating a well-spatial location of initial points for proxy modeling by dispersing initial points all over the parameter domain [9, 18]. More precisely, the design of spread points is regular because the technique of the LHS maintains the greatest distance possible between each design point and each other point [15].

There is no clear and accurate workflow to determine the number of initial experiments to be generated by LHS because it depends on the issues' complexity and the number of uncertainty parameters [14].

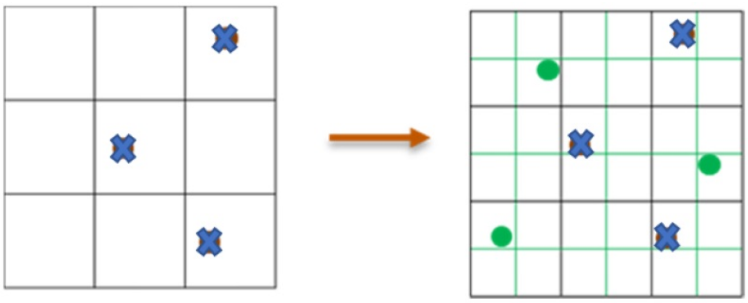

Figure 2: Latin hypercube sampling (LHS) concept [16].

3.2 Proxy modeling

A proxy model is a mimicking of numerical reservoir modeling with approximation estimation to the original model's results. The Necessity of this type of model is to replica the traditional numerical model which is characterized by complexity, and long time-consuming to conduct the simulation run. The term proxy model is used interchangeably with other terms such as surrogate model and response surface model, but the main goal of each is the same.

Proxy models can be as simple as linear or quadratic equations, or complex polynomials, or artificial neural networks. All of these proxies types work to build a correlation between a set of input parameters to an output (outcome). In this paper, the input parameters are the oil production rate, water injection rate, and well position while the output is the oil cumulative production.

3.2.1 Artificial Intelligence proxy model

It is another type of proxy model which depends on state-of-art to develop the proxy model. In this study, a radial basis function network (RBFN) was used, which is considered a variation of the artificial neural network according to its structure that was proposed by [2]. RBFN consists of an input layer of source nodes, one hidden layer where all calculations are conducted in it (nonlinear processing units) with a special activation function called the radial basis function, and an output layer of linear weights. The input-output mapping carried out by the RBF network is best characterized as:

$$y(x_p) = w_o + \sum_{i=1}^{M} w_i \varphi(x_i, x_p) \tag{3.1}$$

where: $\varphi(x_i, x_p)$ represents the radial basis function, which depends on the distance between the input parameter vector x_p and the center x_i and, in the general case, on the mutual orientation of these vectors in N-dimensional parameter space. The distance and scale orientation, as well as the precise shape of the radial function, are fixed parameters of the model. $y(x_p)$ is representing the value of an objective function at the point x_p in N-dimensional parameter space, and M is the size of the training data. Centers x_i correspond to the training parameters in the initial Latin Hypercube Design. Any function can be represented by a radial basis function and then utilized as a building block for a network. Gaussian kernels are an example of this function which are based on the hypothesis that the network's reaction monotonically declines as it moves away from central locations. The RBF can best be approximated by the following power function:

$$\varphi(x_i, x_p) = 0.01L^{0.75}(x_i, x_p) \tag{3.2}$$

where: L function defines the square of the distance between points x_i and x_p in the general case of anisotropic metrics. Normally, the anisotropy factor is neglected for high-dimensional cases due to the infeasibility of full-scale multidimensional analysis, in which case, L is selected based on the squared Euclidean distance between parameters: $\vec{x} + \vec{z}$ and $\vec{x}$ The model may face two issues which are underfitting and overfitting. In the radial basis function network case, these issues' occurrence depends on architecture where the difficulty in setting up an appropriate number of hidden layers, the number of neurons in each layer, and the type of neurons that should be used. The quality of prediction of any proxy type will be improved by increasing the size of the training LHD; however, a threshold is eventually reached, after which further improvement will be marginal, as shown in Fig. 3. Therefore the number of the Job ID at which the curve of typical prediction error dynamics starts at the beginning of leveling out depends on the type of proxy and the number of parameters. This is important to be understood and get known before constructing the Latin Hypercube design.

Fig. 4 show the workflow of the Latin Hypercube plus proxy Optimization technique which was used in this paper to perform the objective function of infill wells drilling.

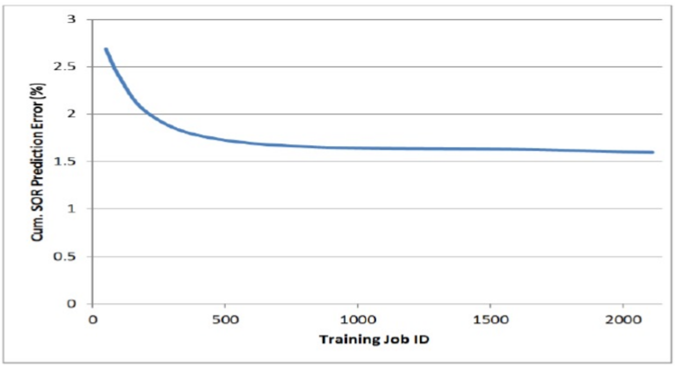

Figure 3: The curve of typical prediction error dynamics vs. Training Job ID.

4 Proposed Field Development Optimization Plan

In This work, the optimization strategies on 3D reservoir modeling will be applied for full field scale. To perform this goal, CMG software (computer modeling group) and its tool CMOST-AI were used which offers a combination of engineering expertise with advanced statistical analysis, machine learning, and non-biased data interpretation to improve business decisions and processes of the reservoir [4].

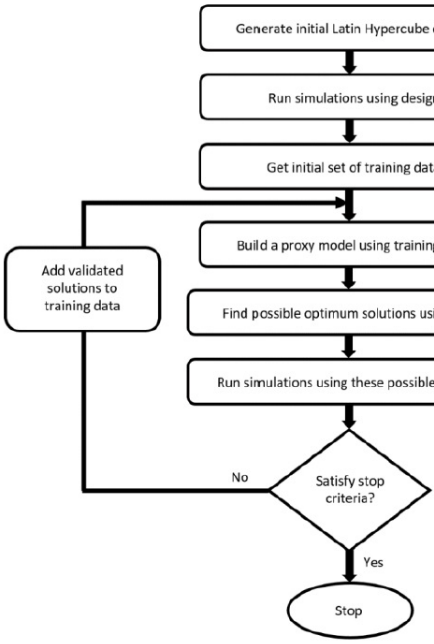

Figure 4: Optimization algorithm in Latin Hypercube plus proxy optimization.

The future prediction strategies are various. The variety depends on continuing with the current situation, drilling new produced wells, increasing injected wells by converting production wells into injection wells or/and adding new injected wells, and also changing parameters for some strategies. The FDP in this study will carry out over six years (2021, 2022, 2023, 2024, 2025, and 2026). Each future optimization plan for each year includes adding new wells which are distributed along the field randomly as shown in table 1. The constraints of the wells are the oil rate of 700 m^3/D and the water injection rate is 2000 m^3/D. In this paper, two strategies of the optimization process will conduct and compare with the base case of FDP without the optimization process.

Table 1: Optimization plan for each year.

Year	**New Produced Wells**	**New Injection Wells**	**Well Type**
2021	5		vertical
2022	5		vertical
2023	10		7 vertical + 3 horizontal
2024	15		vertical
2025	15		vertical
2026		15	vertical

1. Strategy-1- sequence optimization strategies method
   In this strategy, an integrated optimization process was done for field development. The workflow of this procedure will be as follow:
   (a) Identify the FDP for the reservoir and the duration of prediction in advance. Table 1 illustrates the FDP for this study.
   (b) Applying the first year of the FDP (2021) on the original simulation case (Considering the FDP includes just the 2021 plan without applying the other years' plans) and then conducting the optimization process on the simulation case until the end of the prediction duration.
   (c) Take the optimal optimized simulation case as a base and a fixed case for the next year's development plan (Consider the FDP includes just the 2022 plan without applying the other next years' plans) and conduct the optimization process on the simulation case until the end of the prediction duration.
   (d) Then take the optimal optimized simulation case as a base and a fixed case for the next year's development plan. This workflow will repeat the same procedure until applying the last year of FDP.

   In the end, the simulation case will conduct the FDP with optimal and optimized well location to achieve the objective function of the FDP. Therefore, this process is called (the sequence optimization strategies method).

This strategy aims to find the optimal well placement location, which gives a high cumulative oil production. The parameters which impact this goal and must be optimized are the coordinates of the new wells. As the added wells are vertical, the coordinate in the horizontal domain in two directions X and Y (IJ - 2D Areal) are considered. While in the horizontal wells, the impact variables are the coordinate of wells in the JK direction. The ranges of x and y will generate a rectangular or square area, in which the wells will search for the optimal location to increase the objective function as shown in Fig. 5. The definition of the searching area boundary depends on avoiding intersecting the position of other wells which leads to aborting the simulation run.
The newly added produced wells are organized into groups as shown in Fig. 6, the objective function of each plan is to increase the cumulative oil production for these groups of new wells to achieve the goal of finding the best optimal location.

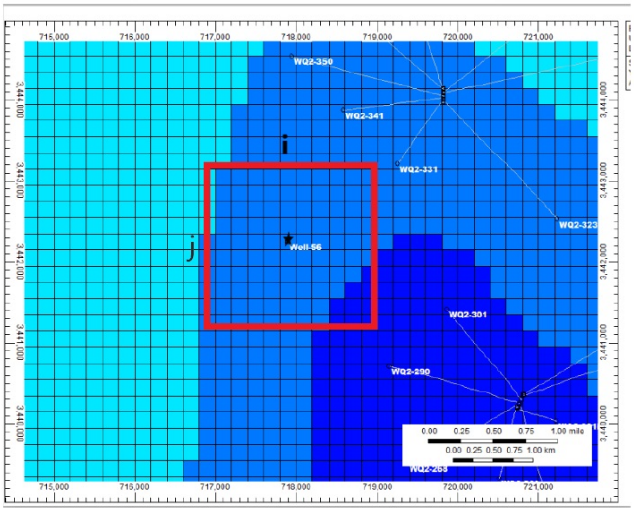

Figure 5: Search area boundary for infill well.

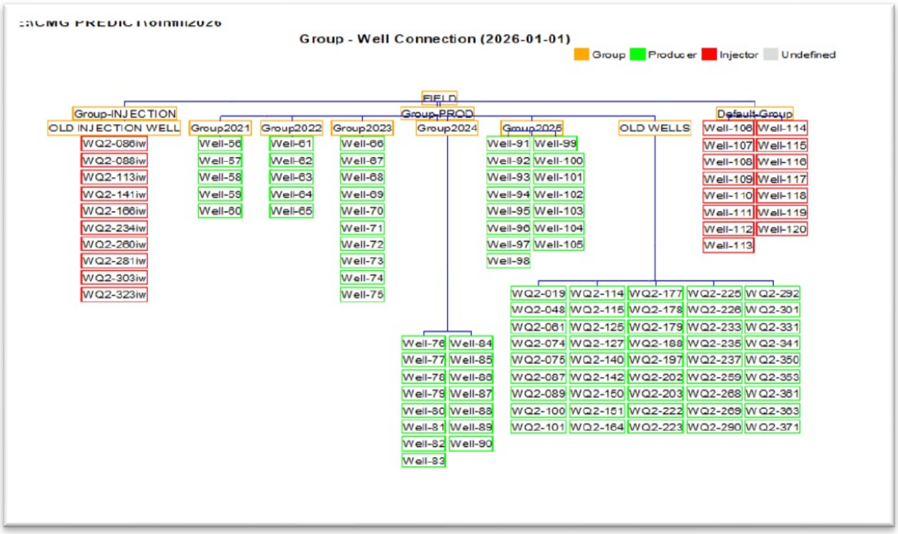

Figure 6: Group and Wells connection (Group Affiliation).

The Latin hypercube plus proxy optimization succeeded to achieve the objective function of each year's plan by finding the optimal location for the new wells to increase the cumulative oil production of the newly added wells' group and consequently increases the cumulative oil production for the entire field. Table 2 shows the increasing in the cumulative oil production for both groups of added newly wells and the entire field before and after the optimization process for each year.
The sixth year of the optimization process is conducted in 2026. This strategy included adding infill wells for water injection. The pattern of water flooding used to perform this strategy was a peripheral pattern. The

Table 2: The increase in the cumulative oil production for both group-added wells and the entire field before and after the optimization process.

Year	Group cumulative oil production,%	Field cumulative oil production,%
2021	39	1.8
2022	67.5	1.2
2023	58	2.3
2024	38	1.7
2025	44	1

number of water injection wells is 15 wells which are distributed at the flanks of the reservoir as shown in Fig. 7. The optimized process's goal was to increase the cumulative oil production of the field. The position of the most of injection well became closer to the crest and the results of the optimization were good and encouraging where the field cumulative oil production increased by 1.25% which represents about $16 * 10^6 bbl$ and a decrease in the field cumulative water production by 2% which represents about $4.5 * 10^6 bbl$.

2. Strategy-2- single fully batch optimization method (one-time)
   In this Strategy, the simulation reservoir case will include all the future development plans that were conducted in the previous strategy-1 and shown in table 1 about the adding producers and injectors' wells, but the optimization process will be conducted one-time for the future strategies of the simulation case. The aim of this strategy is to examine the single fully batch optimization method in achieving the objective function and compare its results with Strategy-1 (sequence optimization strategies method) by conducting the simulation runs on the two strategies for future prediction duration extending to 20 years from 2020 until 2040.

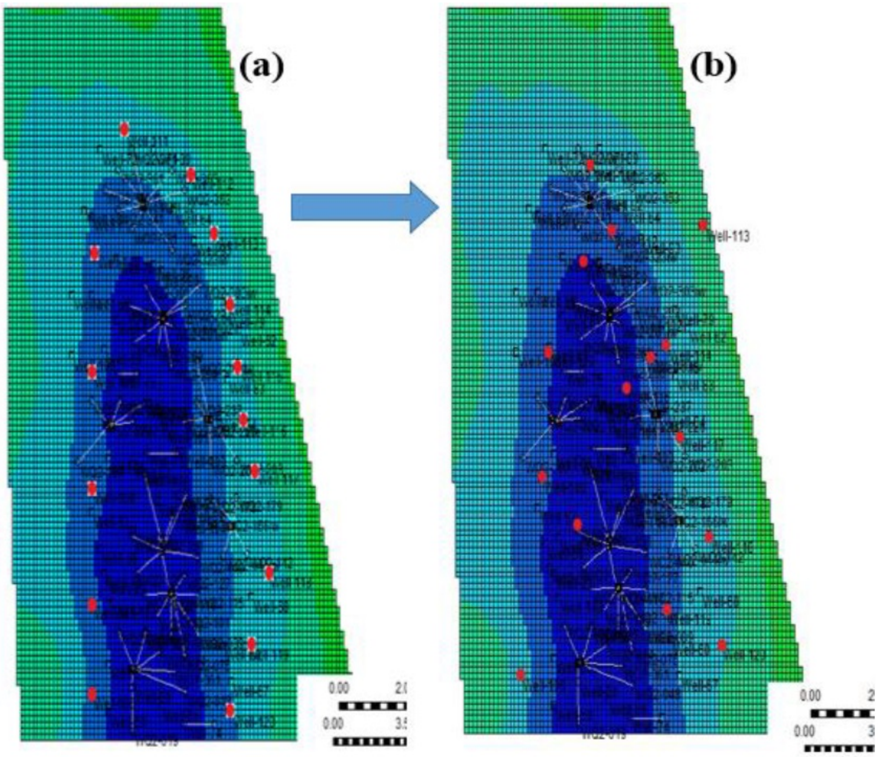

Figure 7: Water injection wells (a) Before optimization of the injection wells (b) After optimization of the water injection wells.

5 Results Comparison for Optimization Types and Discussion

The comparison is carried out between three models which are (1) Base case without optimization process on the supposed wells locations (2) model with sequence optimization strategies, and (3) model with single fully batch optimization. Where the simulation run was conducted on these three models and the base case without the optimization process is taken as a base of the comparison.

The results show that the model with sequence optimization strategies increases the field cumulative oil production by 6.45% which represented about $126 * 10^6 bbl$ and also decreases the field cumulative water production by 16.11% which represented about $155 * 10^6 bbl$ while the model with single fully batch optimization increases the field cumulative oil production by 2.8% which represented about $55 * 10^6 bbl$ and also decreases the field cumulative water production by 8% which represented about $63 * 10^6 bbl$ for 20 years from 2020 to 2040 as shown in the Fig.s (8 and 9). The difference between the two strategies is 3.65% in cumulative oil production and 8.11% in cumulative water production. These numbers have a huge effect on the net present value of the field economy. Also, from Fig.s (8 and 9), we can notice that the difference cap between the cases increases incrementally as the year of production increases.

These results illustrate the advantages of the sequence optimization process over single fully batch optimization process in increasing the field cumulative oil production and decreasing the field cumulative water production. This advantage come from simplification the optimization process when is conducted by sequence method due to few number of optimized variable during each optimization process consequently decrease the interaction effect between them. In contrast of the single fully batch optimization process, all variables will be optimized during one-time optimization process consequently the interaction effect will be more sophisticated. Also, the using artificial intelligence represented by radial basis function network to learn from generating data by the DoE represented by the Latin Hypercube proves its capability and performance to construct a model to predict the optimum solution for the objective function of the study.

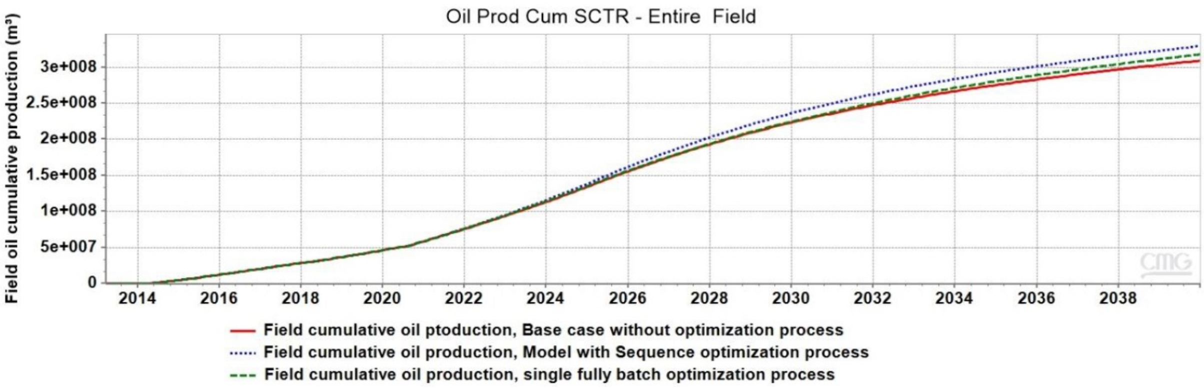

Figure 8: Comparison between sequential optimization, single fully batch optimization, and Base case without optimization process models in field cumulative oil production.

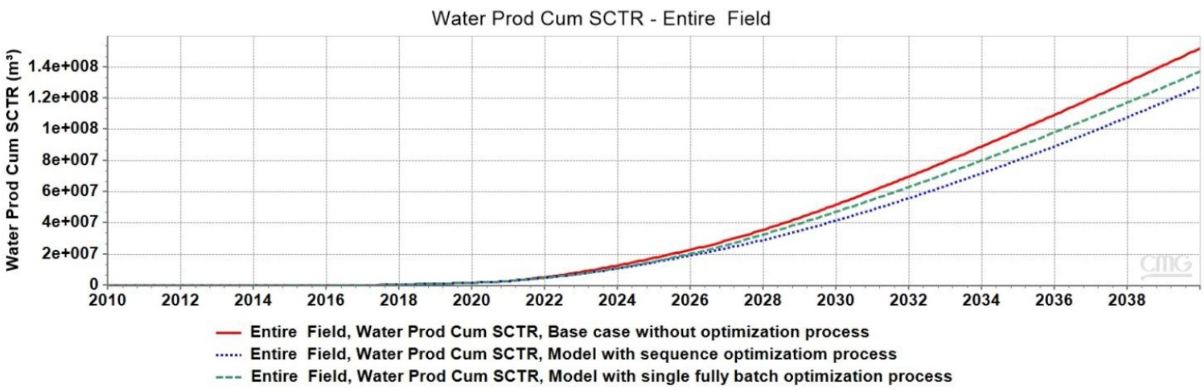

Figure 9: Comparison between sequential optimization, single fully batch optimization, and Base case without optimization process models in field cumulative water production.

6 Conclusion

In this paper, the artificial intelligence technique was used to conduct infill drilling to increase oil recovery. The technique is the Latin Hypercube Plus radial basis function network. This technique proves that it is a powerful tool to decrease time-consuming and computational costs. Also, it provides a good model which can predict the objective function which is select the best infill wells location to increase field cumulative oil production and decrease the field cumulative water production with high accuracy. This study shows that the proxy model will require more data generation to train and learn as the optimized parameter increase. So, the number of simulation runs will increase also. The sequence optimization process has more advantages than the single fully batch optimization process in achieving the best optimal solution for the objective function due to its capability to simplify the optimization process. For that, the optimization technique is extremely important to perform on infill drilling due to its effect and benefit to increase the net present value of hydrocarbon extraction.

Nomenclature and Abbreviation

ANN Artificial neural network

CMA-ES Covariance Matrix Adaptation Evolution Strategy

CMG Computer modeling group

DoE Design of experiment

ES Evolution Strategy

FDP Field development plan

GA Genetic Algorithm

L Defines the square of the distance between points x_i and x_p

LHD Latin Hypercube Design

LHS Latin hypercube sampling

M The size of the training data

NPV Net present value

PSO Particle Swarm Optimization

RBFN Radial basis function network

x_i Center parameter vector

x_p Input parameter vector

$y(x_p)$ Representing the value of an objective function

$\varphi(x_i, x_p)$ Represents the radial basis function

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