Multi-well placement optimisation using sequential artificial neural networks and multi-level grid system

Ilsik Jang, Seeun Oh, Hyunjeong Kang and Juhwan Na

Department of Energy and Resources Engineering,
Chosun University,
309 Pilmun-daero Dong-gu, Gwangju 61452, South Korea
Email: isjang77@chosun.ac.kr
Email: ocean060701@gmail.com
Email: hj_kang@chosun.kr
Email: juhwan_na@chosun.kr

Baehyun Min*

Department of Climate and Energy Systems Engineering,
Ewha Womans University,
52 Ewhayeodae-gil, Seodaemun-gu, 03760, South Korea
Email: bhmin01@ewha.ac.kr
*Corresponding author

Abstract: This study suggests a sequential artificial neural network (ANN) method coupled with a multi-level grid system to optimise multi-well placement in petroleum reservoirs. As the number of scenarios for placing wells increases exponentially with the number of wells, the difficulty in finding the global optimum increases accordingly due to the intrinsic uncertainty of ANNs. The multi-level grid system can reduce the size of the search space by allocating only one well grid block per several grid blocks in the basic grid system. A higher level of grid system consists of finer grid blocks to gradually improve the resolution of the grid system. Repetitive implementation of the sequential ANN at each level of the grid system narrows the search space, and the global optimum is determined. The proposed algorithm is validated with applications to two- and three-infill-well problems in a coal-bed methane (CBM) reservoir. [Received: March 16, 2018; Accepted: September 19, 2018]

Keywords: sequential artificial neural network; multi-level grid system; multi-well placement; optimisation.

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Biographical notes: Ilsik Jang is an Associate Professor in the Department of Energy and Resources Engineering at the Chosun University. He holds a PhD, MS and BS degrees in Petroleum Engineering from Seoul National University. He has seven years of E&P industry experience as a reservoir engineer. His current research interests are in reservoir simulation with soft computing, unconventional resources development, and digital oil field.

Seeun Oh is a PhD candidate in the Department of Energy and Resources Engineering at the Chosun University. She holds an MA degree in Space Design from Hongik University. Her current research interests are optimisation using soft-computing, reservoir simulation of unconventional resources, and uncertainty analysis.

Hyunjeong Kang is a researcher at the Chosun University. She holds an MS degree in Energy and Resources Engineering from Chosun University. Her current research interests are optimisation using soft-computing and reservoir characterisation.

Juhwan Na is a PhD candidate in the Department of Energy and Resources Engineering at the Chosun University. He holds an MA and BS degrees in Energy and Resources Engineering from Chosun University. His current research interests are unconventional reservoir simulation and digital oil field.

Baehyun Min is an Assistant Professor in the Department of Climate and Energy Systems Engineering at Ewha Womans University since 2017. He holds a BS and MS degrees in Civil, Urban, and Geosystems Engineering and PhD degree in Energy Systems Engineering from Seoul National University. He served as Postdoctoral Fellow and Research Associate at the University of Texas at Austin from January 2014 to February 2017.

1 Introduction

Optimal well placement is one of the most critical tasks for maximising the economics of oil and gas field development and requires computationally expensive reservoir simulations. Various optimisation methods have been introduced in the petroleum industry for reducing computational costs. Hou et al. (2015) reviewed details of optimisation methods such as gradient-based and gradient-free algorithms including artificial intelligence methods. They also discussed key issues for future developments. Although many authors have used gradient-based methods in optimisation problems (Bangerth et al., 2006; Wang et al., 2007; Sarma and Chen, 2008; Forouzanfar et al., 2010), there is an intrinsic limitation in that the solution tends to be stuck in local optima despite the fast convergence.

To circumvent the drawback of the gradient-based methods and increase the likelihood of identifying the global optimum, stochastic search algorithms have been utilised in well placement optimisation: genetic algorithm (GA), particle-swarm optimisation (PSO), imperialist-competitive algorithm (ICA), artificial bee colony (ABC) algorithm, bat inspired algorithm (BA), and so on. The GA has been widely used in well placement optimisation because of its ability to find the global solution (Bittencourt and Horne, 1997; Yeten et al., 2003; Emerick et al., 2009; Lee at al., 2009; Salmachi et al., 2013; Sayyafzadeh, 2017). Onwunalu and Durlofsky (2010) applied the PSO to investigate the optimum type and location of new wells and showed that the PSO outperformed the GA. Feng et al. (2012) presented a framework that integrated a reservoir simulator into the PSO algorithm and optimised well placement in a CBM reservoir. Humphries et al. (2014) used the PSO with a local generalised pattern search algorithm to determine optimal well placement and control strategy.

Al Dossary and Nasrabadi (2015) utilised the ICA to determine optimal well location for maximum well productivity. The ICA mimics socio-political imperialist competition. They showed that the ICA achieved a better solution than the PSO and GA. Nozohour-leilabady and Fazelabdolabadi (2016) compared the ABC algorithm with the PSO, indicating the great promise of the ABC algorithm for well optimisation. Naderi and Khamehchi (2017) applied the BA for optimal determination of well locations in the PUNQ-S3 benchmark model and showed that the BA provided better net present value over the GA and PSO. Compared to gradient-based methods, stochastic algorithms are more robust and have greater opportunities to search for the global optimum. However, the stochastic algorithms require more simulation runs than the gradient-based methods (Hou et al., 2015).

To reduce the number of simulation runs, surrogate model techniques have been adopted in stochastic approaches. One of the promising models is the ANN, which comprises input, hidden, and output layers with neurons in each layer (Masters, 1993). The training data is transferred from the input to the output layer via one or more hidden layers. Weights interconnecting neurons between the layers, which represent a latent characteristic of the network, are calibrated by back propagation. The trained ANN is then utilised to predict reservoir behaviours.

Centilmen et al. (1999) suggested a two-step approach using ANNs for well placement optimisation with a limited number of scenarios. Gűyagűler et al. (2000) reduced the number of simulation runs required to search for the optimal well location using GA, polytope algorithm, hybrid GA with Kriging algorithm, and an ANN. Yeten et al. (2003) optimised well locations, well types, and trajectories simultaneously in unconventional fields using GA with ANNs, hill climbers, and near-well upscaling techniques. Reflecting production potential as a quality map into an ANN improved the predictability of the ANN (Min et al., 2011). Sayyafzadeh (2017) applied two ANNs with GA for well placement optimisation: the first ANN approximated the objective function, while the second one estimated the accuracy of the first ANN over the search space. Recently, Jang et al. (2018) suggested a sequential ANN method for single horizontal well placement. In this method a series of ANN models were used sequentially to reduce the search space and the global optimum was determined from near optimal candidates. The result showed that the sequential ANN method outperformed the population-based PSO in that it required a smaller number of simulation runs and verified the capability of finding the true global optimum.

However, the sequential ANN method should be used carefully when applied for multi-well placement problems: there might be too many scenarios to consider in a single procedure. For example, let us consider a 2D reservoir of 50 × 50 grids (i.e., total of 2,500 grids). When exploring the optimal placement of one vertical well, there are 2,500 scenarios. However, there are 3,123,750 (= C(2,500, 2) = 2,500 × 2,499 / 2!) scenarios for a two-well placement problem and 2.6×10^9 (= C(2,500, 3)) scenarios for a three-well placement problem, where C(*n*, *k*) is the number of *k*-combinations from a set of *n* elements. In other words, the number of scenarios to be explored using the sequential ANN method increases exponentially with number of wells. This huge number of scenarios deteriorates the reliability of the method. Furthermore, a relatively small amount of training data compared to the size of the search space aggravates the predictability of the ANN. In addition, the total number of cut-off procedures to reduce the search space increases exponentially. These issues increase the probability of not finding the global optimum at affordable computational costs.

This study proposes an improved method that can overcome the aforementioned limitations by coupling a multi-level grid system with the sequential ANNs. In the proposed method, sequential ANNs are repeatedly applied from coarse to fine grid systems, which maintains the search space at a manageable size. The proposed method is applied to two- and three-well placement problems in a CBM reservoir.

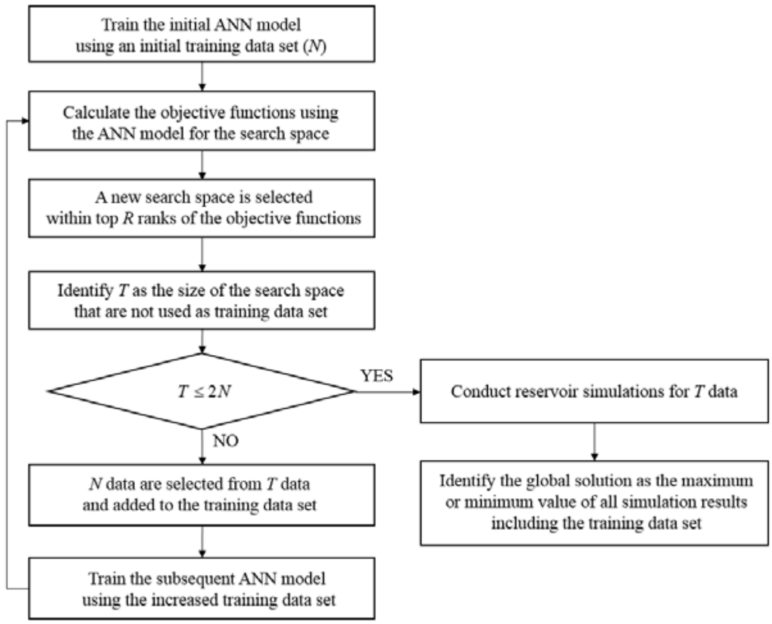
2 Methodology

2.1 Sequential ANN

A new methodology is proposed for solving multi-well placement optimisation. The key scheme incorporates a multi-level grid system in the sequential ANN method. The procedure of the sequential ANN method, as shown in Figure 1, is briefly described as follows.

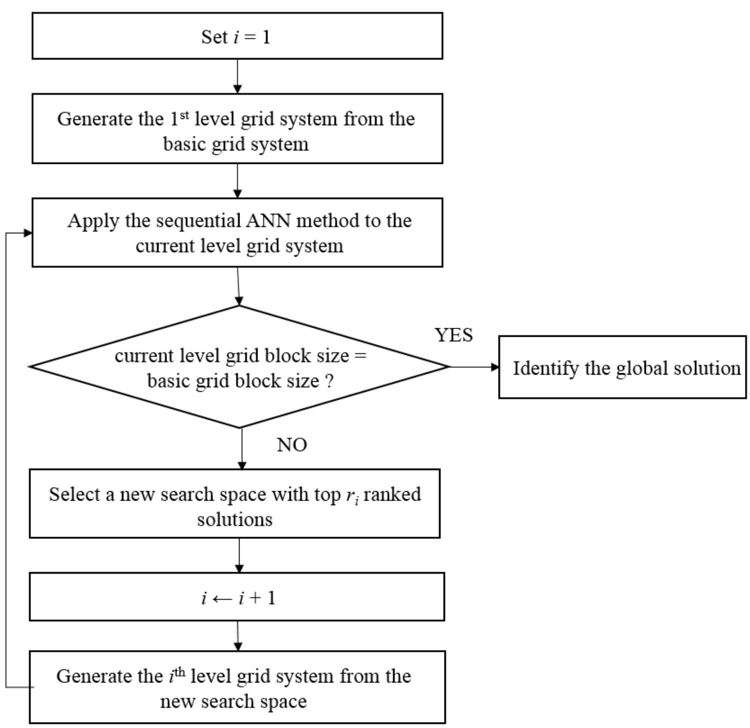
1. An initial ANN model is trained using initial training data obtained through reservoir simulation.
2. After defining the search space to find the global optimum, objective functions are estimated in the search space by the ANN model. The objective functions can be defined as oil or gas production, economic indicators, or both.
3. A new reduced space for the subsequent search is determined with top *R* ranks among the objective functions. Note that *R* is a cut-off criterion.
4. To train the subsequent ANN model, *N* data points are newly chosen from the reduced search space and added to the existing training dataset after simulation runs. Note that *N* is equal to or smaller than the number of the initial training data, thereby improving the prediction performance of the subsequent ANN model.
5. Objective functions are estimated in the reduced search space by the subsequent ANN model.
6. Steps 3 through 5 repeatedly reduce the search space until stopping criteria are satisfied. One of the stopping criteria can be defined as follows: let the reduced search space *T* be the number of data points not including the training data. When *T* is not greater than $2 \times N$, the stopping criterion is satisfied.
7. Once the stopping criteria are satisfied, reservoir simulation runs should be performed for the *T* data. The global solution can be found as the optimal value among the simulation results including the training data. The total number of reservoir simulations is equal to the sum of the numbers of the *T* and training data. An application of the sequential ANN for single well placement in a CMB reservoir is described in the Appendix, and more details can be found in Jang et al. (2018).

Figure 1 Flowchart of the sequential ANN method



Source: Jang et al. (2018)

Figure 2 Flowchart of the proposed sequential ANN incorporated with multi-level grid system



2.2 Multi-level grid system

The multi-level grid system is implemented to alleviate the burden of considering too many scenarios in invoking a single ANN model. Figure 2 shows a flowchart to apply the sequential ANN method in the multi-level grid system. Introduction of the multi-level grid system significantly reduces the size of the search space and narrows the region in which the global solution is likely to exist, thereby increasing the probability of finding the global optimum. Details of the procedure are as follows.

1 Each grid block in the 1st level grid system is composed of $n_1 \times n_1$ blocks of the basic grid system. Figure 3(a) shows an example of the 1st level grid system, denoted by thick solid lines, with the underlying basic grid system composed of 50 × 50 grid blocks. In Figure 3(a), $n_1 = 5$: each block in the 1st level grid system consists of 5 × 5 blocks of the basic grid system. A red dot represents a well block where one infill well can be placed in the 1st level grid system. Note that this grid approach is different from the upscaling of grid property. The property of the basic grid system is still used to run reservoir simulations for the 1st level grid system, but only one well can be located in the centre of the 5 × 5 grid blocks. Although each grid block has a different production performance owing to reservoir heterogeneity, the performance of the well block can be considered a reference regarding the local area near the well. The 1st grid system has 10 × 10 grid blocks; therefore, the search space is radically reduced to 4,950 (= C(100, 2)) scenarios for a two-well placement problem and 161,700 (= C(100, 3)) scenarios for a three-well placement problem, compared to 3,123,750 and 2.6×10^9 scenarios in the basic grid system, respectively.

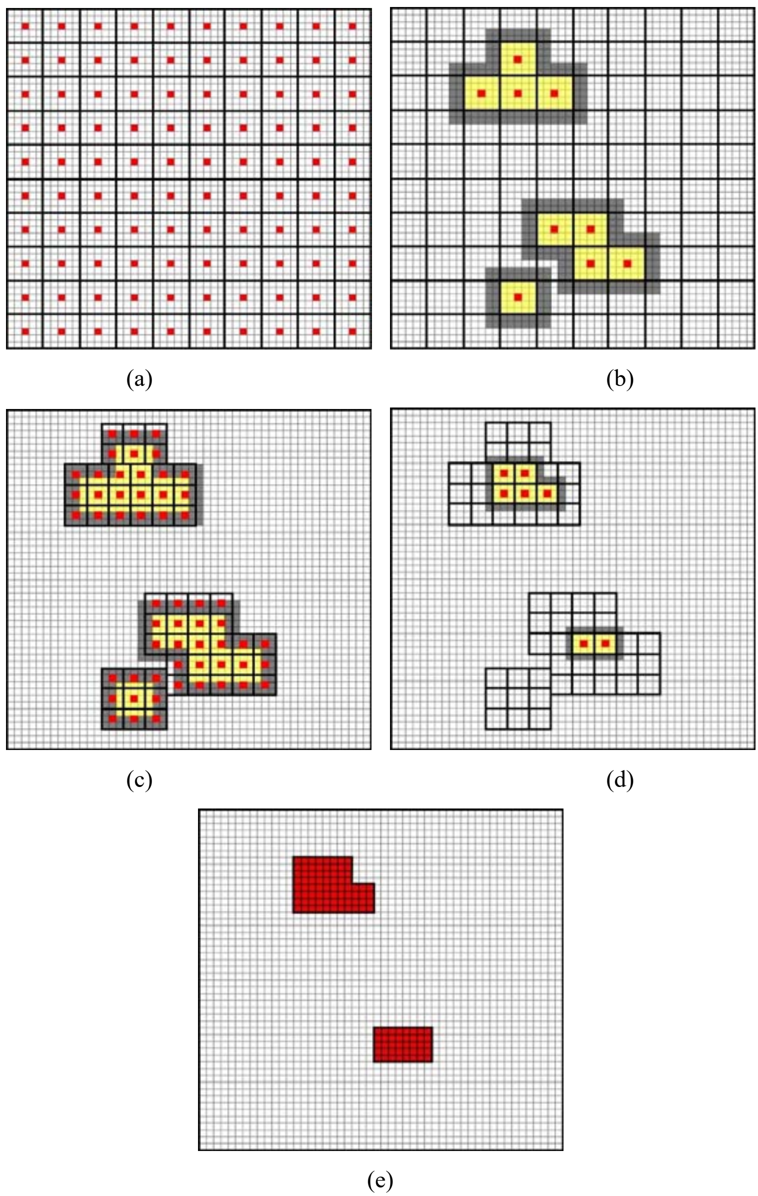
2 The sequential ANN method is applied in the 1st level grid system, and the top r_1 ranks of the objective functions are selected as a new search space for the 2nd level grid system. The optimal solution in the 1st level grid system is not necessarily the true global solution in the basic grid system because reservoir heterogeneity results in uncertainty in the performance of neighbouring grids. Therefore, combining the top r_1 ranked solutions increases the probability of finding a true global solution in the selected region. Grid blocks with yellow colour in Figure 3(b) represent a reduced search space composed of the top r_1 ranked solutions. Note that the grey region near the yellow coloured blocks is also included in the search space to consider reservoir heterogeneity.

3 The 2nd level grid system is generated with the reduced search space where each grid block is composed of $n_2 \times n_2$ blocks of the basic grid system. Figure 3(c) shows the 2nd level grid system, of which a block is composed of 3 × 3 blocks of the basic grid system. To increase the reliability of well performance, the size of each block is kept smaller than that of the 1st level grid system.

4 After applying the sequential ANN method in the 2nd level grid system, top r_2 ranked solutions are selected to make a new search space where the 3rd level grid system is constructed with a smaller block size than that of the previous grid system. The shaded area in Figure 3(d) represents the new search space for the 3rd level grid system.

5 The sequential ANN method is repeatedly applied for higher levels of the grid system until the block size is the same as that of the basic grid system. The global optimum is determined once the sequential ANN method is applied in the final grid system. Figure 3(e) shows the 3rd level grid system with the same block size as the basic grid system.

Figure 3 (a) Initial search space in the 1st level grid system (b) Top r_1 ranked solutions in the 1st level grid system (c) Initial search space in the 2nd level grid system (d) Top r_2 ranked solutions in the 2nd level grid system (e) Initial search space in the 3rd level grid system (see online version for colours)



3 Results and discussion

3.1 Application to a CBM reservoir

The proposed sequential ANN method with the multi-level grid system is applied to two cases of multi-well placement problems in a CBM reservoir, which was used for optimising single well placement in Jang et al. (2018). The reservoir produces methane gas for three years through six vertical wells (p1–p6), as shown in Figure 4. The common goal of the two case studies is to find the optimal locations maximising 20-year field production for two and three infill wells. The reservoir size is 6.1 × 3.7 km discretised into 61 × 37 × 3 grid blocks. The size of each block is 100 m in the x and y directions with reservoir thickness in the range of 3–10 m. The reservoir properties are summarised in Table 1.

Figure 4 Sector model of CBM reservoir (see online version for colours)

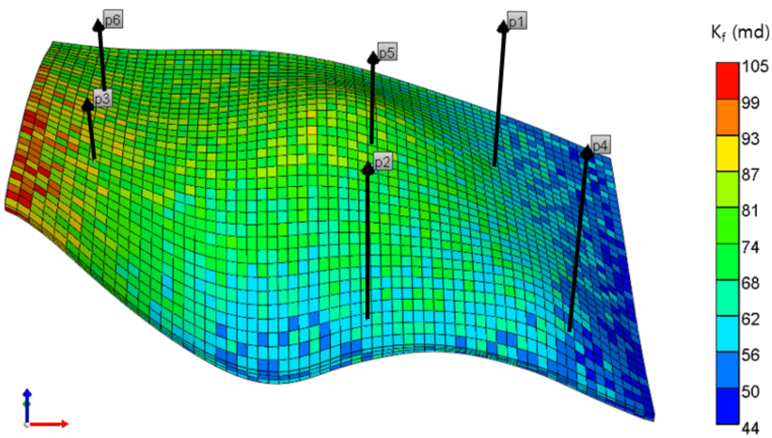


Table 1 Properties of CBM reservoir

Reservoir parameters	*Values*
Cleat spacing	10 cm
Sorption time	1 day
Reservoir pressure	5,456 kPa at 300 m
Gas type	CH_4
Langmuir volume, V_L (CH_4)	0.14–0.74 gmol/kg
Langmuir pressure, P_L (CH_4)	2,887 kPa
Permeability model	Palmer and Mansoori
Matrix permeability	0.001 md
Permeability of face cleat	44–105 md
Permeability of butt cleat	11–26 md
Matrix porosity	0.08
Cleat porosity	0.02–0.03

The total number of scenarios wherein the infill well can be located in the reservoir is 2,532,375 and 1,898,437,125 for the two- and three-well placement problems, respectively, indicating that it is not feasible to conduct reservoir simulations for every scenario. Instead, if it is possible to perform simulation runs for all scenarios in a certain level of grid system, the global optimum is identified in advance from the simulation to verify the proposed methodology. Simulation runs are conducted using GEM developed by Computer Modelling Group Ltd. (CMG, 2016).

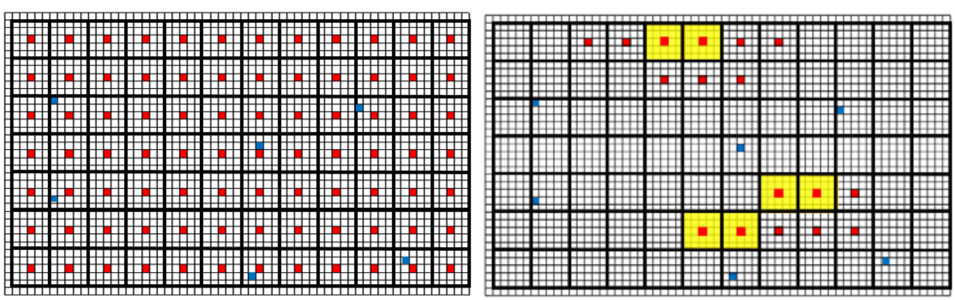
3.2 Optimisation of two-well placement case

The ANN model consists of one input, one hidden, and one output layer. The numbers of neurons in the input, hidden, and output layers are 30, 10, and 1, respectively. The input and output data types used to train the neural networks are listed in Table 2.

Table 2 Input and output data for artificial neural network

	Data type	*# of neurons*
Input data	Infill well x-y coordinates	4
	Distance from the infill well to reservoir boundary	8
	Permeability of infill well blocks	6
	Inter-distance between existing wells and infill well	12
Output data	Field total of 20-year gas production	1

Figure 5 (a) Search space in the 1st level grid system (b) Reduced search space after sequential ANN (see online version for colours)



(a) (b)

Notes: Search space.
Existing wells.
Search space of top 5 ranks.

Figure 5(a) shows the 1st level grid system with the size of 12 × 7 grids (thick solid line) and candidate well locations (red dot) that overlap the basic grid system (thin solid line). Note that each block of the 1st level grid system is composed of 5 × 5 blocks of the basic grid system. The results of applying the sequential ANN in the 1st grid system are summarised in Table 3 and Figure 6. The cut-off value R starts from 15% at an increment of 5% until 30% for subsequent ANN models. The increment in *R* increases the likelihood of including the global solution in subsequent search spaces (Jang et al., 2018).

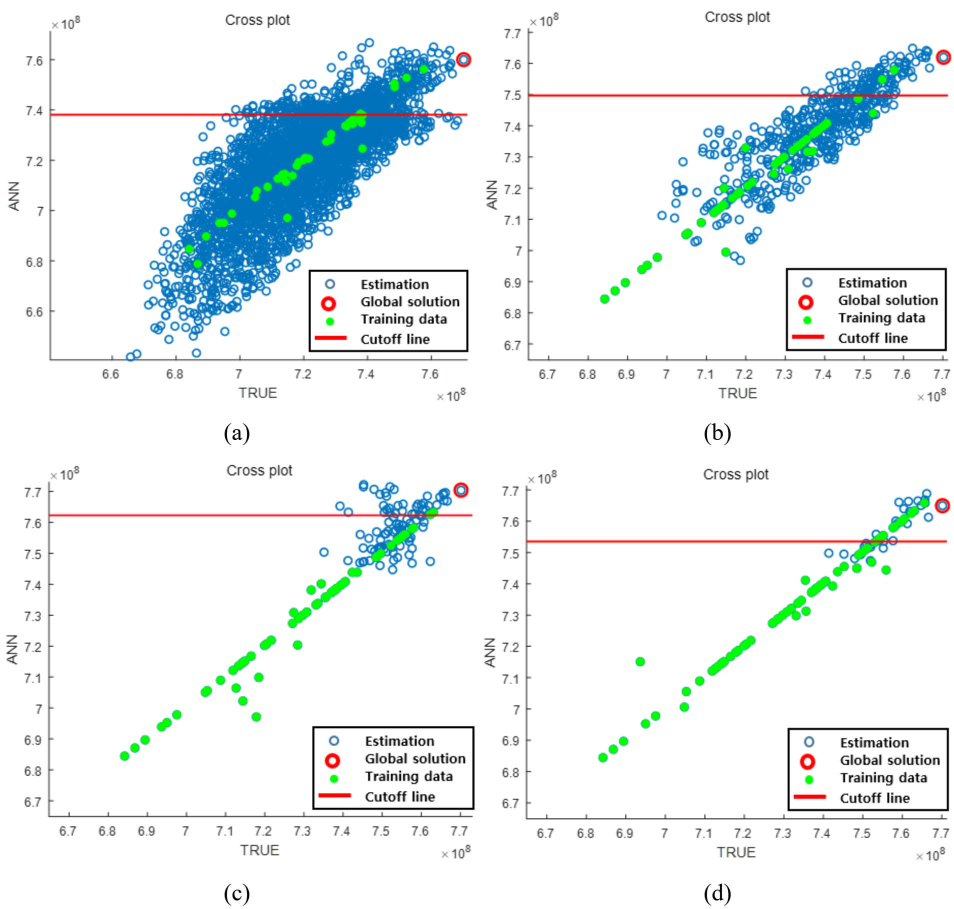
The number of initial training data is 40, and ten data are newly added from the reduced search space whenever a subsequent ANN model is trained.

Table 3 Result of sequential ANN method with the 1st level grid system for two-well case

ANN model	*Cut-off value R (%)*	*# of training data*	*Size of search space[1)]*	*Rank of the global solution (%)*	*# of simulation runs*
1st	15	40	3,486	0.46	40
2nd	20	50	557	1.62	10
3rd	25	60	159	3.77	10
4th	30	70	98	9.18	10
-	-	-	-	-	18[2)]

Notes: [1)] The size of the search space is the union of the top *R* ranked data and the training data in each iteration. [2)] Simulations for the remaining search space after the final cut-off process are counted.

Figure 6 Cross plots of sequential ANN models and simulation results for the 1st level grid system using the (a) 1st ANN, (b) 2nd ANN, (c) 3rd ANN and (d) 4th ANN (see online version for colours)

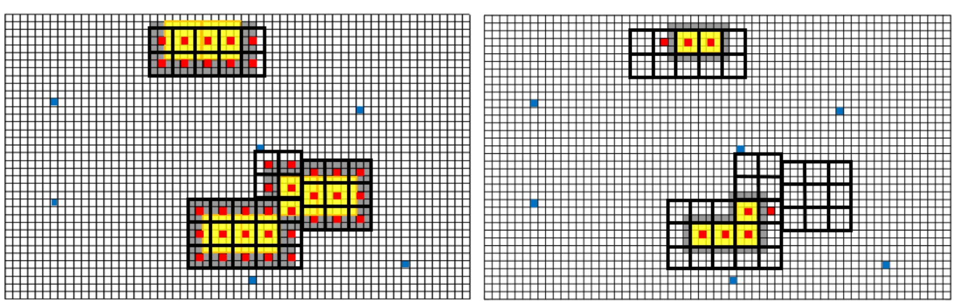


The size of the initial search space is 3,486 (= C(84, 2)) for two-well placement. An initial ANN model is generated using 40 data randomly selected in the search space. Figure 6(a) shows the performance of the initial ANN model. Note that all scenarios in the search space are simulated in advance to verify ANN predictability. The horizontal and vertical axes represent the simulation and ANN results, respectively, where a closed circle with green colour denotes training data, and an open circle with blue colour denotes a scenario in the search space. The open circle with red colour represents the global solution in the 1st grid system. Note that the global solution is in the rank of 0.46% from the top. With the cut-off value of 15% (red horizontal line), a new search space is generated. The size of the new search space is 557.

The 2nd ANN model is trained using new ten data from the new search space in addition to the previous training data. The performance of the 2nd ANN model is shown in Figure 6(b). When the cut-off of 20% is applied, the search space decreases further to a size of 159. Figures 6(c) and 6(d) show the results of the 3rd and 4th ANN models in the subsequent search space, respectively. The stopping criterion is satisfied after the 4th ANN model. It is observed that only 18 scenarios without simulation results remain in the final search space. After performing simulation runs for the 18 scenarios and considering all the simulation results including the training data, the top five ranked solutions are identified.

Figure 5(b) shows the results obtained using the final ANN model, where the red dot represents the remaining search space for two-well placement. The search space is composed of two regions in the upper and lower parts of the reservoir with each well in each region. The grid blocks with yellow colour indicate the top five ranked solutions. The number of simulation runs is 88, and the global solution is within the top 10% for each ANN prediction.

Figure 7 (a) Search space in the 2nd level grid system (b) Reduced search space after sequential ANN (see online version for colours)



(a) (b)

Notes: Search space.
Existing wells.
Search space of top 5 ranks.

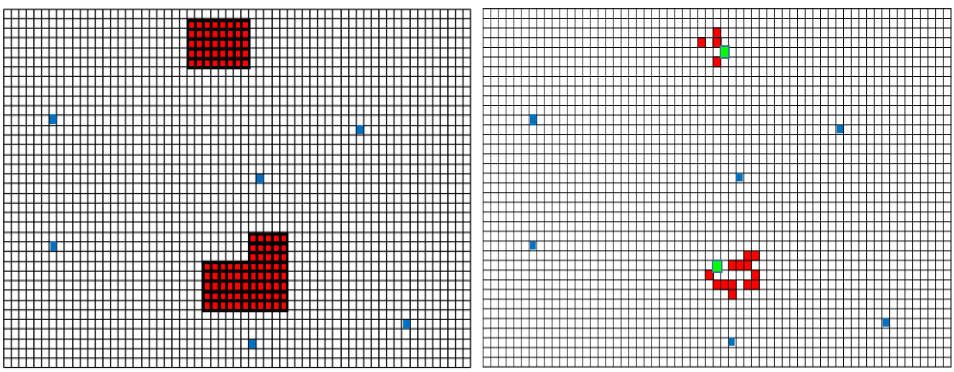
The 2nd level grid system, denoted by thick solid lines in Figure 7(a), is based on the top five ranked solutions yielded in the 1st level grid system. Note that each block in the 2nd level grid system consists of 3 × 3 blocks of the basic grid system. The results of the sequential ANN are summarised in Table 4. The number of initial training data is 30, where ten data are selected from the previous training dataset, and 20 data are newly selected within the search space. After applying the 2nd ANN model, the stopping criterion is satisfied. A total of 39 simulation runs are required. Figure 7(b) shows the remaining search space with the top five ranked solutions in yellow colour.

Table 4 Result of sequential ANN method with the 2nd level grid system for two-well case

ANN model	*Cut-off value R (%)*	*# of training data*	*Size of search space[1)]*	*Rank of the global solution (%)*	*# of simulation runs*
1st	15	30	280	4.83	20
2nd	20	40	71	5.63	10
-	-	-	-	-	9[2)]

Notes: [1)] The size of the search space is the union of the top *R* ranked data and the training data in each iteration. [2)] Simulations for the remaining search space after the final cut-off process are counted.

Figure 8 (a) Search space in the 3rd level grid system (b) Reduced search space after sequential ANN (see online version for colours)



(a) (b)

Notes: Search space.
Existing wells.
Global solution.

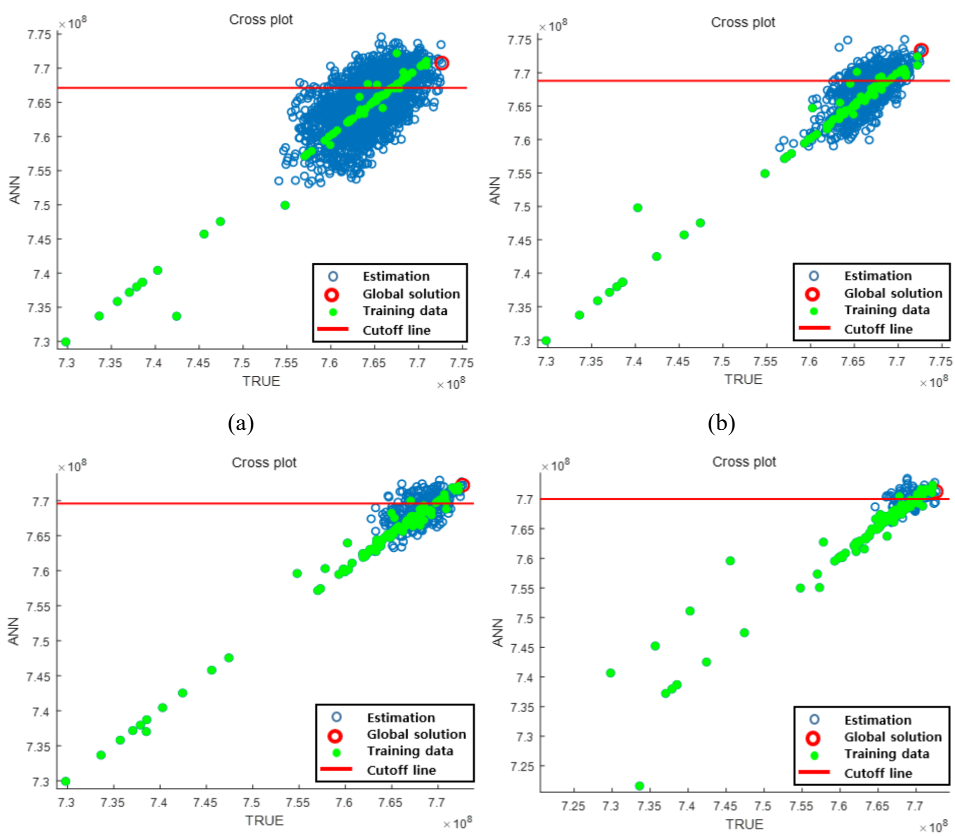
Table 5 Result of sequential ANN method with the 3rd level grid system for two-well case

ANN model	*Cut-off value R (%)*	*# of training data*	*Size of search space[1)]*	*Rank of the global solution (%)*	*# of simulation runs*
1st	30	70	2,800	4.07	40
2nd	30	85	900	0.89	15
3rd	30	100	341	1.47	15
4th	30	115	190	11.05	15
5th	30	130	155	1.29	15
					17[2)]

Notes: [1)] The size of the search space is the union of the top *R* ranked data and the training data in each iteration. [2)] Simulations for the remaining search space after the final cut-off process are counted.

The 3rd level grid system is generated on the basis of the yellow colour region [Figure 8(a)]. The block size is the same as that of the basic grid system. The sequential ANN results are listed in Table 5. As shown in Figure 8(a), the search space can be regarded as saturated with near-optimal solutions, which means that most data points in the search space evolve toward the global solution. Therefore, a cut-off value of 30% is used to increase the likelihood of retaining the global solution in reduced search spaces throughout the process despite slow convergence. The number of initial training data is 70: 30 from the existing training dataset and 40 from newly selected data within the search space. Five iterations of the ANN models are required, and the global solution is mostly within the top 10% in each ANN prediction. The final search space is shown in Figure 8(b) where the optimal well placement is presented as green dots of (32, 33) and (31, 11). The cross plot of each ANN result is shown in Figure 9. Sub-optimal values are gradually excluded from the reduced search space as the process continues.

Figure 9 Cross plots of sequential ANN models and simulation results for the 3rd level grid system using the (a) 1st ANN, (b) 2nd ANN, (c) 3rd ANN and (d) 4th ANN (see online version for colours)



The cumulative gas for 20-year production with two optimal infill wells is 772,690,560 m^3 (Figure 10). The total numbers of simulation runs are 244: 88 for the 1st, 39 for the 2nd, and 117 for the 3rd level grid system. The top five ranked solutions for the multi-level grid systems are listed in Table 6, where it is observed that the solutions become saturated with near-optimal solutions as the level of grid system is high.

Figure 10 Cumulative gas production profile for two-well case (see online version for colours)

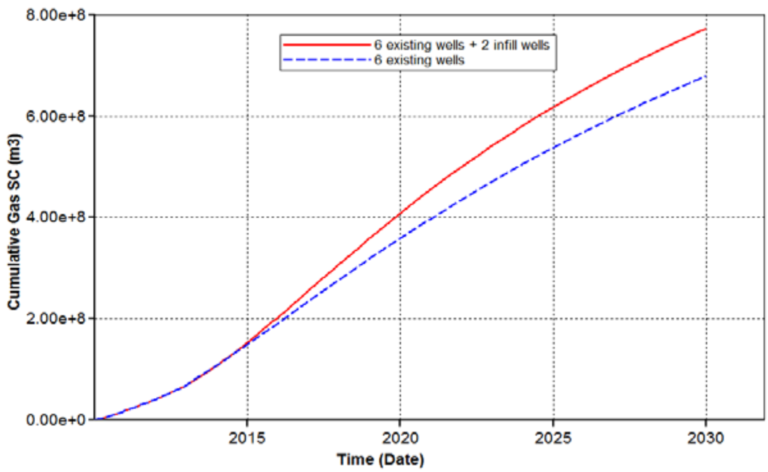


Table 6 List of top five ranks with multi-level grid system for two-well case

Rank	*Infill well 1*		*Infill well 2*		*Objective function (m^3)*
	I	*J*	*I*	*J*	
			1st level grid system		
1	29	34	34	9	770,267,520
2	24	34	29	9	766,720,130
3	29	34	44	14	766,270,270
4	29	34	39	14	765,902,460
5	24	34	34	9	765,812,610
			2nd level grid system		
1	30	34	35	9	770,929,340
2	30	34	32	9	770,922,430
3	30	34	35	12	769,344,320
4	27	34	32	9	768,472,000
5	30	34	29	9	768,291,900
			3rd level grid system		
1	32	33	31	11	772,690,560
2	32	33	33	9	772,508,220
3	32	33	33	11	772,444,540
4	32	33	32	9	772,242,110
5	32	33	35	9	772,240,770

3.3 *Optimisation of three-well placement case*

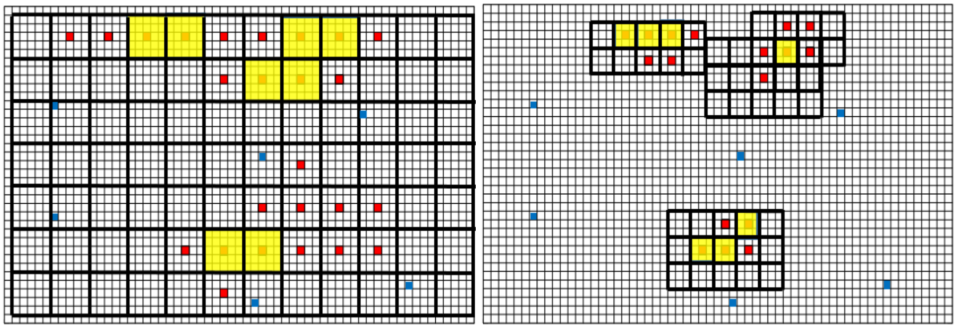
The same design parameters as for the two-well placement case are used to find the optimal placement of three infill wells except the number of training data. In consideration of the size of the search space, a larger number of data are used to train the ANNs. The overall performance of the method is summarised in Table 7. The total number of scenarios is 95,284 in the 1st level grid system, and seven iterations of the cut-off process are performed with 189 simulation runs. The sequential ANN method in the 2nd level grid system, generated with the top five rank solutions, results in 4 ANN models and 80 simulation runs. The 3rd level grid system requires seven ANN models with 293 simulation runs before the global solution is identified. Thus, the total number of simulation runs is 562. The rank of the global solution is within the top 10% in the 2nd level grid system but cannot be assessed for the 1st and 3rd level grid systems because it is practically infeasible to conduct simulation runs for all scenarios.

Table 7 Result of sequential ANN method with multi-level grid system for three-well case

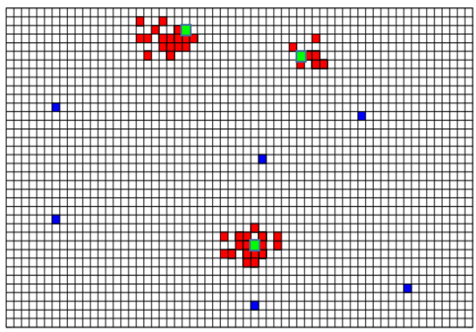
ANN model	*Cut-off value R (%)*	*# of training data*	*Size of search space*[1)]	*Rank of the global solution (%)*	*# of simulation runs*
			1st level grid system		
1st	15	50	95,284	N/A	50
2nd	20	70	14,335	N/A	20
3rd	25	90	2,925	N/A	20
4th	30	110	813	N/A	20
5th	30	130	344	N/A	20
6th	30	150	219	N/A	20
7th	30	170	191	N/A	20
-	-	-	-	-	19[2)]
			2nd level grid system		
1st	15	50	3,000	4.80	30
2nd	20	60	502	5.98	10
3rd	25	70	155	1.94	10
4th	30	80	105	0.95	10
-	-	-	-	-	20[2)]
			3rd level grid system		
1st	30	100	83,875	N/A	61
2nd	30	130	25,246	N/A	30
3rd	30	160	7,687	N/A	30
4th	30	190	2,450	N/A	30
5th	30	220	911	N/A	30
6th	30	250	468	N/A	30
7th	30	280	353	N/A	30
					52[2)]

Notes: [1)] The size of the search space is the union of the top *R* ranked data and the training data in each iteration. [2)] Simulations for the remaining search space after the final cut-off process are counted.

Figure 11 Search space remaining in the (a) 1st level grid system, (b) 2nd level grid system and (c) 3rd level grid system (see online version for colours)



(a) (b)



(c)

Notes: Search space.
Existing wells.
Search space of top 5 ranks.
Global solution.

Figure 12 Cumulative gas production profile for three-well case (see online version for colours)

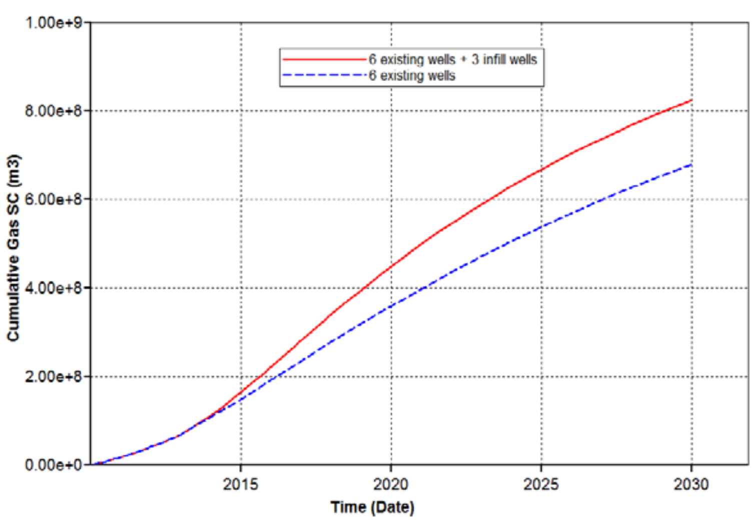


Figure 11 shows the trend of reduced search space according to level of the grid system. Once the sequential ANN method is applied to the 1st level grid system, three distinct regions are identified as potential locations for each well [Figure 11(a)]. After narrowing the search space using grid systems with higher resolution, the optimal placement for the three wells is identified, as shown in Figure 11(c). The three green dots in Figure 11(c) are the optimal locations determined for the three infill wells. The top five ranks of each level of the grid system are listed in Table 8. The solutions are collected around the optimal solution. The cumulative gas of 20-year production is 824,157,820 m^3 and the corresponding profile is depicted in Figure 12.

Table 8 List of top five ranks with multi-level grid system for three-well case

Rank	*Infill well 1*		*Infill well 2*		*Infill well 3*		*Objective function (m^3)*
	I	*J*	*I*	*J*	*I*	*J*	
1st level grid system							
1	24	34	44	34	34	9	820,813,060
2	24	34	34	29	34	9	820,722,500
3	24	34	39	29	34	9	819,734,780
4	19	34	39	34	34	9	818,328,580
5	24	34	44	34	29	9	818,216,450
2nd level grid system							
1	22	34	40	32	32	9	821,426,940
2	22	34	40	32	35	12	820,788,100
3	22	34	40	32	29	9	820,701,180
4	19	34	40	32	32	9	820,650,430
5	25	34	40	32	32	9	820,412,420
3rd level grid system							
1	23	35	39	32	33	9	824,157,820
2	23	35	39	32	31	11	824,004,800
3	23	35	39	32	34	9	823,981,440
4	23	34	39	32	33	9	823,925,820
5	23	35	39	32	32	9	823,904,450

4 Conclusions

In this study, the sequential ANN method incorporated with the multi-level grid system was proposed to optimise multi-well placement, and applied for two- and three-well cases in a CBM reservoir. As the number of wells for optimisation increased, the number of scenarios increased exponentially. Too many scenarios could make it difficult to find the optimal solution only using the sequential ANN method. This limitation was relieved by introducing the multi-level grid system that reduced the number of scenarios in the search space by defining one well block per several blocks in the basic grid system. By repeatedly applying the sequential ANN in each level of the grid system, the search space reduced effectively, and the global solution was determined successfully. Considering that a relatively small number of simulations were required in comparison to the size of search space, the proposed methodology was proved to be efficient for well placement optimisation.

In general, the design parameters of the sequential ANN and the multi-level grid system depend on the characteristics of the problem. When the size of the problem is enormous, the grid block of the 1st level grid system should be large enough to reduce the search space to a manageable size. However, too large a grid block makes it difficult for the well performance to represent the grid block. This issue could be averted by increasing the number of top ranked solutions used to generate a reduced search space for the next level grid system, by reducing model size using a sector model rather than a full-field model if possible, or by focusing on the sweet spots in the reservoir from expert opinions, etc.

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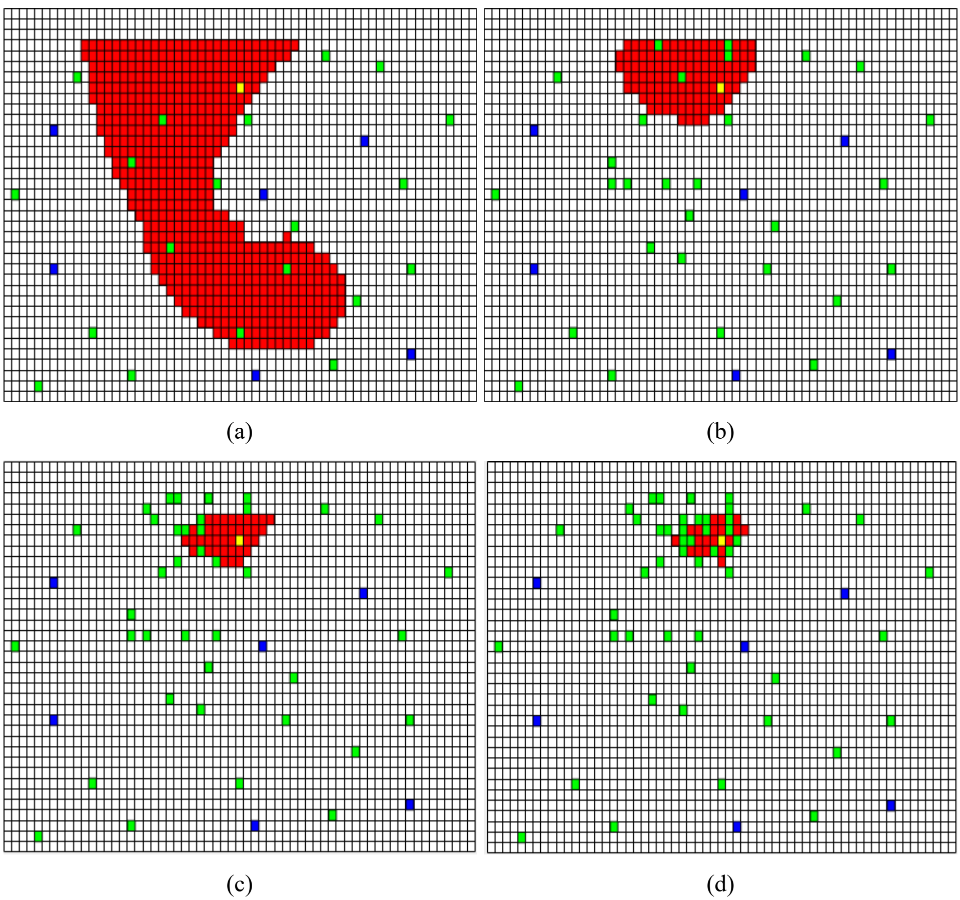
Appendix

Application of the sequential ANN method

Application of the sequential ANN method is briefly summarised for optimal placement of a single horizontal well in the reservoir shown in Figure 4 (Jang et al., 2018). The number of initial training data is 20, with 10 of east-west and 10 of north-south directions. The cut-off value R is set to 15, 20, and 30% for the subsequent ANN models and 40% for the fourth and later models. Ten training data points are newly added to the existing training dataset to train the subsequent ANN model.

Figure 13 shows the search space maps which result from the sequential ANN method. A new search space reduced by the procedure is represented by a red dot, and the training data is indicated by a green dot. Thus, the 1st ANN model reduces the entire search space into a smaller search space, as shown in Figure 13(a), which is the input for the 2nd ANN model. The procedure ends after the ANN model is applied four times, and the global solution is identified by a yellow dot [Figure 13(d)]. The global solution is verified with exhaustive simulation runs, which are performed separately for all scenarios. The optimal well placement is determined as shown in Figure 14(a), and the production performance is depicted in Figure 14(b).

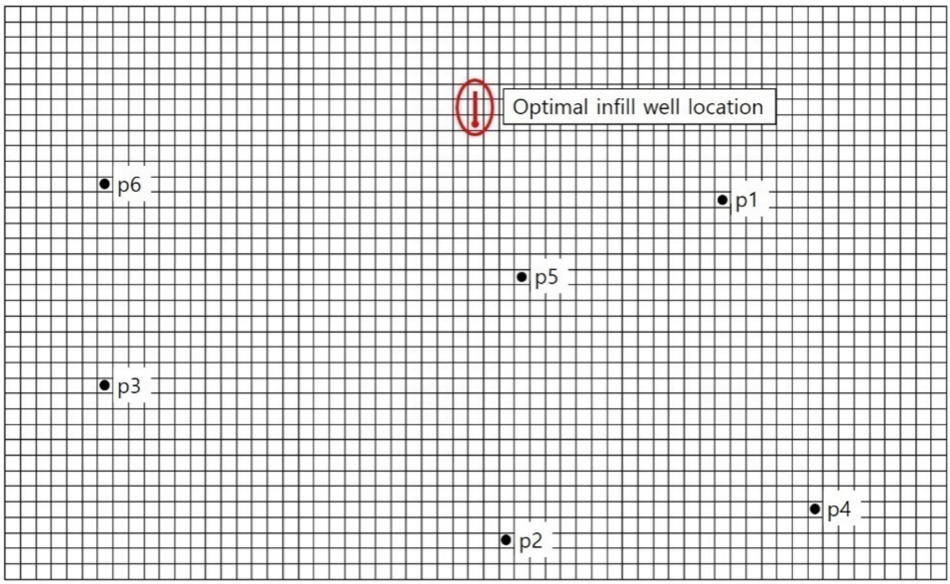
Figure 13 Search space map after applying the (a) 1st ANN model, (b) 2nd ANN model, (c) 3rd ANN model and (d) 4th ANN model (see online version for colours)



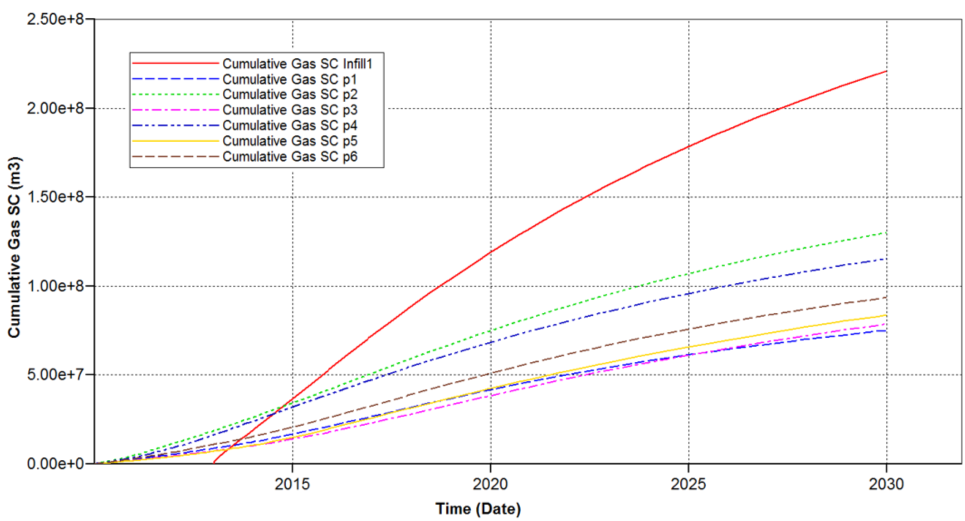
Notes: Reduced search space T;
Existing well locations;
Global solution;
Training data.

Source: Modified from Jang et al. (2018)

Figure 14 (a) Optimal infill well location selected using sequential ANN (b) Comparison of cumulative gas productions for optimal infill well and existing wells (see online version for colours)



(a)



(b)

Source: Jang et al. (2018)