공학석사 학위논문

Well placement optimization using a CNN-based proxy model

합성곱 신경망 기반 프록시 모델을 이용한

유정배치 최적화

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이승희의 공학석사 학위논문을 인준함

2022 년 2 월

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Abstract

Well placement is important for economic development of an oil field. It is affected by various decision variables like the number of wells, well types, and its location. Therefore, optimization algorithms are conventionally used with a reservoir simulation for decision making. However, it requires a large amount of computation time. In this regard, researches on proxy models to replace a reservoir simulation are actively conducted in these days.

Optimization with a proxy model has an ability to provide desirable solutions. However, it is not always successful due to limited training data and inaccuracy of a proxy model. Although re-training of a proxy model throughout an optimization process is suggested for enhancing its accuracy, the re-training procedure degrade the advantage of the proxy model in time efficiency. At the same time, it is difficult to figure out the proper number and time of re-training.

Therefore, in this research, an initial sampling scheme, which is effective for a proxy model training, is proposed to make initial samples to include optimal solutions. Uniform sampling method is firstly tried to spread wells evenly over a whole reservoir area. This allows to obtain overall dynamic data that reflects the behavior of the reservoir for the proxy model training. As a result, the proxy model shows improved accuracy in predicting net present value (NPV) of the optimized solution in general by including optimal solutions. However, the accuracy tends to decrease in higher NPV values.

Next, 2-stage sampling method is suggested to overcome the limitation of the uniform sampling. It is tried to enhance the performance of the proxy model by more

sampling of high NPV value areas. This method includes the optimal solutions successfully by extracting samples over two times based on well configuration probability of samples in the range of high NPV. Therefore, it is proposed as an adequate initial sampling scheme as it significantly improves the prediction accuracy of the proxy model.

Validation for the proposed method is conducted with different reservoir models. Three trials of the optimization are attempted for each reservoir model. As the average of the coefficients of determination are all higher than 0.9, the stability of the 2-stage sampling method is demonstrated. Therefore, it is concluded that the proxy model with the 2-stage sampling method is reliable for replacing the reservoir simulation.

Keywords : well placement optimization, re-training, proxy model, uniform sampling, 2-stage sampling

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Chapter 1. Introduction

1.1 Importance of well placement

Well placement for developing an oil field is a challenging problem. It includes well numbers, types (producer or injector), and locations and is often determined at the early stage of field development. Well placement heavily influences oil productivity of the field, which decides economic feasibility of the business. As well configuration affects oil productivity, it is not overemphasizing to put much efforts and time to figure out optimal well numbers, types, and placement.

The importance of well placement is getting more emphasized as the global demand for energy is continuously increasing every year while more than the half of the previously discovered oil fields are depleted (Stark et al., 2008). It means that the oil productivity of currently producing oil fields are needed to be increased. Otherwise, we should maximize the productivity and the life span of newly revealed oil fields.

Optimizing well placement is one way to achieve this goal. Behaviors of reservoir fluids are largely affected by geological properties of a reservoir. In addition, reservoir fluids show dramatically different behavior even with a small change in well configurations (Nwachukwu et al., 2018). Thus, the number of wells, types, and their locations should be decided depending on reservoir fluid types or its geological properties such as permeability (Park et al., 2017).

Well configuration also affects the life span of a field. Therefore, it is crucial to

reflect possible uncertainties of all geological properties when finding an optimal well placement (Badru et al., 2003). However, heterogeneity and uncertainties of reservoir properties make a complex reservoir to yield even more complicated and non-linear behaviors. It makes finding an optimal well configuration one of the challenging projects in the field development processes.

Furthermore, well placement has to be decided very carefully due to the high cost of drilling wells and difficulty to change the location of existing wells. If the placement of a well is needed to be changed after it is drilled, the well should be abandoned according to procedures considering environmental regulations of a country with resources. Then a new well could be drilled, which costs twice and is also a time-consuming process.

Because most of the developments in the oil and gas industry are conducted with daily rental of the equipment such as drilling rigs, it causes reduction in economic feasibility of the business. Hence, deciding a well configuration requires countless tries of various cases to consider such decision-making variables. Even a small change of a well in a well configuration can yield a substantially different production result because of heterogeneous features of a reservoir. Therefore, necessity of optimization tools is magnified to find the best well configuration for an interested field (Bouzarkouna et al., 2012).

1.2 Well placement optimization

Well placement optimization is a procedure to find the best well numbers, well types, and well locations that are suitable for an interested field under consistent operational conditions. A reservoir simulation is conventionally used for the well placement optimization and production analysis due to its high accuracy.

A reservoir simulation uses finite difference method that includes numerous variables and mathematical equations to express overall process of the fluid flow (Calvette et al., 2019). It is usually utilized with various optimization algorithms to reflect many kinds of variables and complexity of a reservoir with its uncertainties. Utilized with some optimization algorithms, the reservoir simulation considers uncertainties of a reservoir with a number of initial solutions and updates the solutions with the algorithms to find an optimal solution.

For well placement optimization, a variety of algorithms have been studied including deterministic optimization methods and stochastic search algorithms. For deterministic optimization methods, gradient-based algorithms with adjoint methods are implemented by calculating gradients. However, gradient-based methods are inadequate for the problems with an objective function with heterogeneous surface.

An objective function of well placement usually has non-convex, non-smooth, and multi-modal surface. It is owing to features of properties of the reservoir fluids which are spatially heterogeneous (Onwunalu and Durlofsky, 2012). Accordingly, it is uneasy to apply gradient-based methods for this problem.

For stochastic search algorithms, genetic algorithm (GA) is popularly utilized in well placement optimization collaborated with other methods (Yeten et al., 2003;

Tukur et al., 2019). Yeten et al. (2003) use GA to optimize well type, location and trajectory. They employ various acceleration methods together: artificial neural network (ANN), a hill climber, and a near-well upscaling technique. As a result of that, the objective function always shows increment in its value by 30 % or more at its optimal solution compared to its first generation.

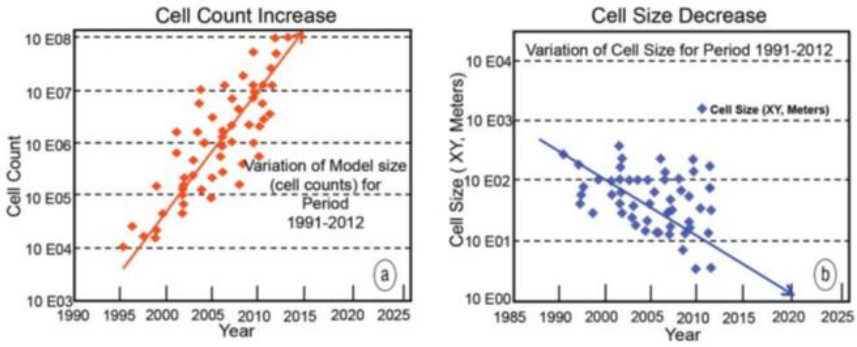
Tukur et al. (2019) apply both GA and simulated annealing (SA) in well placement optimization for optimal recovery of petroleum fluid. They verify the efficiency of their proposed method compared to the conventional method that ascertains sweetspots with visualization of the net-to-gross, porosity, and oil saturation map. Applicating more than one algorithm for the optimization is also investigated to higher the performance of optimization outputs.

Badru et al. (2003) investigate hybrid genetic algorithm (HGA) with polytope algorithm as the helper method. They show it works in both synthetic and real reservoir, thereby suggesting it as a guide for determination of sweetspots in a reservoir. There are also other researches successfully conducted with HGA, but coupled with other helper methods like Tabu search method or kriging proxy.

Many researchers have performed studies by adopting reservoir simulation. A reservoir simulation numerically computes flow of reservoir fluids using properties of a reservoir and information of well placement for an objective function evaluation. However, it is a demanding process as per the fact that it requires a large amount of computation. This limitation is intensified as the dimension of the search space is getting bigger and the size of each grid is getting smaller as time continues (Figure 1.1). Accordingly, it is vibrant recently to research conjugating proxy models with optimization algorithms instead of reservoir simulation.

Bouzarkouna et al. (2012) try to optimize well placement with covariance

matrix adaptation evolution strategy (CMA-ES) and propose two other new techniques to improve the optimization procedure. They adapt a penalization technique to manage constraints for well placement in the manner of banning to locate at physically impossible positions. Additionally, they incorporate a proxy model to CMA-ES method to reduce CPU time to compute with the reservoir simulation.



(a) Model size variation (b) Cell size variation

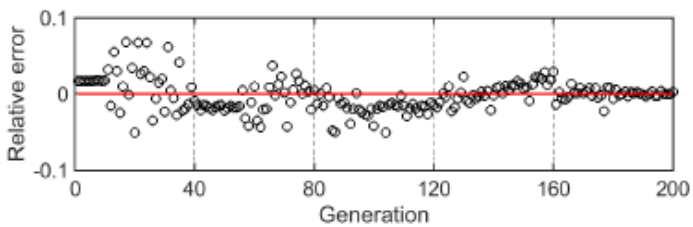
Figure 1.1 Variation of model and cell size over the period (Singh et al., 2013)

Nwachukwu et al. (2018) use diffusive time of flight (TOF) of the pressure front for dynamic information of the reservoir when training a proxy model. At the same time, they emphasize the importance of representing well-to-well connectivity to augment predictor variables, highlighting to provide dynamic data to higher the performance of the proxy model.

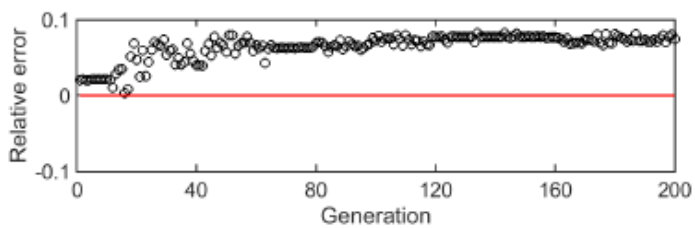
Kim et al. (2020) attempt to conjugate streamline TOF map with a proxy model to effectively reflect the dynamic information of the reservoir when training the model. They try to optimize well placement estimating NPV as the objective function. Predictability increases after streamline TOF is applied. However, it decreases again

as the solutions are updated by the optimization algorithm.

They utilize particle swarm optimization (PSO) algorithm for the optimization. Due to the feature of the algorithm, it is easy for candidate solutions to move to the area that are not trained before and if it happens, a gap between the estimated NPV and the true value will occur. Thus, they add re-training process while the optimization. Figure 1.2 shows the difference of accuracy with relative error between two cases with and without the re-training. Figure 1.2a is when the model is re-trained and Figure 1.2b is result of the model without the re-training. As they re-train the model periodically, it recovers the predictability while the accuracy of the model without the re-training remains low after it decreases.



(a) A proxy model with re-training



(b) A proxy model without re-training

Figure 1.2 Relative error by generation (Kim et al., 2020)

They propose this method to be used in place of a reservoir simulation. It is then proved that it has a certain level of accuracy in both 2 and 3-dimensional reservoir problems. In addition, it takes only 21 % of the computational time compared to the

conventional reservoir simulation.

However, it is uncertain to decide the number of re-training and when to re-train. Also, the computational time increases every time the model is re-trained, since the reservoir simulation is used for the re-training. It weakens the efficiency of the time which is one of the strongest merits of using a proxy model. On top of that, it is daunting to figure out the optimal number and time for the re-training because it has to be found empirically.

In this regard, a proxy model is constructed in this research to optimize the well placement without the re-training. To achieve the goal, analysis of the research by Kim et al. (2020) is executed first to see the construction process. They construct the proxy model with well placement scenarios for input and are randomly sampled. Sampling method used in their research is regarded as random sampling. It is a scheme to choose the number of wells, well types, and their locations randomly with random numbers. As randomly select them, the locations of wells show a tendency to place near to each other as the well number increases.

Streamline TOF map is then achieved for dynamic data. It is vital for wells to locate widely since the dynamic data can be obtained only from near-wellbore. When the wells are crowded at some area, the model can learn the response of the reservoir of that area only. However, since there is a tendency for wells to locate close to each other, it is considered as a cause of low predictability. Since the dynamic data are a key factor that concludes the ability of the model, different sampling methods for the proxy model is studied in this research.

Uniform sampling method is tried first. It is named due to its principle to locate the wells evenly as possible over the reservoir. It shows quite good predictability in general. However, the predicting accuracy slightly decreases around the range of

high NPV. Thereby, 2-stage sampling method is tried for more improvement in the accuracy.

2-stage sampling method is a scheme to sample the well configuration maps in 2 stages as the name indicates. By extracting the samples in 2 steps, the method is able to forecast the NPV better in general and especially in high range of NPV compared to the uniform sampling. It is also stable in its capability showing average coefficient of determination higher than 0.9. After several trials of optimization and validation with different reservoir models, the 2-stage sampling method is finally proposed as a substitute for the reservoir simulation.

Chapter 1 introduces the importance of well placement in developing a field and the concept of well placement optimization. Theoretical backgrounds used in this research are stated in Chapter 2. Chapter 3 discusses the methodology studied and proposed in this research and Chapter 4 shows the results. Chapter 5 organizes the conclusions of the research.

The purpose of this research is summarized as below.

1. To construct a proxy model to estimate NPV with given well configuration maps
2. To figure out a sampling method to train the proxy model that shows a certain level of estimating accuracy without re-training in between the optimization

Chapter 2. Theoretical Backgrounds

2.1 Proxy model

A proxy model is a tool used to mimic results of convoluted judgement or simulation for computational efficiency. As the number of decision variables and the area of searching space are getting bigger, plenty of repeated estimations are needed to calculate complex evaluation functions. A proxy model is emerging to simplify the evaluation procedure substitute for a reservoir simulation. It is also called as a surrogate model, meta-model, or response surface model reflecting its working principle (Bouzarkouna et al., 2012). In this research, a proxy model is used as a representing terminology.

Machine learning algorithms are usually adopted as a training method for constructing proxy models. It utilizes input and output data for the training and it approximates their relationship. Parameters used for a reservoir simulation are usually utilized as input and simulation results are employed as output. A proxy model developed as above is classified as a data-driven model (Cao et al., 2019). It is a model that approximates the relationship between the input and output data without any physical information of the phenomena.

A data-driven proxy model has strong advantage of efficiency in computational cost. It decreases the amount of numerical computation significantly since it does not calculate but approximates the relationship between the input and output data. Fast approximation is available even with the complex reservoir problem because

the model does not require additional physics-based information. It reinforces the advantage of the proxy model because it is sometimes abstruse to solve a problem in numerical way when the problem is highly complicated.

There are also some disadvantages of a data-driven proxy model. Since it does not reflect any physical information, it has lower accuracy than the results of a reservoir simulation. Moreover, it draws physically infeasible solutions occasionally. However, it is still widely used because of its beauty that it only demands much smaller number of simulations to construct the training dataset or it is used with conditions of physical constraints. Today, it is also utilized in company with physics-based model to overcome the limitation of possibility that a data-driven proxy model gives a physically impossible solution (Klie and Phillips, 2015).

Streamline TOF maps are additionally used to give the model some information about dynamic behavior of a reservoir in this research. With some constraints of well spacing and boundary condition, the model can prohibit itself to output infeasible solutions. The main purpose of using a proxy model is to compromise the accuracy and computing time for the estimation of the given objective function to replace a reservoir simulation. Also, it is used to reduce the hardness of calculation of the complex equations and computational costs.

2.2 Time of flight

Streamline TOF refers to travel time (τ) of fluids that flows along with the streamline. It provides quantitative information of the flow of the reservoir fluids which makes a significant improvement in understanding the behavior of the complex reservoir. Streamline TOF can be obtained by tracing the streamline (ζ) from a starting point to the end point based on the velocity field at a designated moment and the time can be computed as Equation (2.1)

$$\tau = \int_0^s \frac{\phi d\zeta}{|\vec{u}|} \tag{2.1}$$

where s is a point the particle arrives, $\vec{u}$ is velocity, and ϕ is porosity. The velocity can be obtained by applying the pressure field that is derived from the flow equation to the Darcy equation.

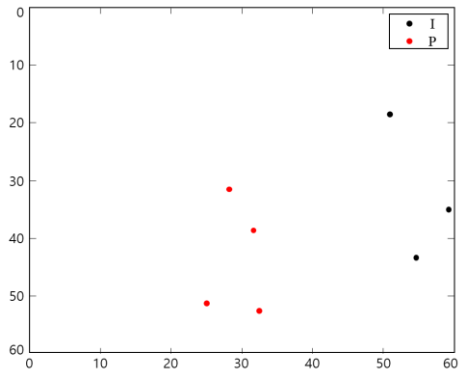
Some assumptions are applied for the calculation of a fluid particle that each velocity component is independent and linear to each direction in 3-dimensional (3D) coordinates system. Then, direction of the exit and the time can be achieved that a particle spent in a grid from every grid. Repeated process of this computing from an injector grid to producer grid gives the result of cumulative time of the particle stayed at each grid which becomes the streamline TOF (Pollock, 1998).

Reservoir fluid particles travel along with the streamline and different well placement gives different TOF map result. As it changes by the well configuration maps, TOF maps refer to dynamic information of the performance of a reservoir in 3D. However, it can be decoupled to 1-dimensional (1D) problem based on the

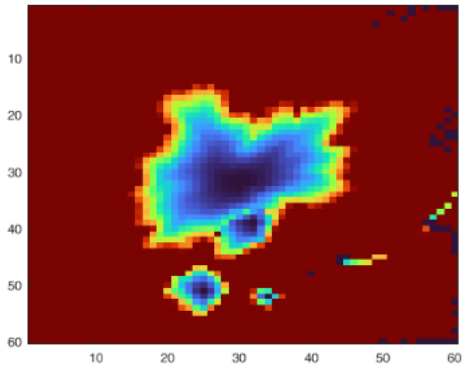
definition of the streamline simulation which makes the time for calculation proportional to the number of grids (King and Datta-Gupta, 1998).

The types of TOF maps differ by its starting point of the fluid particle. TOFP is a TOF map from producers and TOFI from injectors and they are drainage area and swept area, respectively. Both types of TOF maps are employed to reflect the dynamic behavior of a reservoir in this research. Figure 2.1 is showing a well placement scenario and two types of TOF maps when wells are placed as Figure 2.1a.

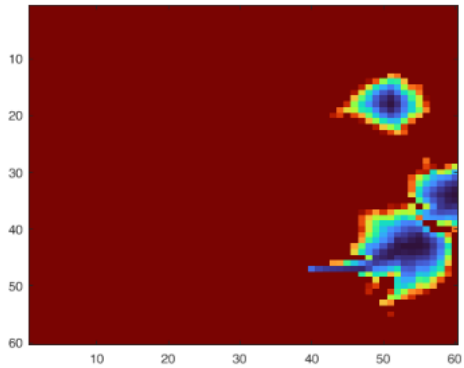
In addition, since streamline simulation is conducted under the condition of almost impressible oil and water without any change in operating conditions, TOF maps are not changeable. Accordingly, TOF maps are used when single phase flow of the oil is dominant after 30 days of the production (Ibrahima et al., 2018).



(a) Well placement scenario



(b) TOFP



(c) TOFI

Figure 2.1 TOF maps accordant to a well placement scenario

2.3 Convolutional neural network

Convolutional Neural Network (CNN) is a supervised deep-learning algorithm, which is commonly used for training image data. Lecun et al. (1998) firstly proposed the method for digit recognition and it is the start of CNN today. It is typically composed of three layers: input, hidden, and output layer. Input data that are put in an artificial neural network (ANN) is used for the input for the next layer after the matrix operation with the parameters of neurons as Equation (2.2)

$$h(I) = f(Iw + b) \tag{2.2}$$

where I is 1D result of arrangement from the former layer, w and b are weight and bias, respectively. f is the activation function and h is 1D result of arrangement in current layer. Various kinds of activation functions are utilized for ANN and rectified linear unit (ReLU) function is employed for this research.

The neural network is trained by repeated process of feedforward and backpropagation. Feedforward indicates the process of estimating the output with iterative calculation by Equation (2.2) and backpropagation is a process of minimizing the loss function. Loss function is defined by the difference between the estimation and the true value. The parameters, weight and bias for each layer are updated and optimized by a gradient-descent algorithm in backpropagation.

CNN is also a kind of deep neural network which utilizes numerous hidden layers more than just one like the typical structure mentioned above. A number of hidden layers for CNN are composed of a set of convolutional and pooling layers.

Figure 2.2 is the structure used in this research with 4 sets of the convolutional and pooling layers.

Convolutional layer is where features of the input image are extracted with several kernels. Kernels extract regional features of the input in both horizontal and vertical directions. Extracted features become a feature map (h^r) with a kernel (k^r) for an arranged r^{th} image data (I) and any feature values in the map are achieved as Equation (2.3)

$$h_{i,j}^r(I) = (k^r * I)_{i,j} = f(\sum_{m=1}^{k_h'} \sum_{n=1}^{k_v'} k_{i,j}^r \, I_{i+m,j+n}) \tag{2.3}$$

where k_h' and k_v' is the size of horizontal and vertical kernels each. In addition, zero-padding is employed for the original data to keep its size when extracting feature maps. Figure 2.3 is an example of convolution extracting a feature map from the input with zero-padding using a kernel and Figure 2.4 shows the activation function.

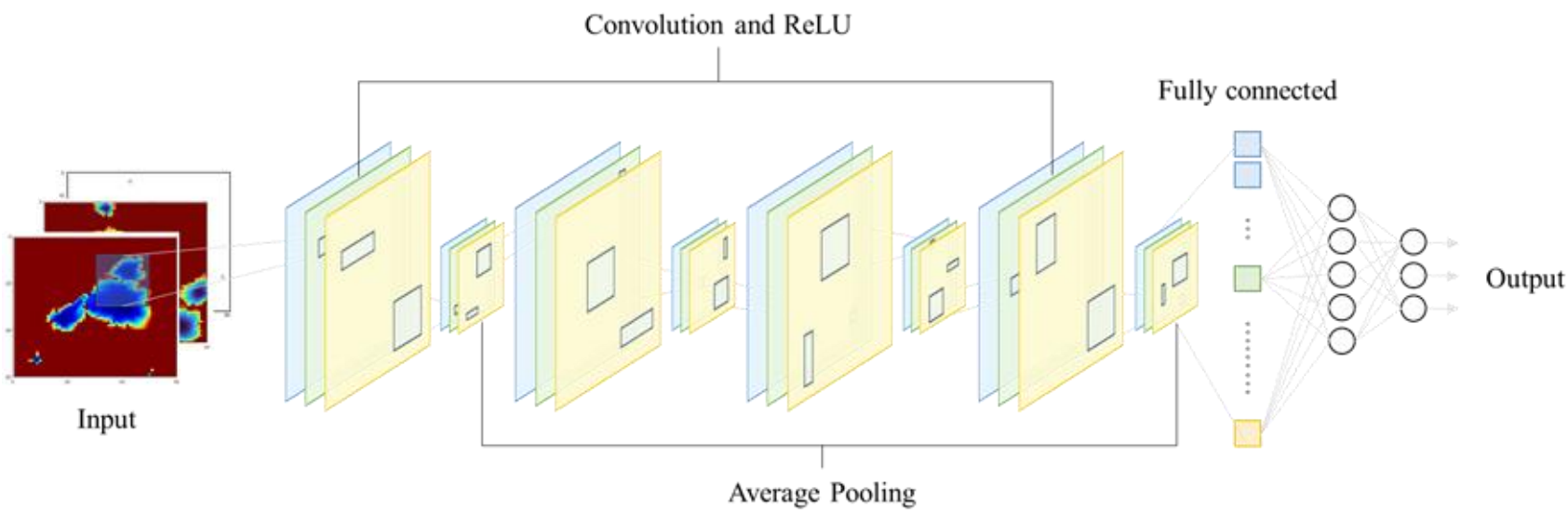


Figure 2.2 Structure used for CNN algorithm

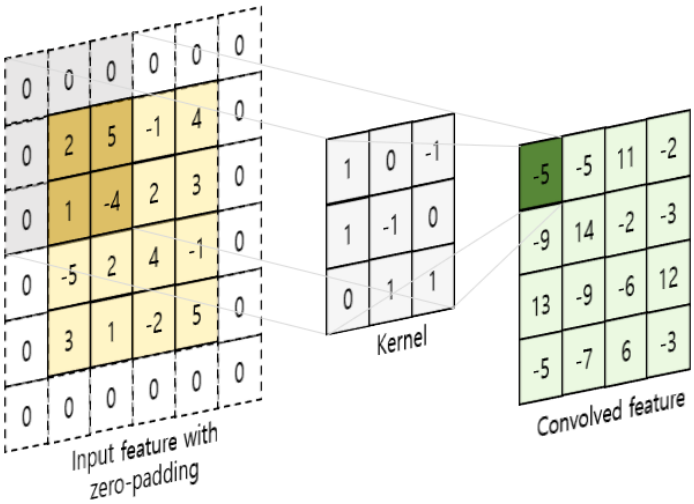


Figure 2.3 Convolution

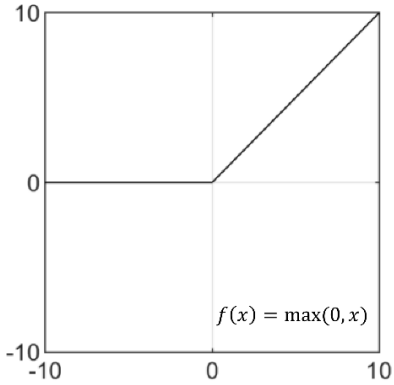


Figure 2.4 ReLU activation function (Kim et al., 2020)

Pooling layer decreases the size of the data by representing the values of sub-regions as its maximum value or average then highlight its feature of the sub-region. With this process, it relieves the change in features of the original data and also, it helps to diminish the time complexity and prohibit the overfitting. Overfitting means that the neural network or some models are trained too much so that it only fits for the trained data and cannot apply to others. Average pooling layer is used in this research. Figure 2.5 shows examples of both max pooling and average pooling.

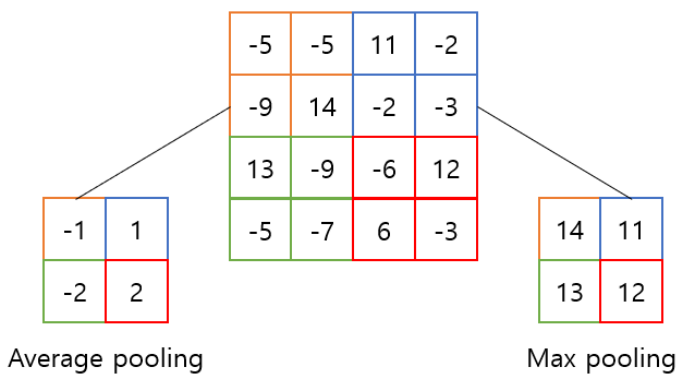


Figure 2.5 Pooling

2.4 Particle swarm optimization

Particle Swarm Optimization (PSO) algorithm is a stochastic global search method that uses solution populations for the optimization. It was proposed by Kennedy and Eberhart (1995) and originally developed reflecting the behavioral tendency of the social groups of living organisms. It is now widely used in many optimization problems (Onwunalu and Durlofsky, 2010; Kim et al., 2020).

PSO uses randomly generated N_p candidate solutions to search the space for an optimal solution. Each candidate solution is referred as a particle and all of them is called swarm. In the optimization process, each particle repeats searching the space to exchange the information they get remembering their searching histories. It has position and velocity vectors. The ith position vector of the kth generation is updated for the next generation by the ith velocity vector of the $(k+1)^{th}$ generation as Equation (2.4).

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{2.4}$$

where x is the position and v is the velocity vector.

For the updates, weights are also used as Equation (2.5)

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(x_{i,pbest}^k - x_i^k\right) + c_2 r_2 \left(x_{i,gbest}^k - x_i^k\right) \tag{2.5}$$

where ω, c_1, and c_1 are weights that affect the performance of the algorithm. The weights are designated as $\omega = 0.729$, $c_1 = c_2 = 1.494$ each in this research and

are referred to the research of Kim et al. (2020). r_1 and r_2 are randomly extracted numbers between 0 and 1 to give the process of the search arbitrariness.

The velocity vector affects the position vector and it composes of three terms: inertia, cognitive, and social. Each term reflects the velocity vector in former generation, the best solution for the current generation, and the best solution for the whole generation, respectively. Figure 2.6 shows updating process of PSO algorithm in the ith generation with a particle.

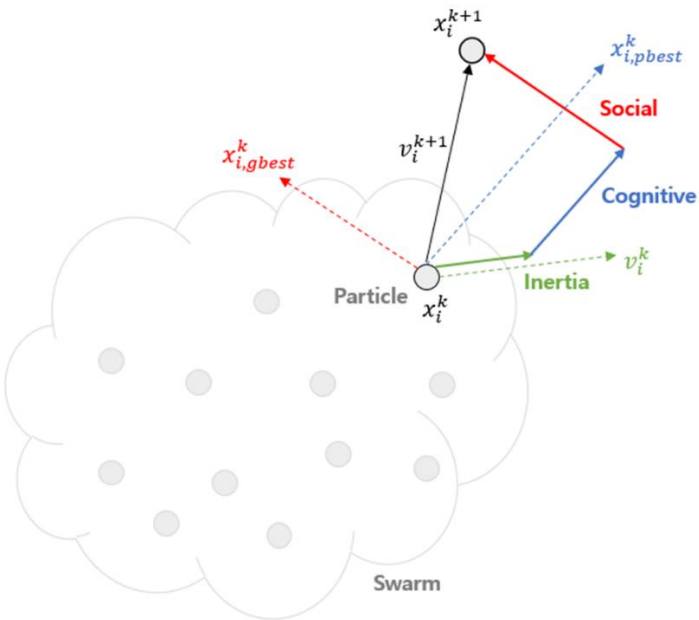


Figure 2.6 Schematic of updating a particle in the ith generation

In this research, 40 candidate solutions are used and NPV is estimated with the particles of PSO algorithm. Constraints of well spacing and boundary condition are applied during the optimization and the calculation for NPV is conducted as Equation (2.6)

$$J(x) = \begin{cases} \sum_{t=1}^{T} \frac{(C_o Q_o^t - C_w^p Q_{wp}^t - C_w^i Q_{wi}^t)}{(1+d)^t} - N \times C_d & (RS) \\ F_{CNN}(x') & (CNN\ proxy) \end{cases} \tag{2.6}$$

where x is the optimization vector, x' is the pre-processed data arrangement for the proxy model. C_o, C_{wp}, C_{wi}, and C_d refer to the cost of oil, process of water disposal, water injection, and drilling, respectively. Q^t is the quantity of the flux produced or injected between $[t-1,\ t]$. T is the overall period of the production, d is the rate of annual discount, and N is the number of wells are drilled.

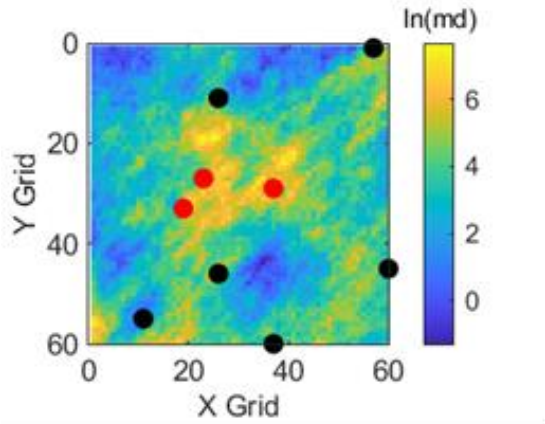
Chapter 3. Methodology

3.1 Sampling methods

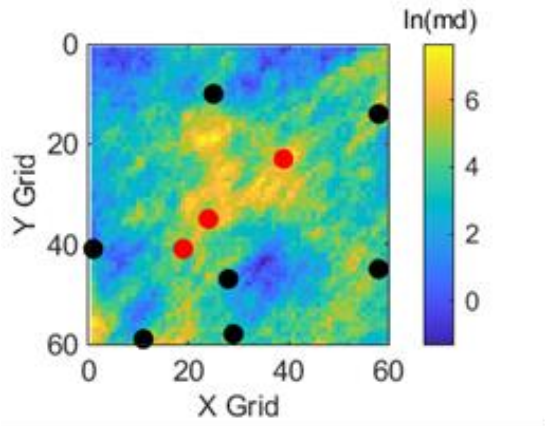
A CNN-based proxy model is used to echo the behavior of the reservoir simulation. Well configurations are extracted first to utilize them as input data for training the proxy model. Because the quality of data affects the predictive capability of the model, extracting fine quality of samples is vital.

A sample indicates a well placement scenario in this research, and each sample has different number of wells, types, and locations. Figure 3.1 shows three other samples for a 2D synthetic reservoir extracted with a random sampling method. The color variation of the reservoir demonstrates the permeability of the field. The dots indicate the wells, and the types are differentiated with the colors. The reds and blacks are producers and injectors, respectively.

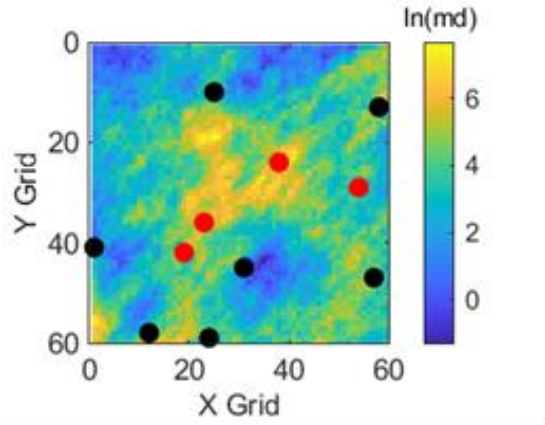
Random sampling is a method that Kim et al. (2020) used in his research. He generates all samples at a time and designates well numbers, types, and locations randomly. As setting all the variables for a well configuration randomly with the least constraints, it can cause a bias issue of the well placements. They are sometimes concentrated nearby each other. It then leads to a problem that the proxy model cannot experience adequate and even dynamic data across the entire reservoir.



(a) 9 wells



(b) 10 wells



(c) 11 wells

Figure 3.1 Well placement scenarios with different number of wells

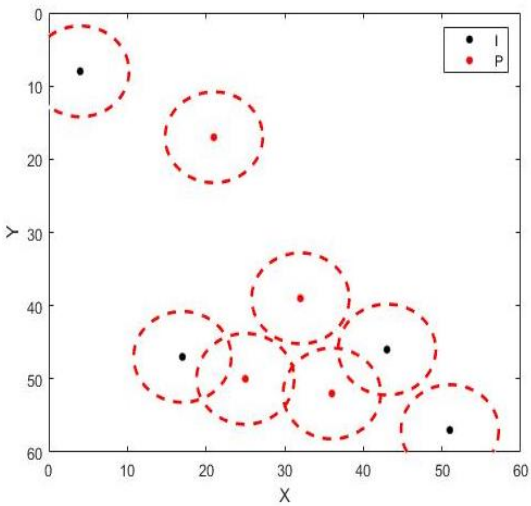
For better understanding of the bias issue, the procedure of the random sampling method is briefly introduced here. First, it arbitrarily selects 14 grid points among 3,600 points of the reservoir and assign random numbers between -1 and 1. These points become the locations of the wells. Next, the types of the wells are decided with the previously assigned random numbers by dividing the range into three sections. If the number is bigger than 1/3, smaller than -1/3, or in between 1/3 and -1/3, a corresponding well is assigned to be a producer, injector, or not drilled, respectively. In this step, the number of wells is also chosen by trisecting the range of given random numbers and adding "no well" option.

A streamline TOF map is adopted for dynamic data in this research. It shows flow of fluids between wells that informs about the behavior of a field. Hence, gaining good quality and quantity of dynamic data is critical for predicting capability of a model. However, it is obtainable only from the nearby grids where the wells are located. The problem is, when the samples are obtained with the random sampling method, there are possibilities that the wells are biased to few grid points, which incurs the proxy model to acquire inadequate dynamic data.

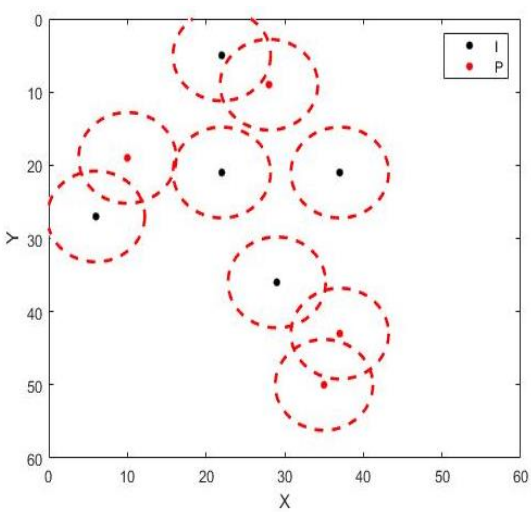
Consequently, the quality of the dynamic data is decided by well configuration. Appropriateness of the distances between the wells would be the key factor that determines the ability of a proxy model. If the wells are positioned too far, spots that streamline TOF is shown would be isolated around each well, so it would not be able to show the connectivity of a reservoir. Yet, the spots will be overlapped if the wells are too close, owing to the limited flowing area to well surroundings. Thus, it may include the information of a reservoir partially. Figure 3.2 illustrates the well configuration examples of the random sampling, and it can be identified that some wells are lopsided in the both cases. The number of wells is 8 and 9, respectively.

The red dotted lines around every well show the application of the well spacing constraint while sampling.

As the bias problem is clearly shown in Figure 3.2, different techniques to obtain samples are studied. In this respect, various ways for sampling are considered and discussed in this section. Besides, how evenly wells are occupied is mainly concerned for better quality of samples.



(a) 8 wells



(b) 9 wells

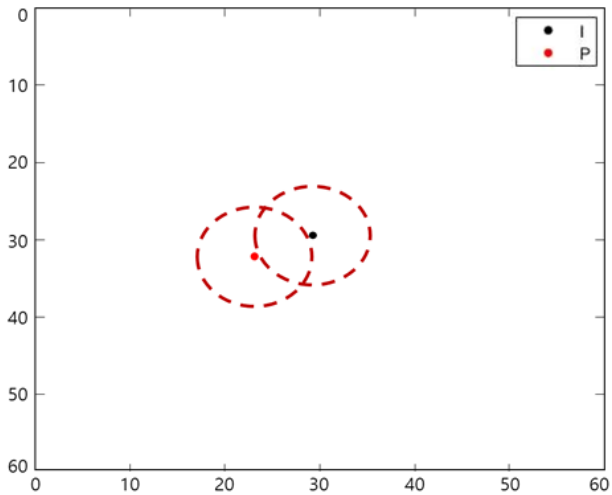
Figure 3.2 Examples of well configuration of the random sampling

A. Uniform sampling

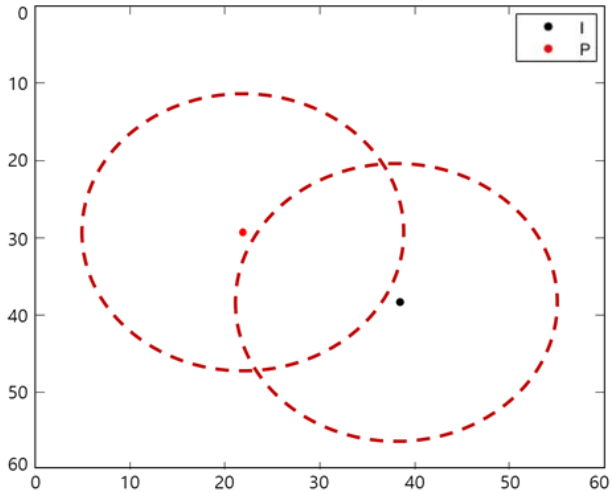
In the consideration of evenly placed well configuration over the whole area of a reservoir, a uniform sampling method is applied. Kim et al. (2020) applies the random sampling method with a constraint to have a minimum well spacing for wells to spread freely. Rather, it gives the wells more opportunities to be assembled together. Thus, dispersing the wells in a proper way is studied in this research, and a uniform sampling method is attempted.

Uniform sampling is a way to place wells wider adjusting minimum well spacing between the wells. By calibrating the well spacing, the wells could have a further distance between each other than before even if a side of the wells is overlapped as much as they can. It is depicted in Figure 3.3 compared with the random sampling. The both cases have 2 wells and they are adjacent to each other. The only difference between the two methods is that they are assigned with the different minimum well spacing values.

Well spacing is a minimum area of a well should occupy in a reservoir. It was introduced due to regulations of the U.S. government to prohibit excessive exploitation of a reservoir (Hyne, 2012). Oil wells commonly use 10, 20, or 40 acres, and gas wells use 640 acres. If the well spacing is regulated as 40 acres, it indicates that the area per well for a reservoir should be bigger than 40 acres. To be specific, when the area of the reservoir is divided by the total number of the wells, it should be bigger than 40 acres. It allows the wells to be placed next to each other so that some part of the well space circles is wrapped over. In the bargain, wells do not always have to be at the center of the space, but it cannot be at the edge of the area.



(a) Random sampling



(b) Uniform sampling

Figure 3.3 Difference in well spacing between 2 sampling methods

Well spacing area of the random sampling is 40 acres. It can be converted to field unit. Then radius of well spacing is computed as 744.7 ft when the well spacing area is expressed as a circle. A proper spacing area is practically marked as a square. However, in this research, it is expressed as a circle for convenience with red dotted lines supposing the well is located at the center. This is still not breaking the rule of 40 acres, since the maximum number of wells is set as 14 in advance while the reservoir can hold maximum 29 wells according to the well spacing regulation. The maximum number of wells is empirically decided after several trials of optimization, which often ends up being 13.

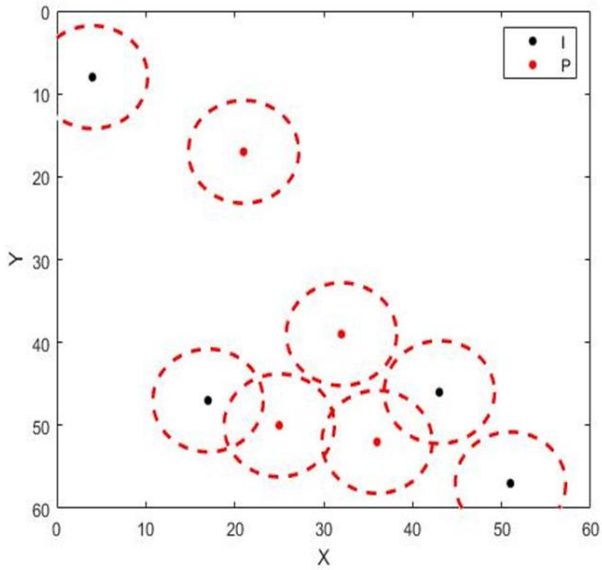
A different computing approach for well spacing radius is tried for the uniform sampling. The purpose of this method is to place the wells uniformly over the reservoir so that the proxy model can obtain the dynamic data from a larger section of the reservoir. It is tried as enlarging the minimum well spacing area.

In the uniform sampling method, the area of the reservoir is divided by the number of wells and is used as the well spacing area. A radius of the well spacing is then calculated and used as the minimum well spacing radius. By doing so, each well can be positioned with a certain distance from each other, and it helps them to locate across the whole reservoir. The number of wells used in this method is from 5 to 14. The same maximum well number is used in every method for consistency, and the minimum well number is also decided based on experiences.

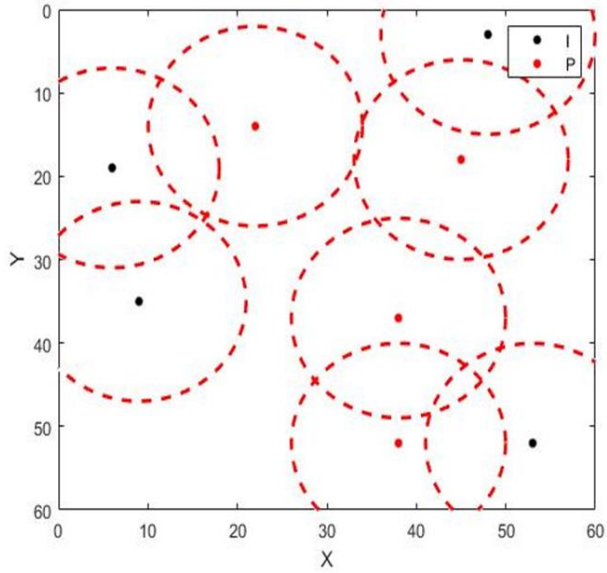
Another differentiation of the uniform sampling is that it extracts each case, from 5 to 14 number of wells, equally unlike random sampling. For the random sampling, the number of wells is also decided automatically with the locations in the algorithm by assigning random numbers between -1 and 1. However, in the uniform sampling, it designates the locations and types of wells with random number but does

not trisect the range of random number since the number of wells is fixed first. The range is divided into two depending on whether it is greater or smaller than 0. If the number is less than 0, well type is decided as an injector, otherwise, it is a producer.

Each sampling method uses 2,000 samples. In other words, 200 samples are extracted for each well number case in the uniform sampling. Figure 3.4 represents the well placement scenarios of the random and the uniform samplings with 8 wells. For the uniform sampling, it is ascertainable that the wells are spread relatively all over the reservoir even with the small change in constraint (Fig. 3.4b). At the same time, because it utilizes all cases in the same quantity, this method is named as "Uniform sampling". The detailed procedure of the uniform sampling method is described in Table 3.1.



(a) Random sampling



(b) Uniform sampling

Figure 3.4 Well placement scenarios with 8 wells

Table 3.1 Procedure of the uniform sampling

Sample the data

For i = 5:14, where i is the number of wells

1. Draw WA_i by dividing the area of the reservoir by i, where WA_i is well spacing area
2. Calculate R_i by extracting square root of (WA_i/π), where R_i is well spacing radius

For j = 1:200, where j is the number of samples for i wells

3. Generate random integer INT_j between 1 to 3,600, where INT_j is the integer for j^{th} well placement sample
4. Divide INT_j by nx, where nx is the grid size of a side of the reservoir
5. Draw $(x, y)_i^j$ letting the quotient to be x and the remainder to be y, where x^j and y^j are the areal coordinate locations for i wells
6. Generate random number for tp_i^j, where tp is the type of well

   If $tp_i^j \geq 0$

   $tp_i^j = 1$

   Else

   $tp_i^j = -1$

   End if, where the number indicates producer for 1 and injector for -1
7. Well placement scenario $(x, y, tp)_i^j$ for j^{th} scenario is completed

   Check constraints for minimum well spacing and boundary

   If all constraints are satisfied

   Go to $j + 1$

   Else

   Resample for j^{th} scenario

   End if

End for

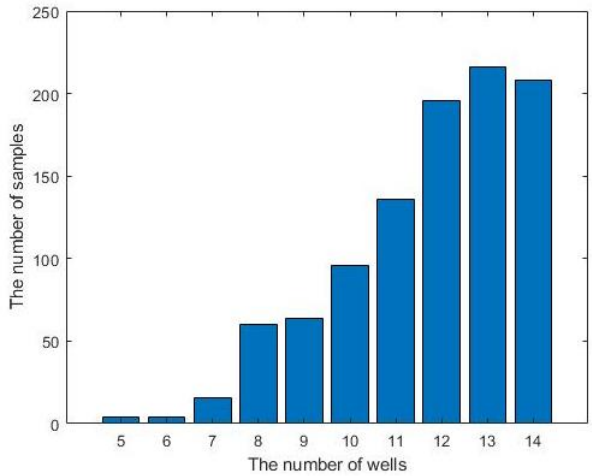
End for

B. 2-stage sampling

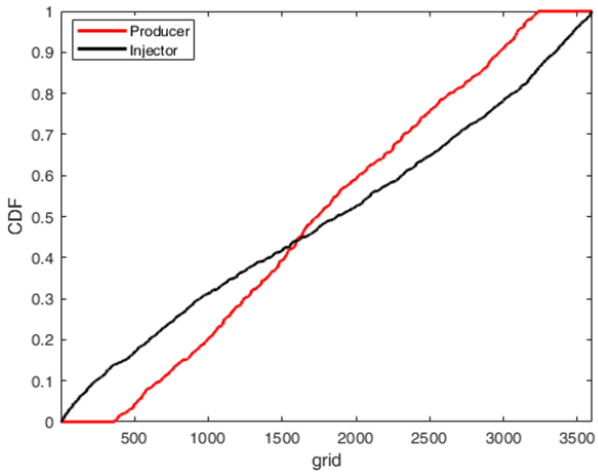
A 2-stage sampling method is tried to overcome the limitation of the uniform sampling method. When well placement is optimized with the proxy model constructed with the uniform sampling, it shows fine predictability overall. However, when it comes to the higher NPV values, the accuracy of the prediction decreases slightly. Since the objective of this research is to anticipate NPV precisely around the optimal solution which mostly has high NPV value, extracting samples in 2-stages are discussed additionally.

To guarantee a certain level of predictability, primary sampling is done with the uniform sampling method for the first step. At this time, 100 samples are extracted for each well number case so total 1,000 samples are selected. Before the second sampling, analysis on the primary samples with high NPV is performed to see the distribution of well numbers and the probability of the wells to locate in each grid per well types.

For the analysis, primary samples are resorted in the highest order of NPV. Then the top 25 % of them are used. Figure 3.5 presents the results of the analysis. As shown in Figure 3.5a, the distribution of the selected top quarter samples is mostly populated when the number of wells is between 12 to 14 and 13 at most. Figure 3.5b exhibits the probability of wells to locate in each grid in cumulative probability separately in its types. As the size of reservoir is 60×60×1 in grid system, there are total 3,600 grids. Numbers are assigned to the grids from 1 to 3,600 in the upside-down book order and possibility of each type of wells to locate in each grid is calculated.



(a) Well number distribution



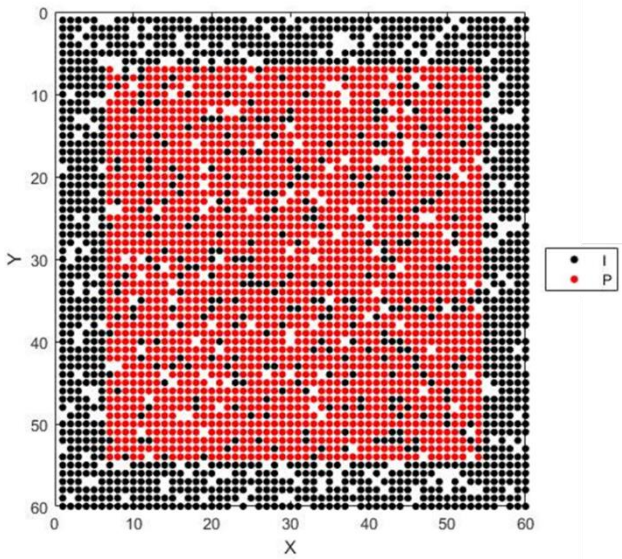
(b) Cumulative distribution function of well placement by its types

Figure 3.5 Results of top 25 % of primary samples analyzed

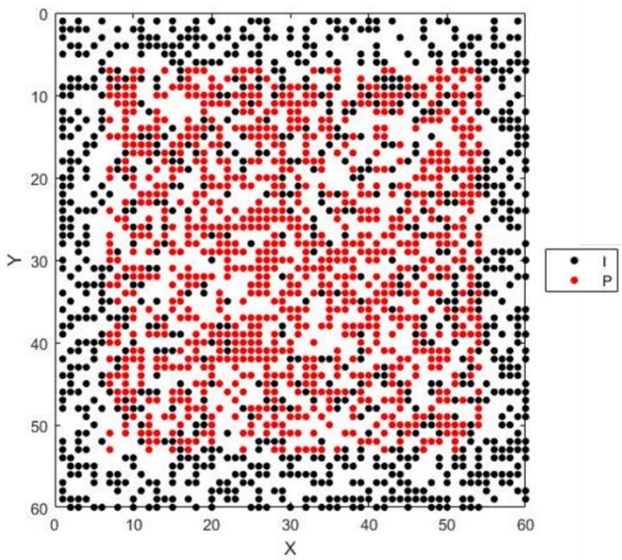
For the second sampling, additional 1,000 samples are extracted based on the analyzed results of the top 25 % of the primary samples. Whole samples in the both stages are used for the proxy model training. The total number of samples is 2,000 as the other methods tried beforehand. Unlike the primary sampling that all the well number cases are extracted uniformly, the distribution of the second samples with different well numbers follows the result of the analyzation. Hence, more samples with a greater number of wells are extracted.

Figure 3.6 shows the distribution of wells in each grid of both primary and second sampling. Entire wells of 1,000 samples are marked and well types are differentiated by the colors: reds are producers and blacks are injectors. Although the number of samples of the two stages is same as 1,000 each, the number of grids that any type of wells is placed in the second sampling seems much smaller even at the first glance. In fact, the number of grids that wells are placed in the primary sampling is 3,294 and is 1,918 in the second sampling.

With the result of the well distribution in Figure 3.6, it is apparent that a smaller number of grids are used with the same number of samples for the second sampling. This indicates that well placement for higher NPV is concentrated in some part of the reservoir grids and the 2-stage sampling method reflected this probability successfully. Detailed sampling process of the 2-stage sampling method is commented in Table 3.2.



(a) Primary sampling



(b) Second sampling

Figure 3.6 Distribution of the wells in each grid by its types

Table 3.2 Procedure of the 2-stage sampling

Sample the data
< Primary sampling >

For *i* = 5:14, where *i* is the number of wells

1. Calculate R_i as same as uniform sampling

For *j* = 1:100, where *j* is the number of primary samples for *i* wells

2. Generate well placement scenario $(x, y, tp)_i^j$ with uniform sampling and check constraints in the same way, where tp is the type of well
3. Resample the constraints-violated primary samples if any

End for

End for

< Second sampling >

For $all\ primary\ samples$

1. Resort in the highest order of NPV and tear off the top 25 % as PS^k, where PS is the primary sample and superscript k refers to the rank from 1 to 250
2. Figure out the DWN^{PS^k}, where DWN is the distribution of well number, and superscript PS^k is the detached primary samples
3. Figure out the $CDFWT^{PS^k}$, where $CDFWT$ is the cumulative distribution function of well types

End for

For $\omega = 1{:}\,1{,}000$, where ω is the number of second samples

4. Decide DWN^{SS} based on DWN^{PS^k} by multiplying 4 to each case, where superscript SS refers second sampling
5. Decide well placement scenario $(x, y, tp)_i^\omega$ according to the $CDFWT^{PS^k}$
6. Check if the constraints are satisfied and if not, resample the SS

End for

3.2 Model construction

A synthetic two-dimensional (2D) reservoir model is used in this research. The reservoir model is generated with sequential gauss simulation (SGS) to consider the uncertainties that undeveloped fields may have. Commercial software SGeMS from Stanford University is used for SGS to generate the reservoir models. Total 100 models are generated with the simulation setting the mean and the variance of the permeability as 3.5 and 1.5 in log scale, respectively. Then, one model is randomly selected and Figure 3.7 is the selected model for this research. The size of the reservoir is 60×60×1 in grid system and it has 120, 120, 40 ft in x, y, and z directions.

Eclipse 100 and FrontSim from Schlumberger are used for reservoir and streamline simulation required for the proxy model construction and well placement optimization. Table 3.3 shows the reservoir parameters used for the simulation and Table 3.4 indicates the parameters for the optimization. The specific values used are referred from the values Kim et al. (2020) utilized in his research.

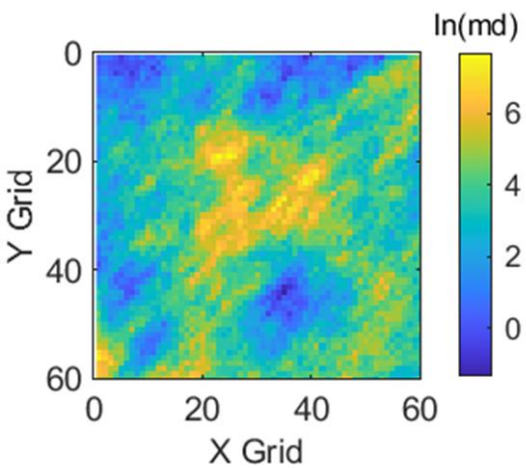


Figure 3.7 2D synthetic reservoir model

Table 3.3 Petrophysical parameters for the simulation

Parameters		Values
Initial reservoir pressure, psia		3,500
Initial water saturation, fraction		0.25
Initial porosity, fraction		0.2
Rock compressibility, 1/psi		3.00E-05 at 3,500 psia
Formation volume factor, rb/STB	Oil	1.0085 at 3,500 psia
	Water	1 at 3,500 psia
Fluid compressibility, 1/psi	Oil	1.00E-06
	Water	5.00E-07
Fluid viscosity, cp	Oil	3
	Water	1
Fluid density, lb/ft^3	Oil	48.62
	Water	62.31

Table 3.4 Simulation and optimization parameters

Parameters	Values
Production BHP, psia	1,500
Injection BHP, psia	5,500
Oil price, $/STB	60
Water disposal cost, $/STB	5
Water injection cost, $/STB	3
Drill cost, $ MM/well	2
Discount rate, %	10

For the proxy model construction, datasets are needed for training. On a basis of well placement scenarios extracted with diverse sampling methods, additional data should be acquired. The random sampling method with 2,000 samples is also tried for the comparison.

With the well placement scenarios, streamline TOF maps and the results of reservoir simulation corresponding to the equivalent well placement scenarios should be acquired. Two kinds of TOF maps are generated for a well placement scenario. They are distinguished between TOF production and TOF injection in accordance with the starting point of the streamline trace. Numerically computed NPV, the key information to recognize the optimal well placement scenario, is able to be obtained from reservoir simulation. Each sampling method should have 2,000 datasets after the simulations are done and one set of data is composing a well placement scenario, corresponding TOFP, TOFI maps, and NPV to the scenarios.

One more preprocess is needed before the training. Obtained well placement scenarios should be converted to well configuration maps for image-based training before the model construction. Well placement scenarios are composed of well placement in coordinates and the well types in arrangement. Table 3.5 shows an example of a well placement scenario how it is formed actually. Converting the scenario into the image means to put -1 or 1 at the corresponding 2D coordinate to mark the positions. Figure 3.8 is converted well configuration map equivalent to the well placement scenario in Table 3.5.

Table 3.5 Example of a well placement scenario of the 2-stage sampling

x_1	y_1	x_2	y_2	x_3	y_3	x_4	y_4	x_5	y_5	x_6	y_6	x_7	y_7	x_8	y_8	x_9	y_9	x_{10}	y_{10}	x_{11}	y_{11}	x_{12}	y_{12}	x_{13}	y_{13}	x_{14}	y_{14}	well types													
39	24	26	57	18	3	60	41	12	60	60	60	10	33	58	5	54	51	60	25	23	19	38	60	24	47	60	39	0.52	-0.16	-0.40	-0.11	-1.00	-1.00	-0.48	-0.99	0.89	-0.36	0.46	-1.00	0.34	-0.56

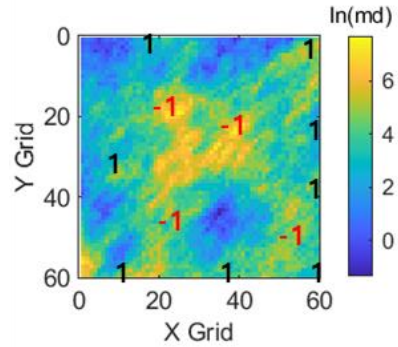


Figure 3.8 Well configuration map of the well placement scenario in Table 3.5

After the full datasets are achieved and converted, the proxy model can be constructed putting well configuration and TOF maps as input and NPV as output. The datasets are divided into three groups for training, validation, and test in ratio of 70, 15, and 15, respectively. The model is firstly trained with the training set to optimize parameters in neural network by minimizing root mean squared error (RMSE) in Equation (3.1).

$$RMSE = \sqrt{E\left[\left(y_i - F\left(x_i'\right)\right)^2\right]} \tag{3.1}$$

where, x' is the input data for the neural network model F, y is the right answer for the input, and E is the expectation value. Validation data is used to prohibit overfitting of the model to the training data. The model is calibrated as many as given epoch and selected a model that has the least RMSE. However, it can also cause overfitting for the validation data, so test data which is not used for the training is utilized again for the estimation. The estimation is conducted by the coefficient of determination (R^2) as Equation (3.2).

$$R^2 = 1 - \frac{\sum_i \left(y_i - F(x_i')\right)^2}{\sum_i (y_i - \bar{y})^2} \tag{3.2}$$

where, $\bar{y}$ is the average of the answers. After several trials with different mini-batch size and learning rate, the final proxy model for each method is selected by the R^2 shows higher than 0.85 in this research.

CNN is chosen for training algorithm due to its strength in learning image data as the input data are images. Detailed process of the construction is described in

Table 3.6. Ways to sample the data are all different but once the data are achieved, the construction procedure of the proxy models is identical.

Table 3.6 Construction procedure of the proxy models

Achieve the data

For *i* = 1:2,000, where *i* is the number of well placement scenarios

1. Convert a well placement scenario to a well configuration map WCM_i
2. Obtain TOF maps $(TOFP, TOFI)_i$ for all scenarios
3. Create initial dataset $d_i = (TOFP, TOFI, WCM)_i$
4. Evaluate NPV_i for the initial dataset
5. Combine the initial dataset as $TD_i = \{d, NPV\}_i$, where TD is the training data

End for

Train the proxy model

1. Randomly divide the TD in TR^{70}:VAL^{15}:$TEST^{15}$, where TR is training, VAL is validation, $TEST$ is test data for TD and the superscripts are the percent of the data
2. Train the model with TR^{70} using CNN algorithm
3. Validate and test the trained proxy model with VAL^{15} and $TEST^{15}$
4. Check the model's coefficient of determination if it is adequate enough to replace the reservoir simulation

   If R^2 of the model ≥ 0.85

   Finish the construction

   Else

   Retrain the model

   End if

Construction of the model is completed

3.3 Optimization with proxy models

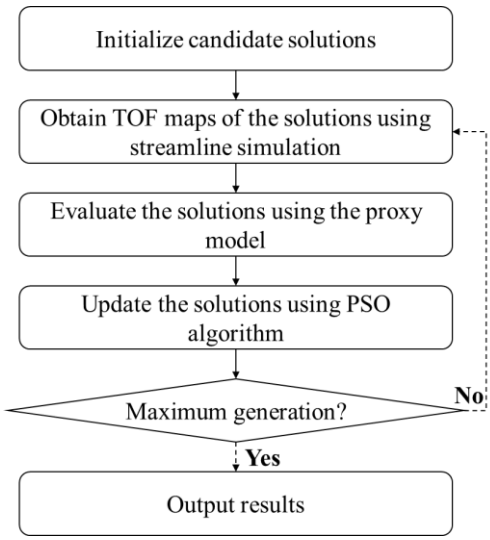
Optimization of the well placement is conducted with the built proxy models. PSO algorithm is utilized for the optimization and 40 candidate solutions are used. Number of the candidate solutions for PSO algorithm is figured out with several trials that 40 is enough to find an optimal solution stably.

The purpose of this research is to build a CNN-based proxy model without re-training while the optimization process. Consequently, optimization is executed without the re-training process that Kim et al. (2020) employ for 4 times in between the updates of the candidate solutions. Figure 3.9a shows the overall flow chart of PSO algorithm conducted with the proxy model in this research. Flow chart of PSO algorithm with the proxy model that Kim et al. (2020) propose is also shown in Figure 3.9b for the comparison.

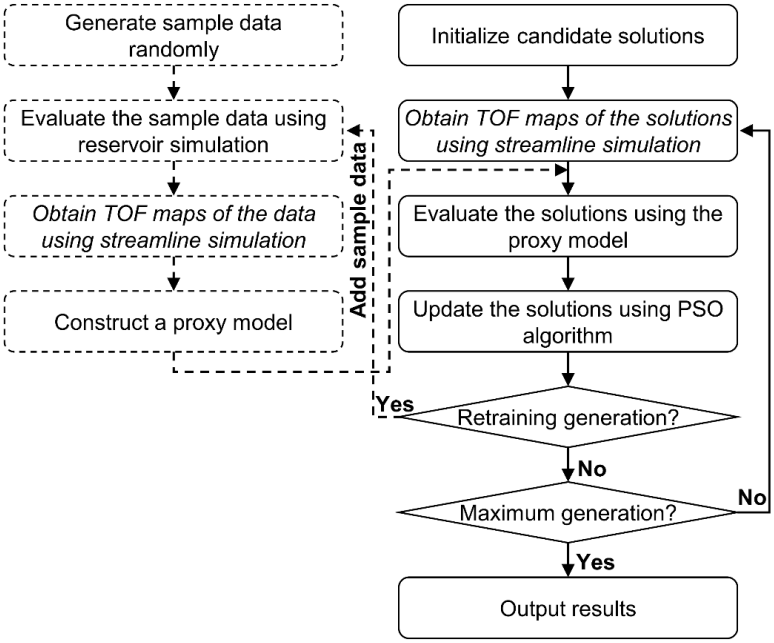
For the realistic well placement optimization, constraints like well spacing and boundary condition are considered. However, because of the features of PSO algorithm, it can violate the constraints while updating the candidate solutions. A candidate solution refers to a well configuration map in this step. Candidates violated the constraints are classified as infeasible solutions and eliminated when PSO algorithm updates the solutions. The process is conducted to find the best solution among the remaining candidates. Then the candidate solutions are updated for the next generation based on the best one.

As updating the candidates with the best solution in former generations repeatedly, they are gradually improved. The maximum generation given in this research is 200 to ensure that the candidates are updated sufficiently to find the

optimal solution. Detailed procedure for the optimization using the proxy model is expressed in Table 3.7.



(a) Re-training excluded



(b) Re-training included (Kim et al., 2020)

Figure 3.9 Flow chart of PSO algorithm using the proxy model

Table 3.7 Optimization process using the proxy models

Initialize the candidate solutions

For $N_p = 40$, where N_p is the number of candidate solutions

For i = 1, where i is the number of generations

1. Randomly sample the N_p candidate solutions
2. Obtain TOF maps $(TOFP, TOFI)_{N_p}^{i}$ for all candidates
3. Create the input dataset $I^i = \left(TOFP, TOFI, N_p\right)^i$
4. Predict NPV^i with the proxy model
5. Check infeasible solutions and eliminate them
6. Figure out the best solution P_b^i among the remaining candidates, where P_b^i is the best solution in ith generation
7. Update the candidate solutions for the $(i+1)$th generation

End for

For i = 2:200, where i is the number of generations

8. Obtain TOF maps $(TOFP, TOFI)_{N_p}^{i}$ for all candidates
9. Create the input dataset $I^i = \left(TOFP, TOFI, N_p\right)^i$
10. Predict NPV^i with the proxy model
11. Check infeasible solutions and eliminate them
12. Figure out the best solution P_b^i among the remaining candidates, where P_b^i is the best solution in ith generation
13. **If** $i < 200$

    Update the candidate solutions for the $(i+1)$th generation

    Else

    The best solution is finalized as the optimal solution

    End if

End for

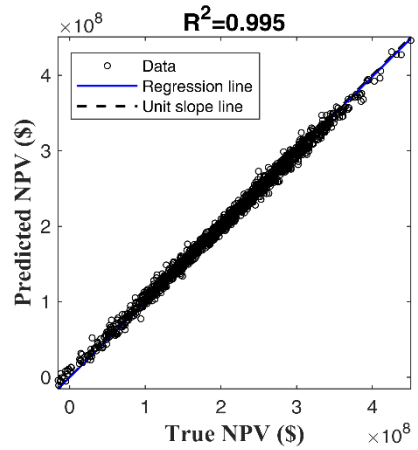
End for

Chapter 4. Results

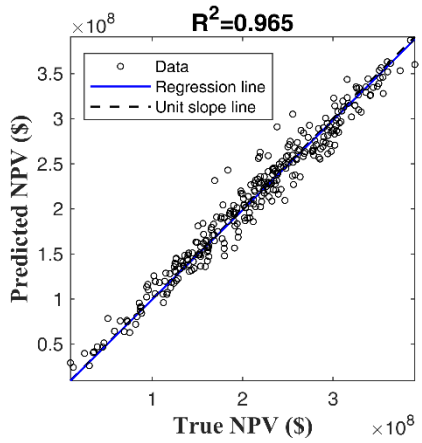
4.1 Results of the uniform sampling

The results of the constructed proxy model and optimizations of the uniform sampling are stated in this section. To show the improvement of the method, the results of the random sampling without the re-training process are also shown here. Selected models are the ones have the highest R^2 for the test dataset.

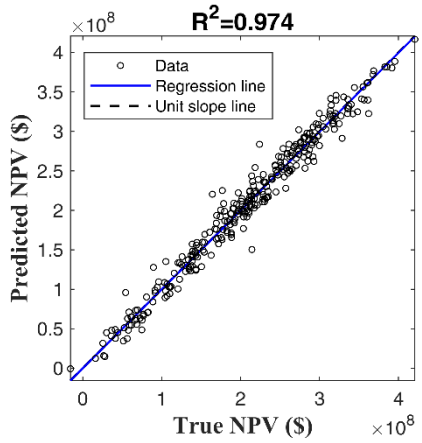
Figures 4.1 and 4.2 show the values of R^2 in training, validation, and test data of the constructed proxy models for the random and the uniform sampling methods, respectively. It shows how well the models are trained. It is regarded that the constructed proxy model is appropriate to be used for an optimization when R^2 value of the model is higher than 0.85. The both models trained by the random and the uniform sampling methods show similar value of R^2 higher than 0.9. Therefore, it is considered that the models are well-trained. Optimization is then tried immediately with the proxy models in evaluation of the objective function.



(a) Training

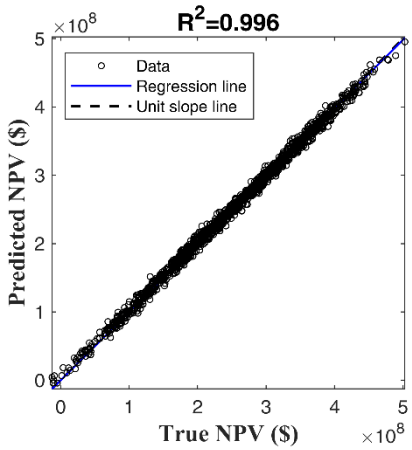


(b) Validation

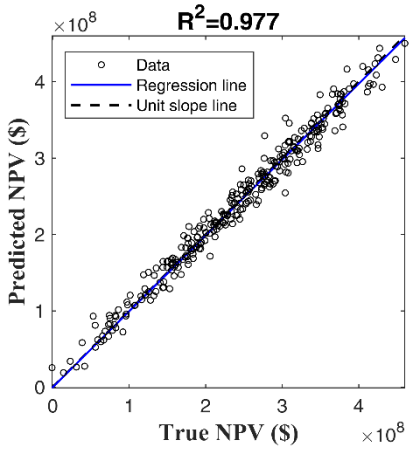


(c) Test

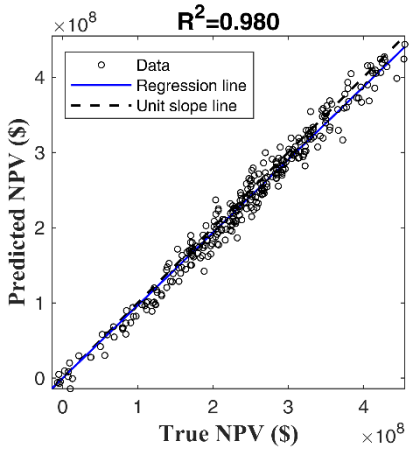
Figure 4.1 Performance of the constructed model – Random sampling



(a) Training



(b) Validation



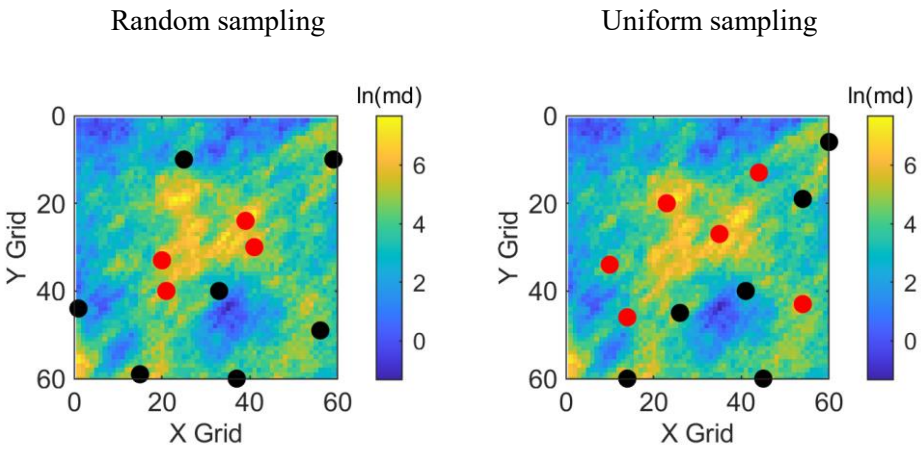
(c) Test

Figure 4.2 Performance of the constructed model – Uniform sampling

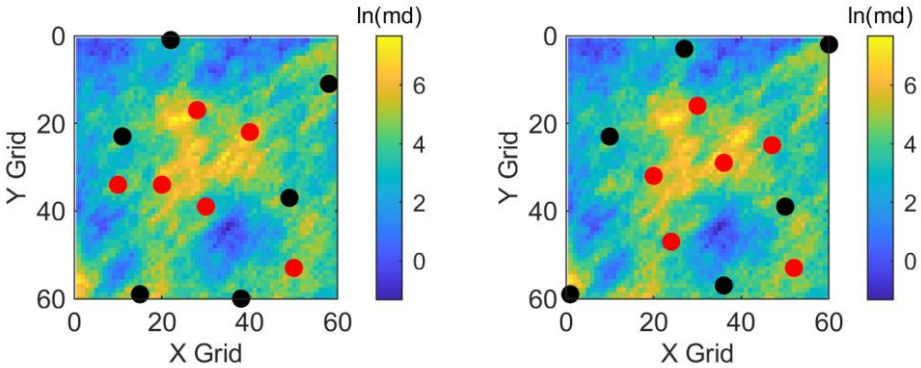
In consideration of the stochastic characteristic of PSO algorithm, well placement optimization with the proxy models is conducted three times for each method. Figure 4.3 shows the results of the proxy models constructed by the random and the uniform sampling methods. Each trial is notated as Run #1, #2, #3 for convenience. It presents the optimal well configurations for the well placement optimization in the 2D synthetic field. The red and black dots are producers and injectors.

Figure 4.3 is the results of PSO algorithm after the updates with 200 generations. While the updates, NPV values are estimated with the proxy models and the reservoir simulation simultaneously to see the predictability of the proxy models. As the generation continues and the candidate solutions move gaily, the difference between the estimations of the proxy model and the reservoir simulation increases in the random sampling. This tendency is shown much less in the uniform sampling, estimating the NPV values relatively in good accuracy. It demonstrates the capability of the estimation of the uniform sampling is improved.

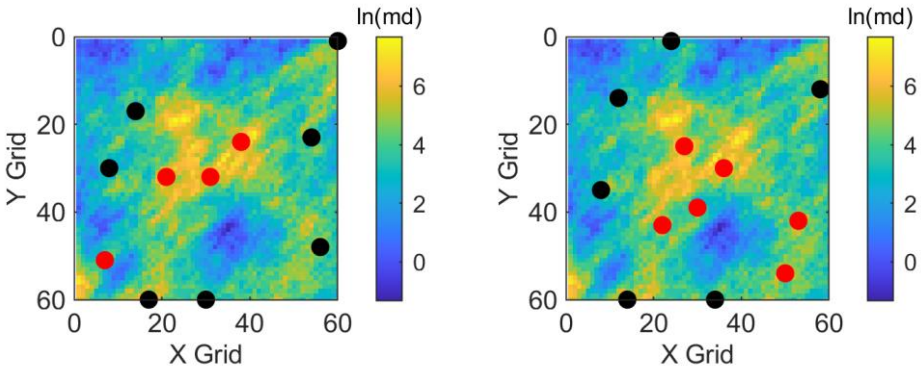
Improvement in performance of the uniform sampling is also proven in Figure 4.4. It shows the accuracy of the proxy models by plotting the NPV values of the proxy models and reservoir simulation estimated in regression with a unit slope line. The more the estimated NPV dots are located on the line, the higher the accuracy of the estimation of the proxy models. Average R^2 of each trial over 200 generations and average R^2 of total three trials of both methods are calculated here and organized in Table 4.1.



(a) Run #1

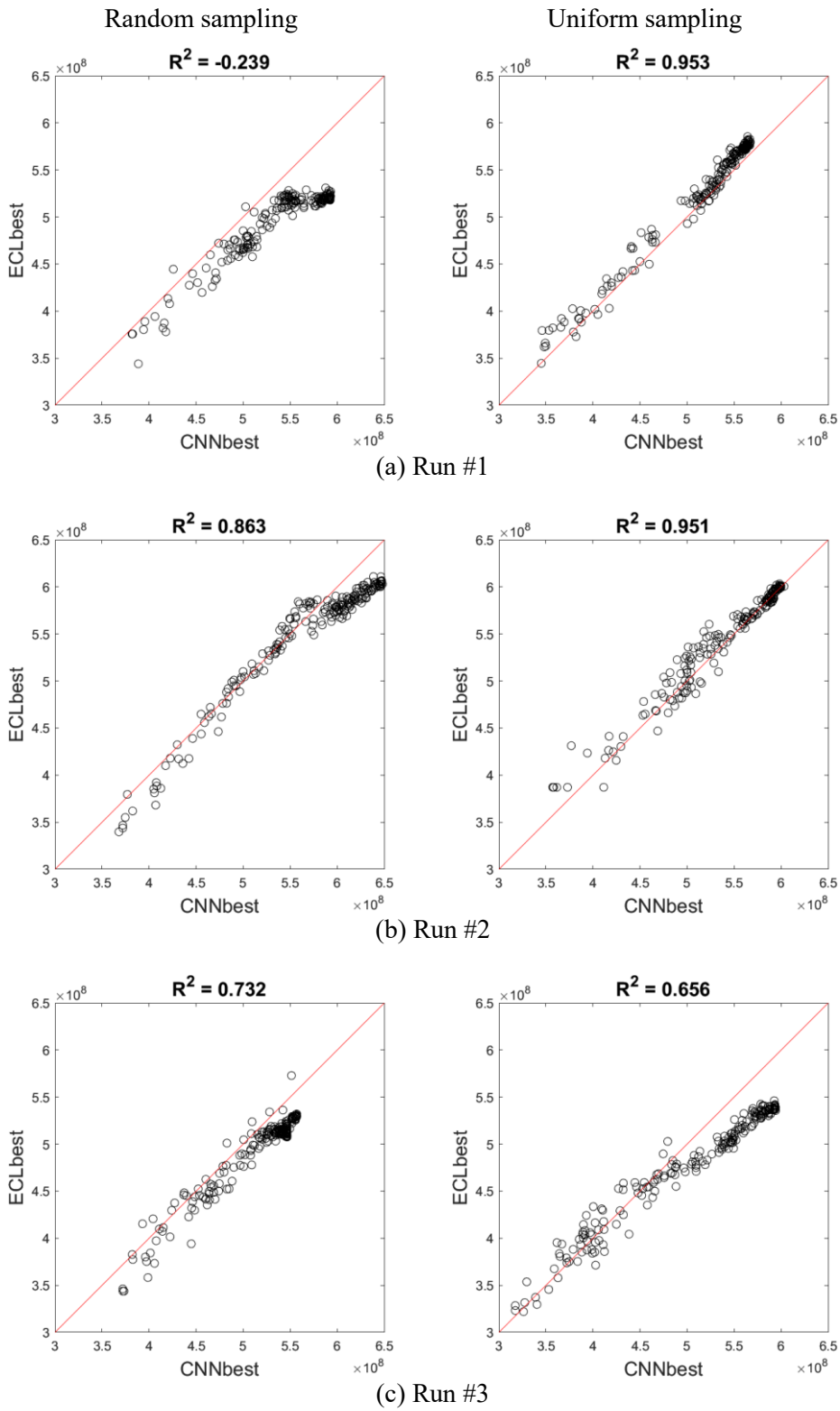


(b) Run #2



(c) Run #3

Figure 4.3 Optimal well placements of the 2 proxy models



(a) Run #1

(b) Run #2

(c) Run #3

Figure 4.4 Regression graphs of the 2 proxy models

As it is shown in Figure 4.4, the uniform sampling method shows better accuracy with the more plotted NPV dots on the line. However, it decreases at higher NPV values as the dots getting far from the line especially at Run #3. The results are reorganized in Table 4.1 with R^2 for the quantitative comparison as the higher R^2 means the more accurate the model.

Table 4.1 R^2 of the proxy models of the two sampling methods

	Run #1	Run #2	Run #3	Average
Random	-0.24	0.86	0.73	0.45
Uniform	0.95	0.95	0.66	0.85

The same standard is applied as the model selection that the proxy model is considered adequate to substitute for the reservoir simulation when it has R^2 higher than 0.85. The average R^2 values of the random and the uniform proxy models are 0.45 and 0.85. The random sampling has a lot lower average R^2 than the standard. The uniform sampling method barely satisfies the standard with average R^2 of 0.85 tight but it also shows unstable performance with lower value in Run #3.

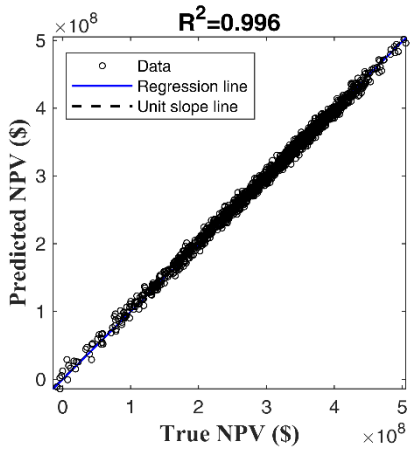
Even though the selected models present similar R^2 with their test data, they are showing very different results of 0.45 and 0.85 in average, almost twice the difference. It indicates the fact that there would be differences in their training data since their training levels are analogous. However, although the uniform sampling method provides better results than the random sampling without the re-training, it is meaningless if the accuracy decreases near the final solution because the purpose of this research is to estimate the NPV as precisely as it can. Therefore, the 2-stage sampling method is tried for better training data.

4.2 Results of the 2-stage sampling

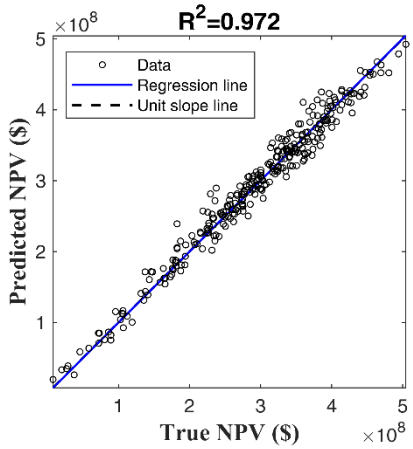
The 2-stage sampling method is applied to see the improvement in the accuracy of the estimation when the well configurations are near the end of the optimization. The average accuracy of the proxy model with the random sampling without the re-training process decreases a lot, because it seldomly estimates the NPV favorably. For the uniform sampling method, it is almost doubled but still, unstable especially in higher NPV values.

To improve this limitation, the 2-stage sampling method is applied. Figure 4.5 shows R^2 of the performance of the constructed proxy model with the 2-stage sampling method. All three data for training, validation, and test show good results with high R^2 values more than 0.9. Since the result of the training is verified, the well placement optimization is executed.

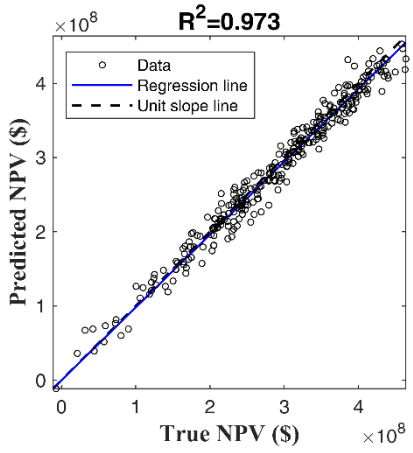
Figure 4.6 illustrates the results of the optimization. It shows the well configuration of the optimal solution of all three trials. For the proxy model constructed by the 2-stage sampling method, it shows highly well predicted results for the whole generations. It can also be identified in Figure 4.7 showing R^2 between the estimated NPV and numerically calculated NPV for the best solution for every generation. Different from the results of the proxy model with the uniform sampling, almost all of the NPV dots are on the unit slope line. Table 4.2 shows R^2 values for the three sampling schemes.



(a) Training



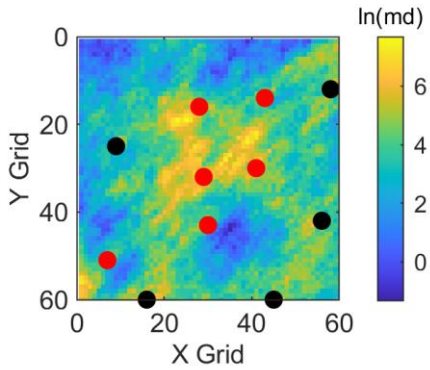
(b) Validation



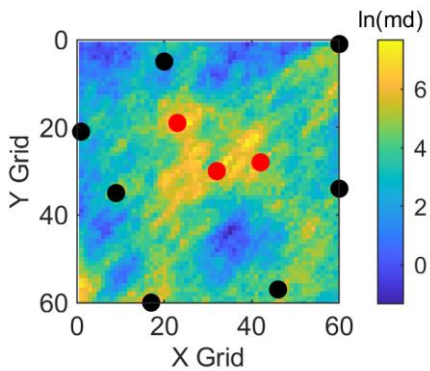
(c) Test

Figure 4.5 Performance of the constructed model – 2-stage sampling

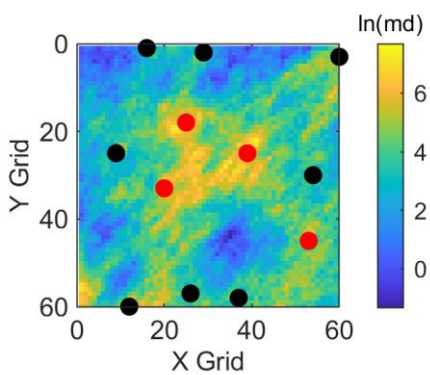
Final solution



(a) Run #1

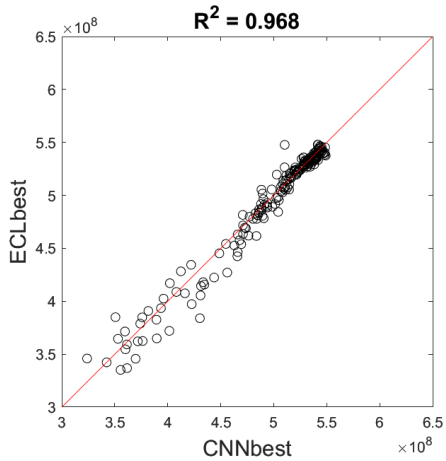


(b) Run #2

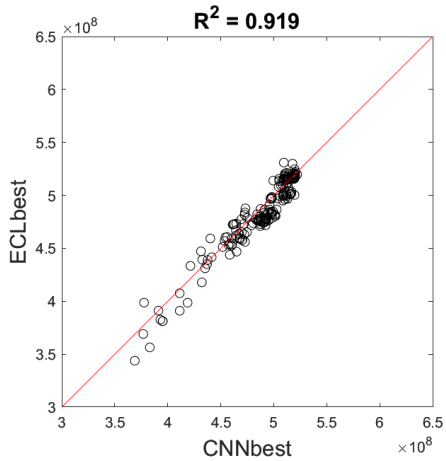


(c) Run #3

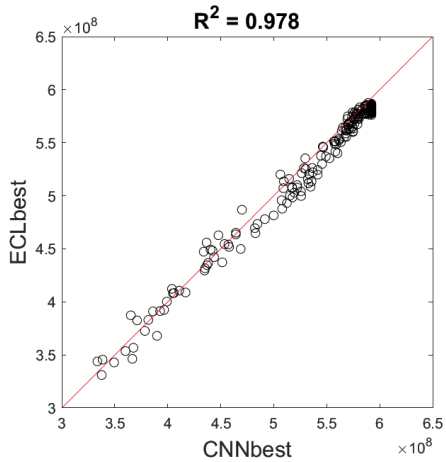
Figure 4.6 Optimal well placements of the 2-stage proxy model



(a) Run #1



(b) Run #2



(c) Run #3

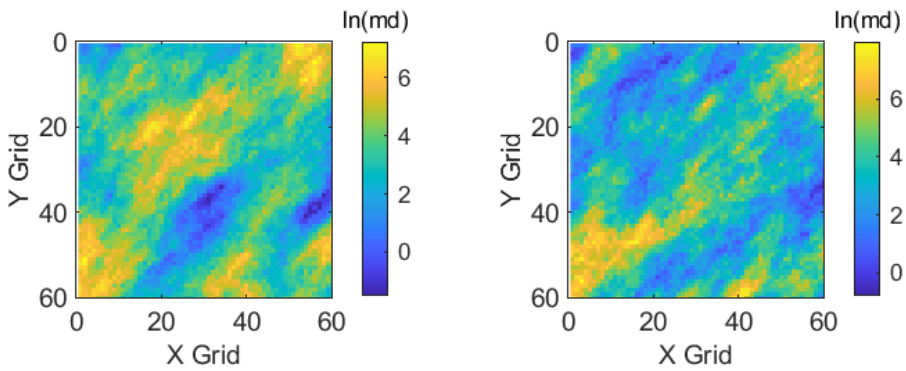
Figure 4.7 Regression graphs of the 2-stage proxy model

Table 4.2 R^2 of the proxy models of the three sampling methods

	Run #1	Run #2	Run #3	Average
Random	-0.24	0.86	0.73	0.45
Uniform	0.95	0.95	0.66	0.85
2-stage	0.97	0.92	0.98	0.95

With the results presented in Table 4.2, the improvement in prediction is proved for the proxy model with the 2-stage sampling method. The average R^2 increases as the random, the uniform and the 2-stage method that are applied in sequence. It can also be seen in Figure 4.7 and Table 4.2. The estimation for NPV matches with the calculated NPV pretty well in overall range. Furthermore, the proxy model with the 2-stage sampling method has stability always showing R^2 value of higher than 0.9.

For the future validation, two other reservoir models are employed in 2-stage sampling method additionally. The other reservoir models are also randomly selected among the 100 models that are generated with SGS at the beginning of the research. Models utilized for the validation are shown in Figure 4.8.



(a) Reservoir model #2 (b) Reservoir model #3

Figure 4.8 Additional reservoir models used for validation

Additional proxy models are also chosen by the same standard that has higher R^2 than 0.85 with their test data. R^2 of the proxy models of reservoir model #2 and #3 are 0.983 and 0.975, respectively. Optimization with these proxy models are also conducted three times each, and the results are presented in Table 4.3.

Table 4.3 R^2 of the proxy models with 3 reservoir models – 2-stage sampling

	Run #1	Run #2	Run #3	Average
Model #1	0.97	0.92	0.98	0.95
Model #2	0.98	0.98	0.95	0.97
Model #3	0.95	0.96	0.85	0.92

For the proxy model constructed with the 2-stage sampling method shows R^2 of 0.9 or more in average for every reservoir model. Hereby, the performance of the 2-stage sampling method is validated as the proxy model shows high and stable predictability even in different reservoir models. Consequently, reflecting the results shown, the 2-stage sampling method is ultimately proposed for a substitute for the reservoir simulation due to its accuracy of the NPV estimation and the stability.

Chapter 5. Conclusions

This research suggests a sampling method for constructing a proxy model to optimize a well placement. A well placement optimization is conventionally performed with some optimization algorithms together with a reservoir simulation. However, it is complicated to figure out an optimal solution numerically and it requires an amount of computational costs.

A proxy model is built for a quick estimation by mimicking responses of a reservoir simulation. It draws the results of estimation fast by learning and imitating the relationship between the input and output data of a reservoir simulation. While the optimization, the proxy model is needed some re-training process to increase its accuracy. However, it is not easy to decide the time and frequency of re-training and they have to be decided empirically.

Two sampling schemes are tried in this research to construct a proxy model without the re-training process: the uniform and the 2-stage sampling methods. They effectively sample the training data for the proxy model. The proposed sampling methods are applied to a 2D synthetic reservoir and the results of optimization are compared.

The uniform sampling method is firstly employed considering the bias issue of the well placement in random sampling. It extracts samples of well placement scenarios calibrating minimum well spacing radius to locate the wells more evenly over a reservoir. By doing that, it covers the general trend of the dynamic data that informs the proxy model for the behavior of the reservoir. However, the accuracy of

the prediction decreases at higher NPV values with this method so the 2-stage sampling method is tried.

The 2-stage sampling method extracts samples in two steps based on the possibilities of well placement that has higher NPV values. As a result, it gives the coefficient of determination value higher than 0.9.

The results of the three initial sampling methods are compared. In the order of the random, the uniform, and the 2-stage sampling methods, R^2 values of the proxy models are 0.45, 0.85, and 0.96 in average of three trials, respectively. Validation of the best scheme is then conducted with three different 2D synthetic reservoirs and the 2-stage sampling method is finally proposed as a substitute for the reservoir simulation. Conclusions for this research are as follows.

1. Well trained proxy models are utilized for the optimization for every scheme that has high coefficient of determination values of more than 0.85 for their test data.

2. The performance of the proxy model with the uniform sampling method is improved as it acquires dynamic data in good quality. It attains the data from wider area of the reservoir by placing wells evenly. With this result, the fact that the dynamic data affects the performance of the proxy models is identified. Therefore, it is vital to achieve initial samples for the training the proxy model that reflects the flow of the fluids effectively.

3. The 2-stage sampling method is attempted due to the limitation of the uniform sampling. The limitation is covered by extracting samples in good quality based on possibilities of well number distribution and well placement in each

grid that is discovered by the analysis on 25 % of primary samples with high NPV values. As the scheme shows good results with the R^2 of 0.9 or more, it is verified that the well placement optimization is available without the re-training if the quality of training samples is high. Accordingly, the 2-stage sampling method is suggested for a scheme to replace a reservoir simulation for fast estimation in well placement optimization.

4. The proposed method shows high and stable accuracy in applying three different reservoirs. It also confirms that it can prevent the fall in performance of the proxy model because the streamline TOF maps effectively reflect the heterogeneity of the reservoir.

The 2-stage sampling method is proposed in this research as it shows high capability and stability in prediction. However, it needs more verification in realistic reservoir models. Even though it draws good results in several synthetic reservoir models, it is only employed in 2D synthetic reservoirs here. Hence, it is recommended to apply the proposed method to additional realistic 3D model or some benchmark models such as Egg or PUNQ-S3 models.

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국문초록

합성곱 신경망 기반 프록시 모델을 이용한 유정배치 최적화

유정의 배치는 사업의 경제성을 좌우하므로 그 개수와 종류, 위치 등을 최적화 해야한다. 유정배치 최적화에는 전통적으로 최적화 알고리즘이 저류층 시뮬레이션과 결합하여 사용된다. 그러나 이는 많은 계산을 필요로 하기 때문에 저류층 시뮬레이션을 대체하기 위한 프록시 모델에 관한 연구가 최근에 활발히 수행되고 있다.

저류층 시뮬레이션 대신 사용되는 프록시 모델은 학습 자료와 프록시 모델의 한계로 인해 그 정확성이 떨어질 수 있다. 프록시 모델의 정확성을 향상시키기 위해 최적화 도중 재학습을 사용하는 방법이 알려져 있긴 하지만, 이는 계산 시간이 빠르다는 프록시 모델의 강점을 둔화시킨다. 뿐만 아니라, 적절한 재학습의 횟수 및 시기를 결정하는 근거가 불분명하여 이를 결정하는 것이 어렵다는 한계점이 있다.

따라서 본 연구에서는 프록시 모델의 학습에 사용되는 초기 샘플이 최적해를 포함할 수 있도록 하는 효과적인 초기 샘플링 기법을 제안하였다. 먼저, 저류층의 전 영역에 걸쳐 유정을 배치시키는 균일 샘플링 기법을 시도하였다. 이는 프록시 모델이 저류층의 전반적인 거동을 반영할

수 있게 하였고 따라서 순현재가치의 예측 정확도가 상승하였다. 그러나 높은 순현재가치를 갖는 구간에서의 예측 정확도는 타구간에 비해 다소 낮았다.

균일 샘플링의 한계를 보완하기 위해 2단계 샘플링 기법이 시도되었다. 높은 순현재가치를 갖는 샘플의 유정 개수 분포와 유정이 각 격자에 배치될 확률을 분석하여 이를 기반으로 2단계로 샘플을 추출하였다. 제안된 2단계 샘플링은 최적해를 효과적으로 포함시켰고 프록시 모델의 정확도 역시 향상시켰다.

제안 기법의 안정성을 보기 위해 2개의 저류층 모델에 대해 추가적인 검증이 수행되었다. 각 모델에 총 3번씩의 최적화를 수행하여 검증을 시도하였고 평균 결정계수가 모두 0.9 이상으로 높은 결과를 보이며 2단계 샘플링의 안정성이 확인되었다.

주요어 : 유정배치 최적화, 재학습, 프록시 모델,
균일 샘플링 (Uniform sampling), 2단계 샘플링 (2-stage sampling)

학 번 : 2020-26648