공학석사 학위논문

Channel Reservoir Characterization by Ensemble Smoother with Selective Water Breakthrough Data

선택적 물 돌파자료를 이용한 앙상블스무더의 채널저류층 특성화

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Kim Gvan Dek의 석사 학위논문을 인준함

2018년 08월

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Abstract

Reservoir characterization is a process to figure out reservoir parameters of interest using available data. Ensemble Smoother (ES) method is one of the main methods of reservoir characterization in petroleum engineering. ES utilizes and assimilates all available data through a single global update. ES is fast but unstable with possible overshooting of parameters and distorting of parameter's distribution.

In this research, a method called selective use of measurement data using ES for each well is suggested in order to improve its performances. The proposed method is to use oil production rates before water breakthrough and water cut rates after water breakthrough for each well.

ES is very sensitive to the initial ensemble members. Therefore, it is necessary to select reliable models, which are similar to the reference one for better stability in the assimilation step. In this study, PCA (Principle Component Analysis) and K-means Clustering are applied to get good reservoir models.

In order to check the superiority of the proposed method, 3 methods are compared in our research: ES with all data; ES with 100 initial models selected by PCA and K-means Clustering; and ES with 100 initial selected models and selective measurement data. 2D synthetic channelized reservoir models are applied with nine-spot waterflooding.

The proposed method can properly overcome the limitation of standard ES and conserve channel connectivity. this method manages high uncertainty ranges, gives the best reservoir characterization results and shows the reliable future performance estimations.

Keywords: channel reservoir characterization, selective use of measurement data, water breakthrough, Ensemble Smoother (ES)

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Chapter 1 Introduction

1.1. Study Background

Reservoir characterization is one of the most important things for decision making in petroleum engineering. The way to make reliable and proper reservoir models is using static and dynamic data together. Static data can be integrated via geostatistical methods in order to generate reservoir models by using available reservoir information, such as seismic data, well logging, core sample, and geological concept. Dynamic data are dependent on time. It can be gas, oil, and water production rates or bottomhole pressures.

Prior reservoir models made by using only static data have high geological uncertainties, since we have limited available data. In order to reduce these uncertainties, history matching is applied to integrate dynamic data, however, the uncertainty range might be still high due to modelling error, limited data, or measurement error. Therefore, quantifying uncertainties is vital for future performance.

For proper decision making, geological ensemble members are very often utilized to various reservoir characterization methods. Ensemble Kalman filter (EnKF) is one of the most popular techniques and it is widely utilized and applied for history matching and uncertainty quantification. In 1960 Kalman first proposed Kalman filter for linear systems and then Evensen (1994) offered EnKF for highly nonlinear problems in ocean dynamics.

In case of reservoir engineering, EnKF was introduced by Nævdal et al. (2002) to figure out permeability distribution. The key

point of EnKF is that it assimilates observed data in real time and gives uncertainty quantification in predicted productions, real-time updating of observed data, easy coupling with any forward simulator, and flexibility with various types of model parameters and observed data.

However, EnKF has two critical limitations: overshooting and filter divergence (Aanonsen et al., 2009; Jeong et al., 2010; Oliver and Chen, 2011). These problems occur, because model parameters of channel field do not follow Gaussian distribution (Evensen et al., 2007) or initial ensemble models are not reliable and quite different from the true model. The importance of overcoming EnKF demerits was described by many researchers. Zhang et al. (2016) estimated relative permeability and capillary pressure for tight formation using EnKF. Yeo et al. (2014) proposed the covariance localization method, which eliminates relatively low correlated data between reservoir parameters and observations. Some researchers (Jung et al, 2017, Jafarpour and McLaughlin, 2009) transformed model parameters using discrete cosine transform or normal score transform.

Even though, these researches have good results of improving reliability of EnKF, the huge amount of computational time is a critical element of applying to real field cases. EnKF basically requires a lot of forward simulations due to recursive updates and multiple number of ensemble models, because the ensemble-based method demands hundreds of models for reliable history matching.

Van Leeuwen and Evensen (1996) applied Ensemble Smoother (ES) for meteorology and compared EnKF with ES for history matching. Skjervheim et al. (2011) first proposed ES to reservoir characterization. They suggested that ES showed quite reliable

results compare to EnKF. ES is very fast and simple, because it assimilates all dynamic data at once, simultaneously. Also it is easier than EnKF for coupling with any reservoir simulator since it does not need any restart option. However, it is still unstable and exposed to the possible overshooting and filter divergence.

In order to overcome these issues and get reliable results, it is necessary to improve available data and select valuable initial ensemble models, because ES is very sensitive to them. The ensemble-based algorithms are based on mathematical theory. Therefore, initial ensemble models have significant influence on prediction performances. The selection of reliable ensemble, which are similar to the true model, is very essential in reservoir characterization.

By using only well-designed initial ensemble models, future performances can be well predicted and also the simulation time can be dramatically reduced by using ES due to one global update. However, the selection of trustworthy ensemble members is not easy to implement, because there are the number of geological models as well as limited data available. Peters et al. (2011) proposed the method of selecting initial models for EnKF using multi-dimensional scaling (MDS). Kang and Choe (2017) and Kang et al. (2017) used K-means clustering and principle component analysis (PCA) for taking the most reliable models. The method of selecting initial models made by them is adopted in this study to have good reservoir models and save computational time.

Using the method called the selective use of measurement data can be also very effective for reliable history matching. Due to a various types of different data, some of them can give a confused

information for the assimilation. Some researchers have suggested solutions for the issue. Park and Choe (2006) eliminated misinterpretable data such as low water rates before water breakthrough for conventional reservoir. Jeong et al. (2013) examined that the uncertainty analysis in reservoir performance is sensitive and reliable when dynamic data after water breakthrough are utilized for history matching. Lee et al. (2014) focused on improving history matching and uncertainty quantification of the standard ES and used the observed data on the basis of the first water breakthrough of the field. Even if the above researches show improved characterization results, they cannot guarantee stable results.

In this research, the selective use of measurement data is suggested in order to improve its performances by reducing the possibility of misuse of observed data in ES. Key idea is that observed data are selected out on the basis of water breakthrough for better reservoir characterization. Oil production rates before water breakthrough and water cut rates after water breakthrough for each well are utilized for predicting future performance, because ES cannot interpret the physical characteristic of water breakthrough properly.

Initially 400 ensemble models are generated by Training Image (TI) simulator, and then 100 initial models are selected by using PCA and K-means clustering. After that non-sensitive data are excluded from the state vector for better history matching. Finally, ES is applied for the calibration step.

In chapter 1, the study background is explained. Chapter 2 consists of methodology information, which is used for the proposed

method. Chapter 3 shows the results of applying the proposed method. The dissertation is finished by conclusions and bibliography.

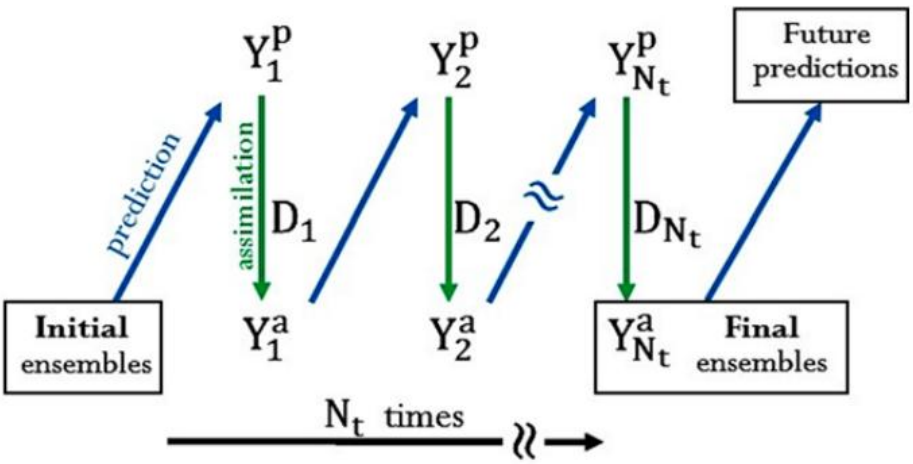


Fig. 1.1 EnKF process (Lee et al., 2016)

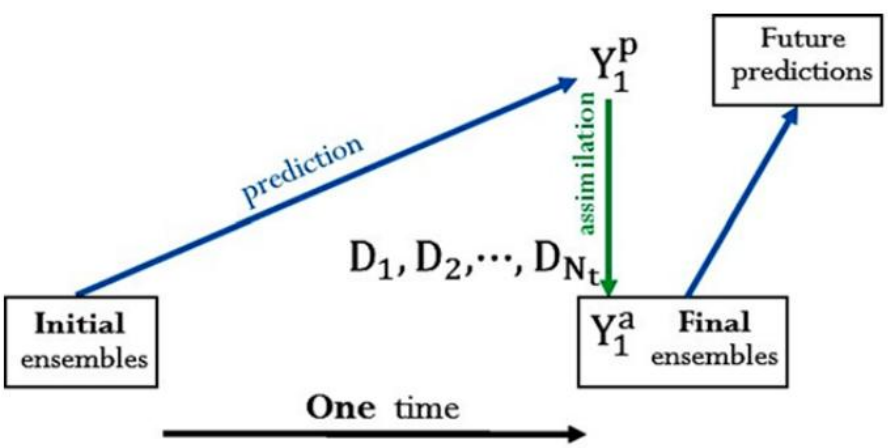


Fig. 1.2 ES process (Lee et al., 2016)

1.2. Purpose of the Research

In order to get reliable future performances of a channel reservoir, proper prediction of reservoir behavior is very essential. Moreover, it is important to keep channel boundary as well as the trend of facies distribution. For checking the superiority of results, 3 methods are compared in this research:

1. ES with all 400 ensemble members.
2. ES with the selection of 100 initial models by PCA and K-mean clustering.
3. ES with the selected 100 members with selective measurement data (the proposed method).

All the 3 cases are applied to two channel reservoir patterns. As the results, log permeability distribution, Well Oil Production Rate (WOPR), Well Water Cut (WWCT), Field Oil Production Total (FOPT), and Field Water Production Total (FWPT) are demonstrated in this study.

The overall procedure of the proposed method is shown below:

- By using static data from the nine wells in the reservoir, one reference field and 400 ensemble models are generated. Ensemble members are equip-probably generated by geostatistical methods.
- By using PCA, the high dimensional permeability distribution is reduced and the ensemble models are plotted on the 2D plane.
- K-means clustering divides the ensemble into 10 groups.
- Afterwards, the nearest ensemble models to the centroid of

each cluster are selected and production estimations of 10 representative models are calculated to find the best model which is closed to the true one.

- Then 100 ensemble models near by the best model are selected.
- WOPR and WWCT are analyzed to identify misinterpretable data and exclude them from the set of data for making reliable results of using ES.
- Finally, the future predictions of 100 models selected and updated with the proposed method are shown.

For more easily understanding the overall procedure is shown in Fig. 1.3.

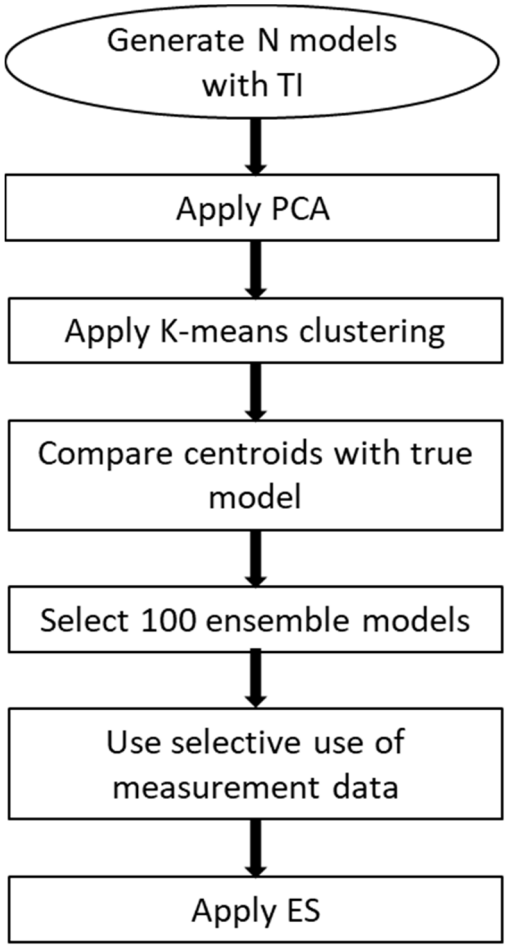


Fig. 1.3 Overall procedure of the proposed method

Chapter 2 Methodology

2.1 Channel reservoir

Hydrocarbons like oil or gas can be stored in reservoir rock such as sandstones or carbonates. There are various types of sandstones. They are shoreline sandstone, dune sandstones, river sandstones, and so on (Hyne, 2012).

Shoreline sandstones are made in beaches, that are long and narrow deposits of well-sorted sand. Waves exclude the particles of salt and clay out of the beach sand. Sand dunes are created by wind in both desert and coastal environments. They have very-well-sorted fine sand. River sandstones are constructed in a meandering river. Sands are collected inside of the river meanders called point bars. For example, in the Powder River basin of Wyomng, Miller Creek field has 5 million bbl of expected oil (Hyne, 2012).

Delta sandstones are common in body of water, such as a lake or ocean. The sediments are deposited there by a river flowing. There are two important process: a constructive force when the river deposits sediments and a destructive force which shaped by wave erosion (Hyne, 2012). All of these types of sandstones can be good oil or/and gas reservoir rocks.

Most channel sandstones are formed in rivers and braided stream makes interconnected channels (Fig. 2.1). In delta structures, channels, called distributaries are created by rivers. As seen in Fig. 2.2, these types of channelized reservoirs have their unique pattern

and connectivity (Lee et al., 2016). The impact of the pattern and connectivity of channel is very high for oil, gas, and water productions. Therefore, it is not easy to characterize channel reservoir due to high heterogeneity and a bimodal permeability distribution. Consequently, that makes very difficult to predict reservoir performances and show proper results of history matching of a channelized reservoir by using standard EnKF or ES methods (Lee et al., 2014).

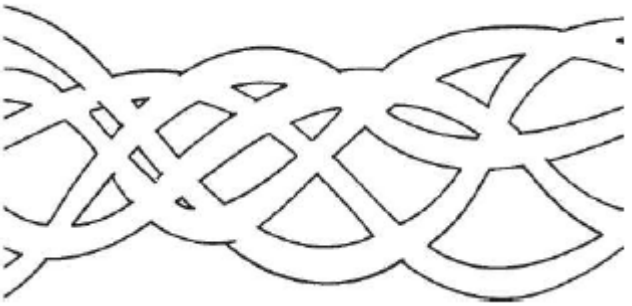


Fig. 2.1 Braided river (Hyne, 2012)

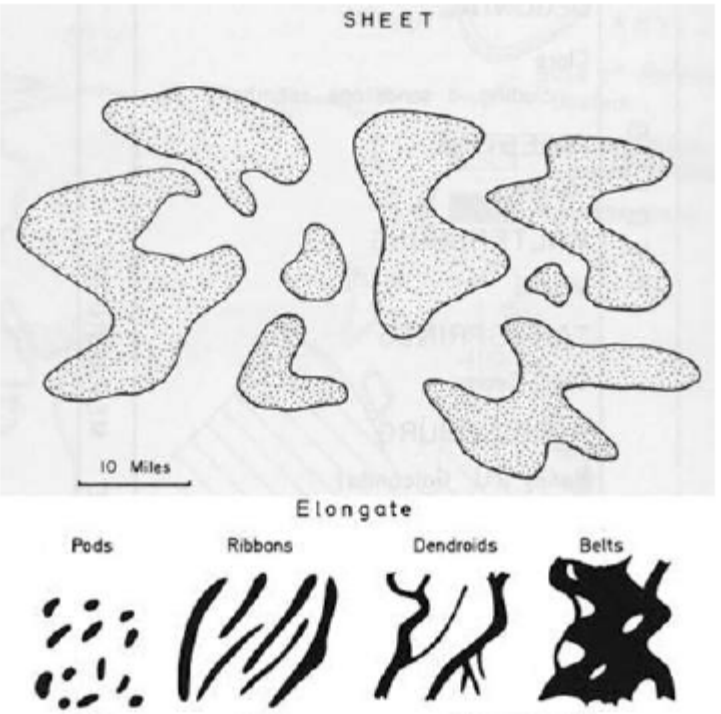


Fig. 2.2 Horizontal connectivity of sand channelized reservoirs (Potter, 1962)

2.2 Principle Component Analysis

By using geological parameters such as permeability or porosity a reservoir model can be generated. It is possible to apply all the data. However, it takes too much computational time and has a noise, which does not help to predict the main geological trend of the data. In order to figure out the similarity among data easily, a low dimensional method should be used.

One of them is Principle Component Analysis (PCA). It is one of the most popular and widely applied multivariate data analysis methods. It can extract a small number of variables, called principal components. This tool is extensively utilized in various areas: seismic data interpretation, history matching, and face recognition (Kang et al., 2017; Chen and Oliver, 2014; Scheevel and Payrazyan, 2001).

By using linear algebra, the first solution to PCA is derived. In other words, covariance matrix is constructed by Eq. 2.1, where $\boldsymbol{X}$ is a data set with mxn matrix, where m is the number of measurement types and n is the number of samples. Then the covariance matrix is decomposed in order to get eigenvectors and eigenvalues as Eq. 2.2.

$$\mathbf{C} = \frac{1}{n-1}\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}} \tag{2.1}$$

$$\mathbf{C} = \mathbf{E}\mathbf{D}\boldsymbol{E}^{\boldsymbol{T}} \tag{2.2}$$

Where, C is the covariance matrix, E is a matrix of eigenvectors and D is eigenvalues.

For the sampling of good initial channel models, PCA is introduced to reduce the high dimensional model parameter of permeability. This algorithm is used to discover common trend of the permeability distribution of reservoir models. Thus, the main direction of data distribution is feasible by calculating the eigenvectors and corresponding eigenvalues. The eigenvectors can illustrate the main directions of data distribution. The large eigenvalues can be found out and then plotted on the plane whose axes are principle directions.

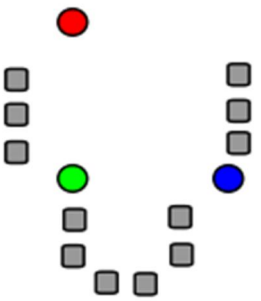
2.2 K-means Clustering

Clustering is a technique of data grouping. It attempts to group individuals in a population together by similarity, but not driven by a specific purpose. Clustering can be considered the most important unsupervised learning problem and it deals with a structure of unlabeled data. The goal of clustering is to determine the intrinsic grouping in a set of the data. It is widely used in many fields: marketing prediction, classification in biology, earthquake studies, geographical and geological locations, and so on.

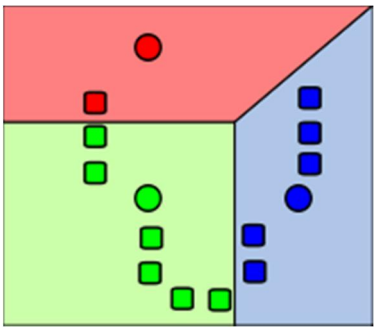
K-means clustering is a one of the popular methods of clustering analysis in data mining. K-means clustering is often called as a classical partitioning technique of clustering that clusters the data set on n objects into k clusters with k known a priori. The procedure of K-means clustering is shown in Fig. 2.3. The algorithm consists of 2 steps: cluster assignment step and moving centroid step. In the first step, the method goes through each of the data points and, depending on which cluster is closer, it assigns the data points to one of the cluster centroids. In the second step, k-mean moves the centroids to the average of the points in a cluster. In other words, the algorithm calculates the average of all the points in a cluster and moves the centroid to that average location. This process is repeated until there is no change in the clusters.

In this research K-means clustering is utilized to divide the ensemble models into 10 groups and select the most reliable 100 ensemble models, which have low dissimilarity with the reference model. The algorithm has a big advantage with reducing simulation

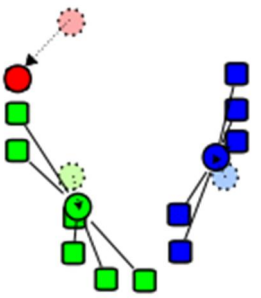
cost by excluding redundancy while preserving the diversity of initially generated models.



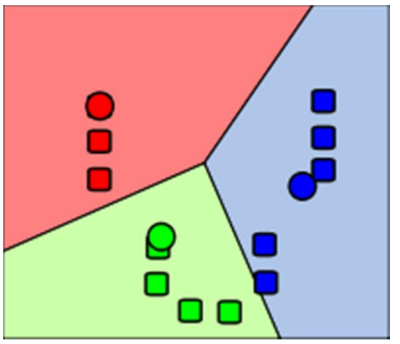
(a) fix number of *k*-means is randomly generated



(b) *k* clusters are created by associating every observation with the nearest mean



(c) The centroid of each of the k clusters becomes the new mean



(d) Steps 2 and 3 are repeated until convergence has been reached

Fig. 2.3 The demonstration of the standard algorithm

2.3 Ensemble Smoother

ES assimilates all observed data through a single global update. In other words, it demands only one forecast step from the initial time to the last observed step (Eq. 2.3):

$$\begin{Bmatrix} m^d \\ d \end{Bmatrix} = \int (m^s, m^d) \tag{2.3}$$

Where, $\mathbf{m^s}$, $\mathbf{m^d}$, and $\mathbf{d}$ mean static parameters, dynamic parameters, and the model prediction, respectively.

After the prediction step, calculations in the assimilation step are based on ensemble model shown as a state vector, $\mathbf{y}$, which contains 3 parameters for the k-th member (Eq. 2.4):

$$y_i = \begin{bmatrix} m^s \\ m^d \\ d \end{bmatrix}_i, \ i = 1, N_e \tag{2.4}$$

Where, $\mathbf{N_e}$ correspond the number of total ensemble members.

The state vector is assimilated by Kalman gain and the difference between the observed data and predicted data (Eq. 2.5). Kalman gain $\mathbf{K}$ is estimated to minimize the estimated error covariance, $\mathbf{C_Y}$ as shown in Eq. 2.6:

$$y_i^a = y_i^p + K \ \ (d_i^{obs} - Hy_i^p) \tag{2.5}$$

$$K \ \ = C_Y^p H^T (HC_Y^p H^T + C_D)^{-1} \tag{2.6}$$

Where, superscripts a and p present the assimilated and the previous state vector respectively. H and C_D represent the measurement operator and the observation error covariance, respectively. Superscript T means the transpose of the matrix and d^{obs} stands for the measurement data. The flow chart of ES is shown in Fig. 2.4.

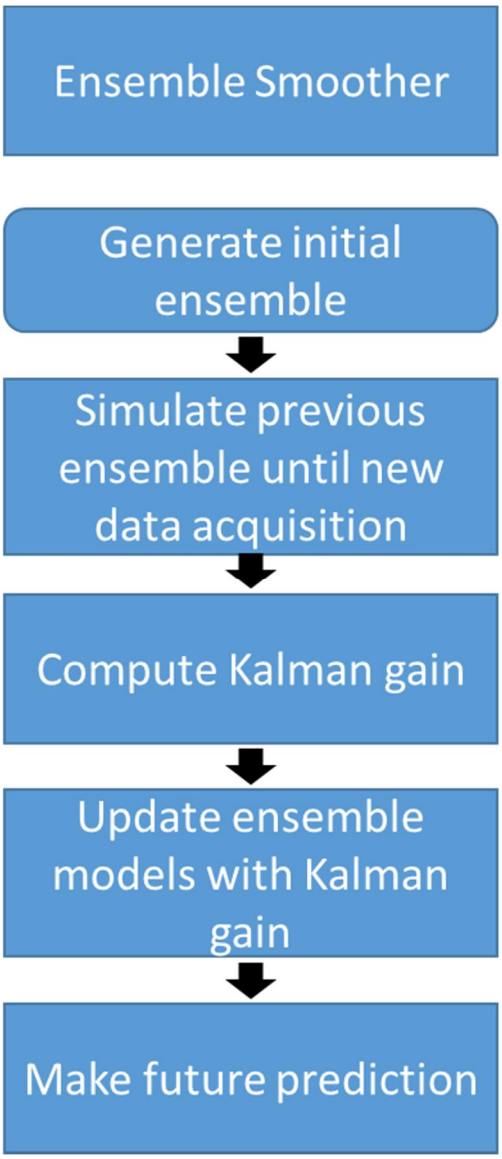


Fig. 2.4 Flow chart of ES

2.4 Selective Measurement Data

Selective use of measurement data is applied for getting reliable results of history matching and uncertainty quantification of the standard ES, because it is a simple and easy concept for reservoir characterization. ES can use different types of observed data at the same time. Therefore, some of incoherent data may give a confused information for history matching and reduce variance of ensemble for the assimilation. So only meaningful production data should be selected logically instead of all available observed data.

The vulnerability of production data can be analyzed by the difference among observed data. Park and Choe (2006) solved the problem of non-sensitive observed data by eliminating the low water saturation at production wells before water breakthrough. Lee et al. (2014) analyzed the sensitivity of observed data such as WWCT after the first water breakthrough. In Fig. 2.5 they demonstrated the mean of ensemble updated by EnKF in every assimilation step. After measuring the average difference between each model and true model by Eq. 2.7 (Zafari and Reynolds, 2007), the result shows that the misfits are harshly increased due to water breakthrough. That gives an evidence that dynamic data such as decreased WOPR and increased WWCT have become very sensitive when water breakthrough happened.

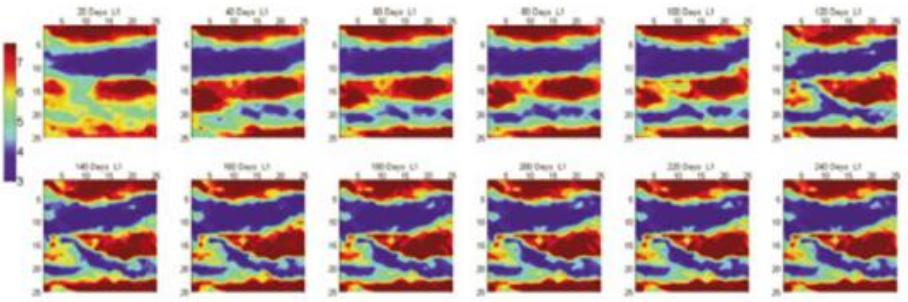
$$\Gamma(\mathrm{m}) = \frac{1}{N_e}\sum_{i=1}^{N_e}\frac{1}{N_m}\sum_{j=1}^{N_m}(m_j^i - m_j^{true})^2 \tag{2.7}$$

Where, $\boldsymbol{N_m}$ is the number of grids, $\boldsymbol{m_j^{true}}$ is j-th grid in the

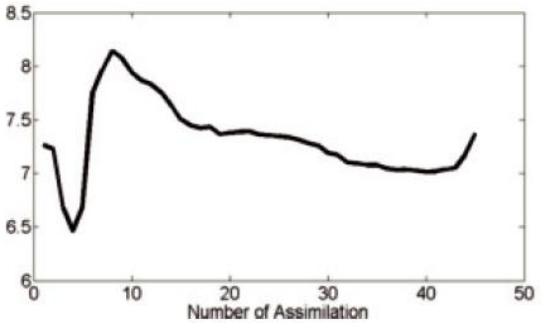
reference field.

In this research, the selective use of measurement data based on the water breakthrough for each well is proposed. It can improve ES performance by reducing the possibility of misuse of observed data. Fig. 2.6 illustrates the conceptual example of the selective use of measurement data. The observed period is divided into 20 steps, where each step has observed data of WOPR and WWCT. The vertical orange lines show the time step where water breakthrough occurred for each well.

Ensemble-based methods interpret reduced WOPR after water breakthrough as a low permeability of the surrounding area of the production wells. However, this is not correct interpretation. The water breakthrough occurs early because of the high permeability between the production and injection wells (Lee et al., 2014). As such, this improper use of observed data may result in misleading information for history matching and lead to a wrong direction of calibration in assimilation steps. Therefore, the method of only using WOPR before water breakthrough and WWCT after water breakthrough is proposed. This method is applied for each well.



(a) The mean of updated ensemble (Lee et al., 2014)



(b) The average of the differences between each ensemble and true model (Lee et al., 2014)

Fig. 2.5 Assessments of updated field as assimilation steps in EnKF

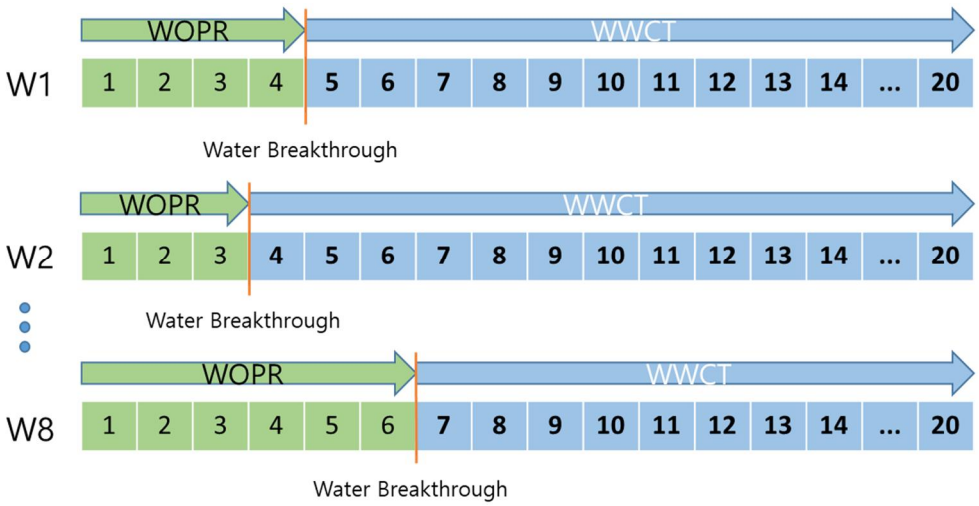


Fig. 2.6 The concept of the selective use of measurement data

Chapter 3 Results

3.1 Model description

The program SGeMS (Stanford Geostatistical modeling software) is used as a software for making 2D synthetic models. By using the module of SGeMS called TI simulator, TI has been made, and permeability distribution has been created by SNESIM. Total 400 initial ensemble models and the reference field are generated for this study. The reference model is shown in Fig. 3.1.

The reservoir is waterflooded with an inverted nine-spot pattern. The injection is located at the center of the model, four producing wells at corners and another four wells at the middle of the four sides. The grid consists of 25 x 25 x 1 cells with $\Delta x=\Delta y=50$ ft and $\Delta z=20$ ft. WOPR and WWCT are used to assimilate ensemble and they are available every 100 days until the end of the observed period at the 500th day. In spite of the 5 time steps of observed data, the initial models using ES are updated only once and after the update, the future productions are predicted for the next 500 days. Therefore, the total production period is 1,000 days.

The detailed information of grid parameters is shown in Table 3.1. Bottomhole pressure condition of each producing well is same and constant as a value of 2000 psia, water injection of 300 STB/day (Table 3.2).

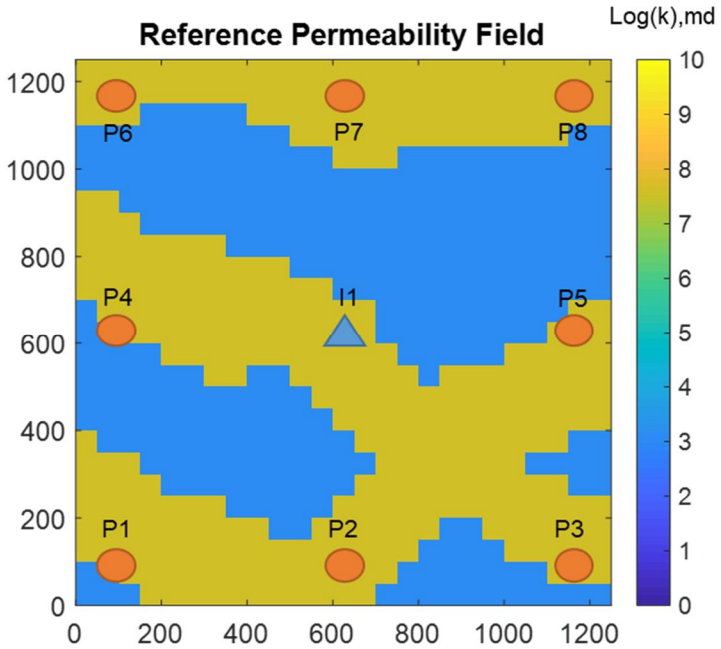


Fig. 3.1 Permeability distribution of the reference field
(O: production wells; Δ: injection well)

Table 3.1 Reservoir parameters

Properties	Values
Grid system, cells	21 ×21× 1
Size of grid, ft	50 × 50 × 20
Well type	Inverted 9-spot
Model generation method	SNESIM
Forward simulator	ECLIPSE 100
Observed period, days	5 x 100 (500)
Production period, days	1000
Sand permeability, mD	20
Shale permeability, mD	2000
Number of initial models generated	400

Table 3.2 Well locations and operating conditions

Well name	Location (ft)	Control target (STB/day or psi)
Injection well	(13,13)	300
Well 1	(2,2)	2000
Well 2	(13,2)	2000
Well 3	(24,2)	2000
Well 4	(2,13)	2000
Well 5	(24,13)	2000
Well 6	(2,24)	2000
Well 7	(13,24)	2000
Well 8	(24,24)	2000

3.2 Log permeability field

As seen in the Fig. 3.1, there are two clearly visible and permeable channel zones. They are not connected to each other. One of them is formed as a streak shape and it goes along the upper edge of the field through wells P6, P7 and P8. Another channel has cross-shaped geometrical figure, which is passed through the injection well I1 and connected with rest of the production wells. The histogram of the reference field is demonstrated in Fig. 3.2 with sand (2000md) and shale (20md).

Fig. 3.3 indicates the water breakthrough in the reference field. The water breakthrough of the first 4 wells P2-P5 occurred in between 200 and 400 days of the production, because they have channel with the injection well. The wells P6, P7, and P8 have not shown any water breakthrough during the whole production period. It is happened, because they are not connected by channel to the injection well. Even when the water is injected, it cannot flow through due to the low permeable shale rock.

Fig. 3.4 illustrates the mean of permeability distribution of the initial 400 ensemble members. It is insufficient compared to the true model, and it shows wrong channel connectivity due to various number of unreliable ensemble models. Fig. 3.6 shows the assimilated permeability that is quite reliable to the reference one.

Channel reservoirs have highly heterogeneous properties. Therefore, it needs suitable number of reservoir models for successful characterization. In order to reduce the members of ensemble and select proper ensemble models, PCA and K-means

clustering are utilized for this research. First, a covariance matrix is constructed and it is decomposed to find the eigenvectors of large eigenvalues. Fig. 3.8 demonstrates eigenvalues of the covariance matrix in the descending order. The eigenvectors corresponding to the two largest eigenvalues are used to make two-dimensional plane. Second, 400 ensemble models were plotted on 2D plane and divided into 10 clusters by using K-means clustering algorithm.

Results of clustering can be different due to randomness of initial settings. After that, 10 representative models, one from each cluster, are selected. The models are the most closely located to the center of the clusters and then compared with the true observed values to find the best model. Finally, 100 ensemble models are picked up near by the best model. The selection results are shown in Fig. 3.9.

Fig. 3.10 provides the permeability distribution of the 100 selected models. As seen, reducing the number of models and picking up only suitable models give much better results. The channel trend almost follows to the reference model and connectivity can be identified. However, the facies boundaries are quite diffused and fuzzy. In Fig. 3.12, the assimilated permeability distribution of the 100 selected models is represented. Even the channel trend looks quite similar to the true model, there is an overshooting problem. The center of the field shows too high permeability distribution and also the connectivity of the lower channel on the left side is hard to be characterized.

After applying the selective use of measurement data as shown in Fig. 3.14, the permeability distribution is illustrated more reliable and clear than the other cases. Excluding misinterpretable data solves the ES issue while preserving key characteristics of the

models. Eliminating redundancy also helps to reduce the total simulation time for history matching.

Figs. 3.2, 3.5, 3.7, 3.11, 3.13, and 3.15 show their histograms. Among them the proposed method has high frequency of lognormal permeability at nearby 3 and 8 which are very close to the true model.

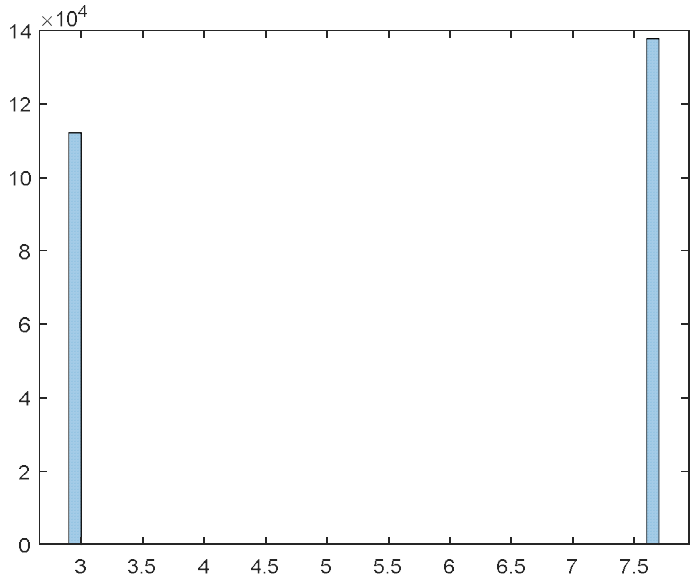


Fig. 3.2 Log-permeability histogram of the reference field

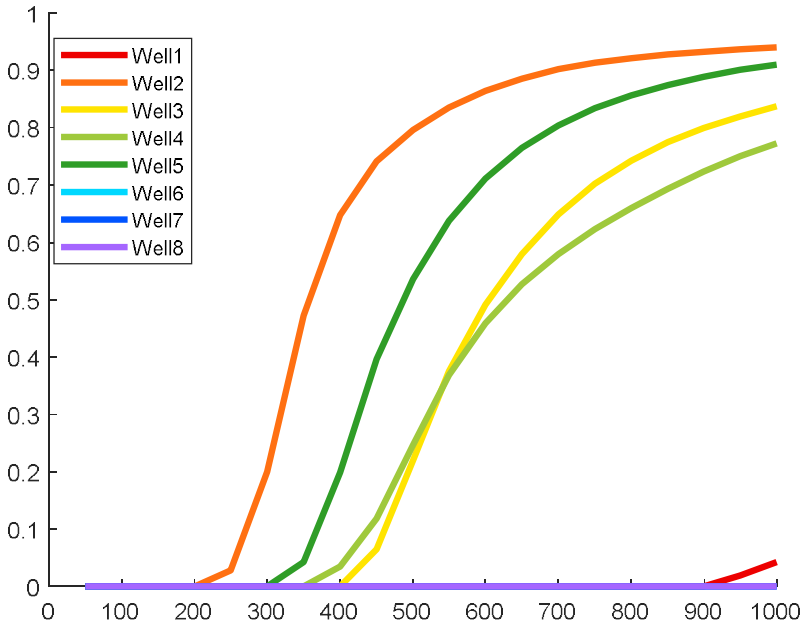


Fig. 3.3 Water cut for each well of the reference field

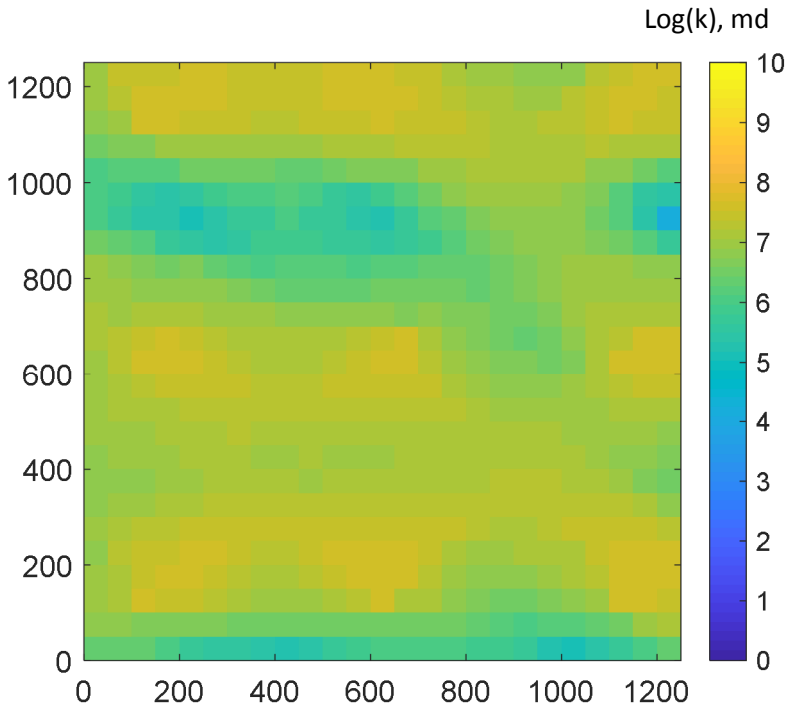


Fig. 3.4 Initial permeability mean of the 400 ensemble models

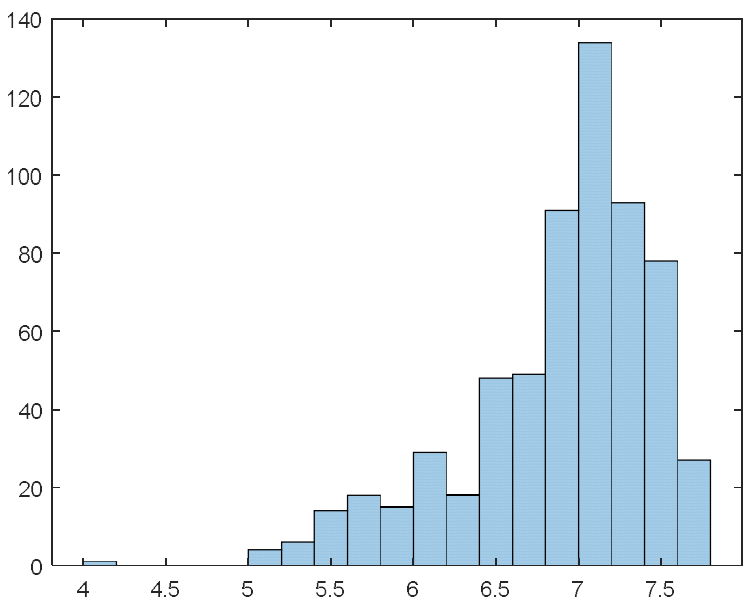


Fig. 3.5 Initial log-permeability histogram of the 400 ensemble models

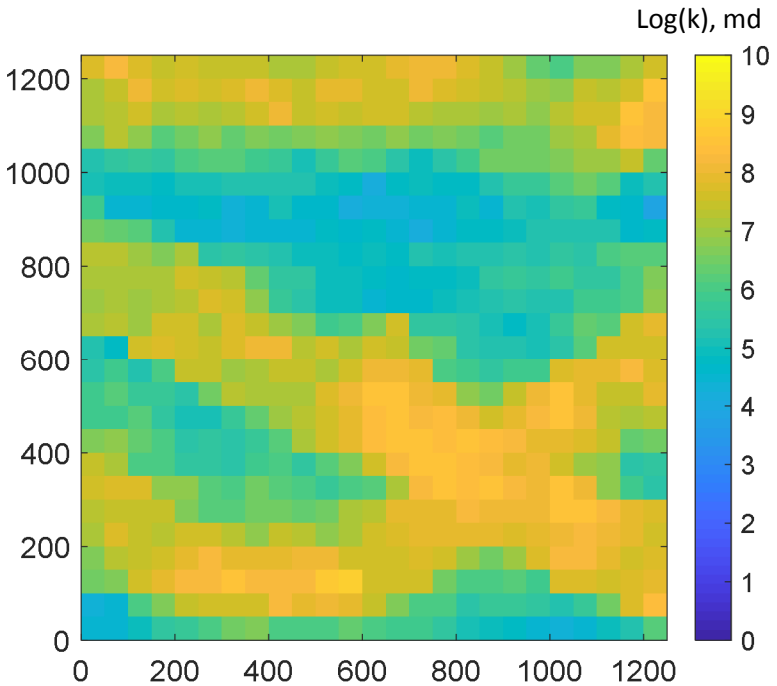


Fig. 3.6 Assimilated permeability of the 400 ensemble models

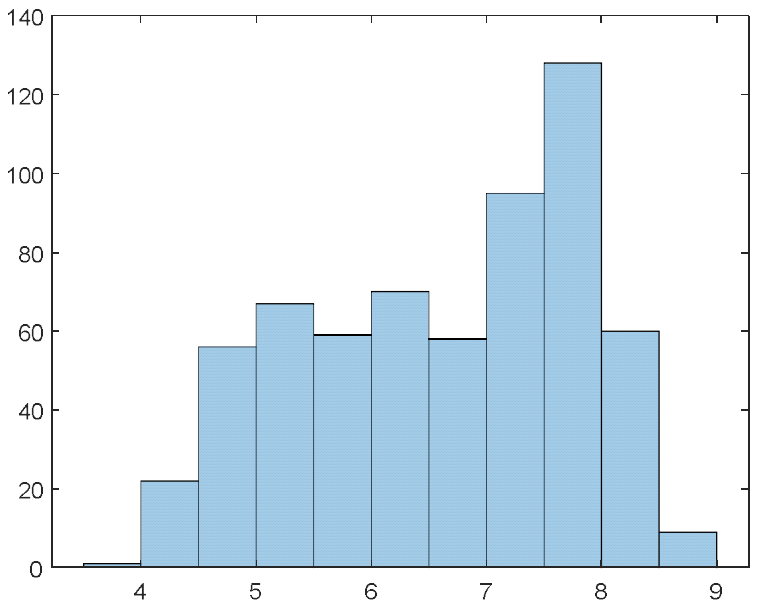


Fig. 3.7 Assimilated log-permeability histogram of the 400 ensemble models

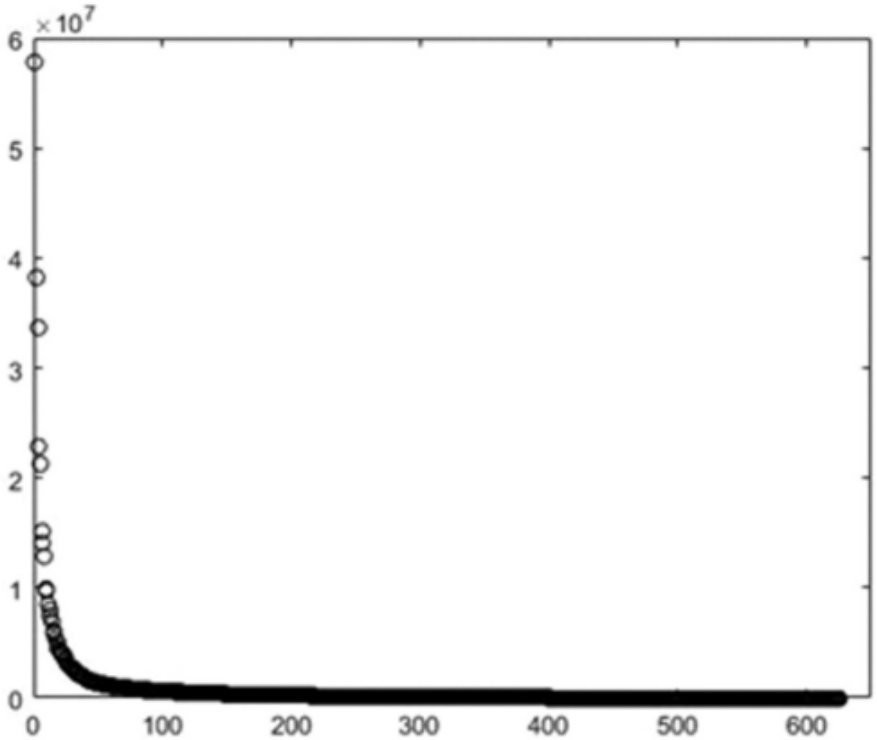
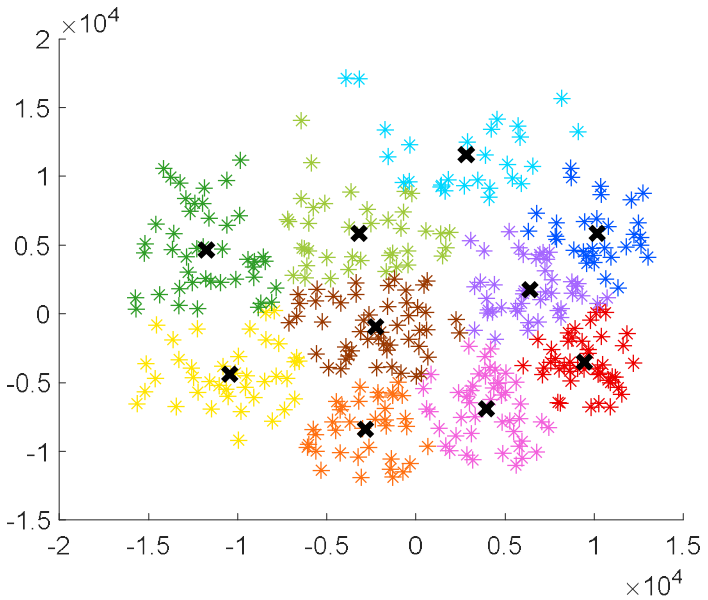
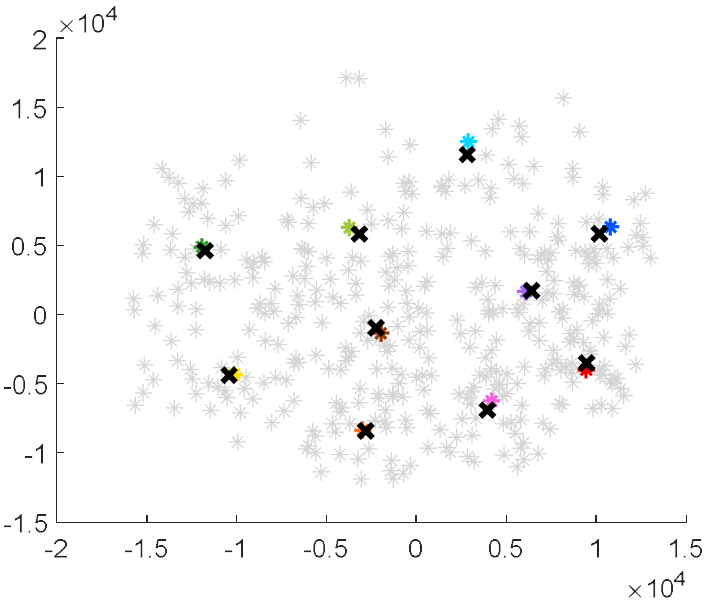


Fig. 3.8 Eigenvalues of a covariance matrix from initially generated ensemble (Kang et al., 2017)

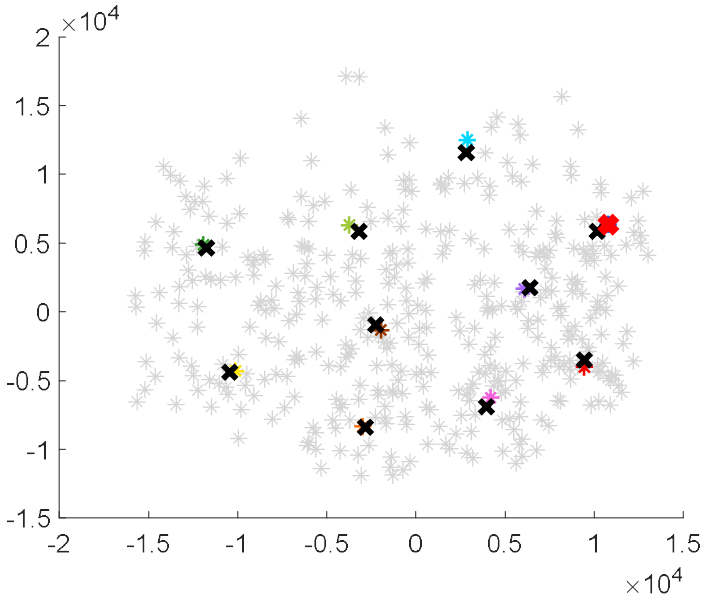


(a) Divide into 10 clusters

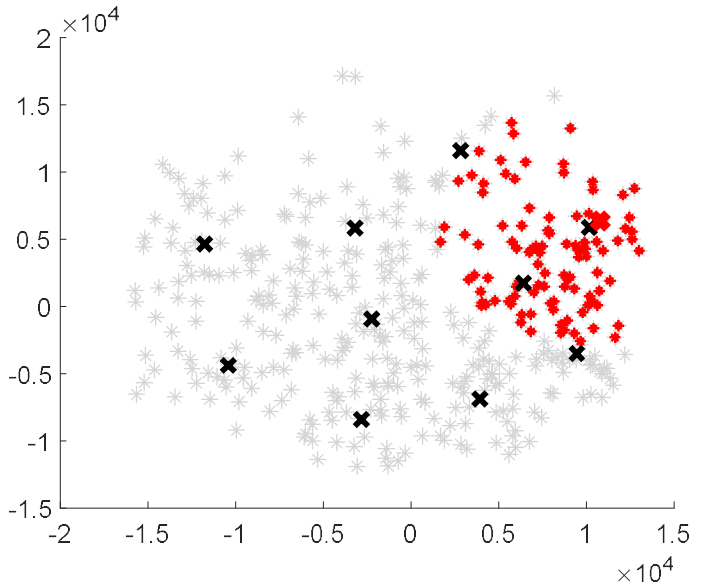
(**x**: the center of each cluster)



(b) Select the representative models closed to the center of each cluster



(c) Find the best model among 10 representative models



(d) Select 100 ensemble models near by the best models

Fig. 3.9 K-means clustering for selecting reliable ensemble models

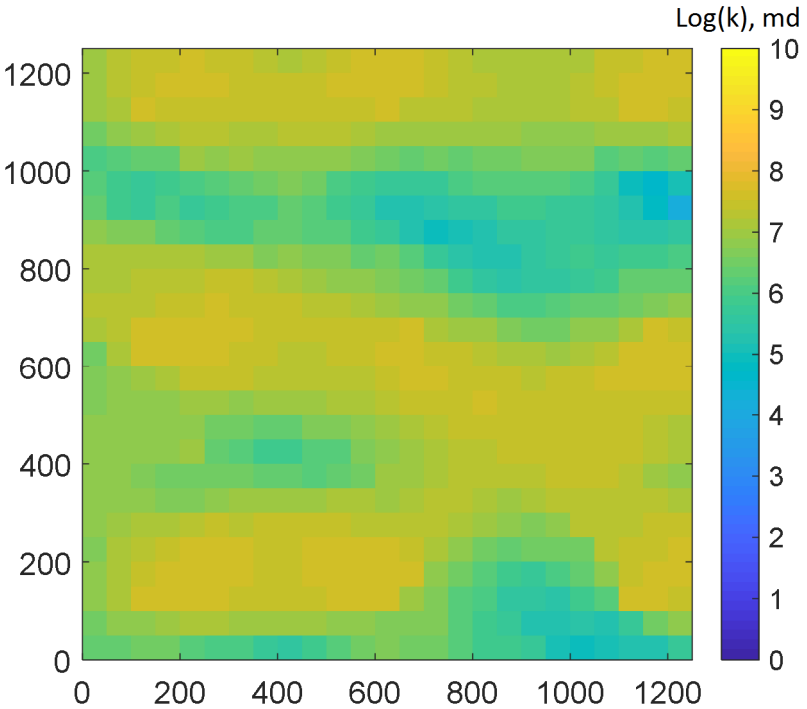


Fig. 3.10 Initial permeability of the 100 selected models

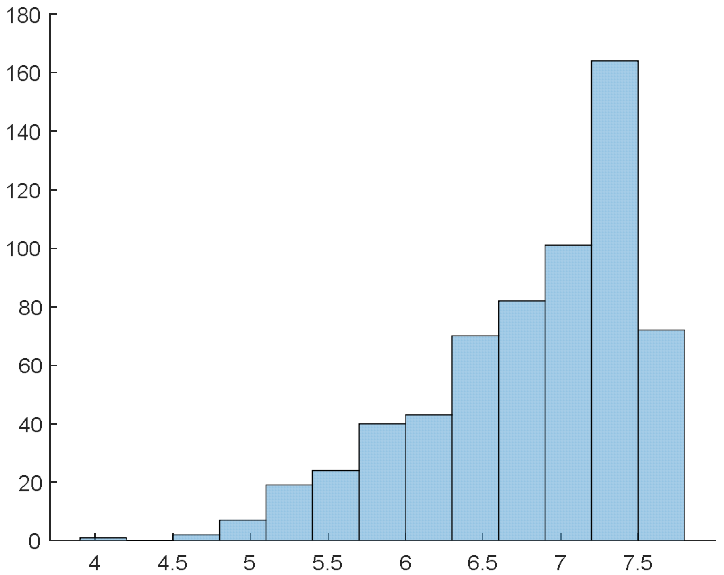


Fig. 3.11 Initial log-permeability histogram of the 100 selected models

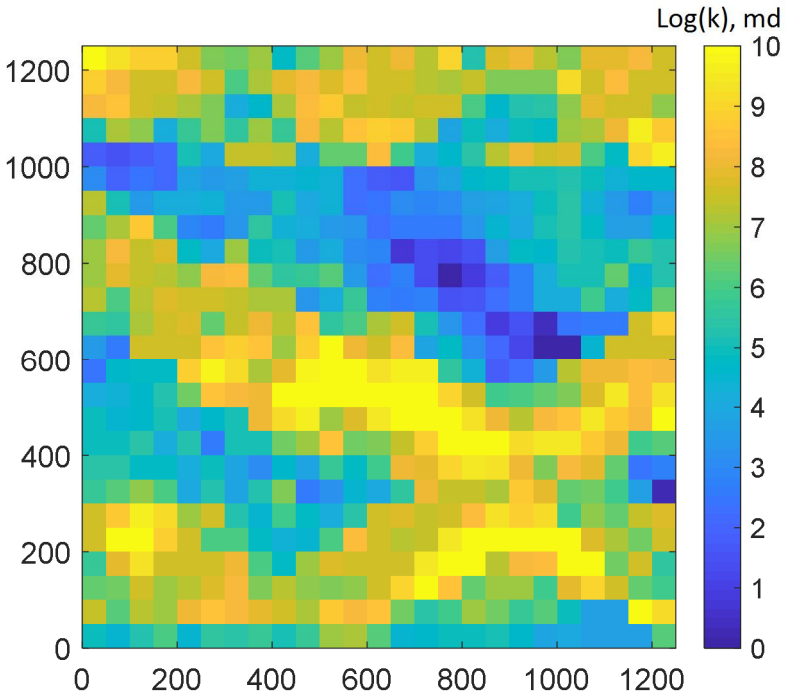


Fig. 3.12 Assimilated permeability of the 100 selected models

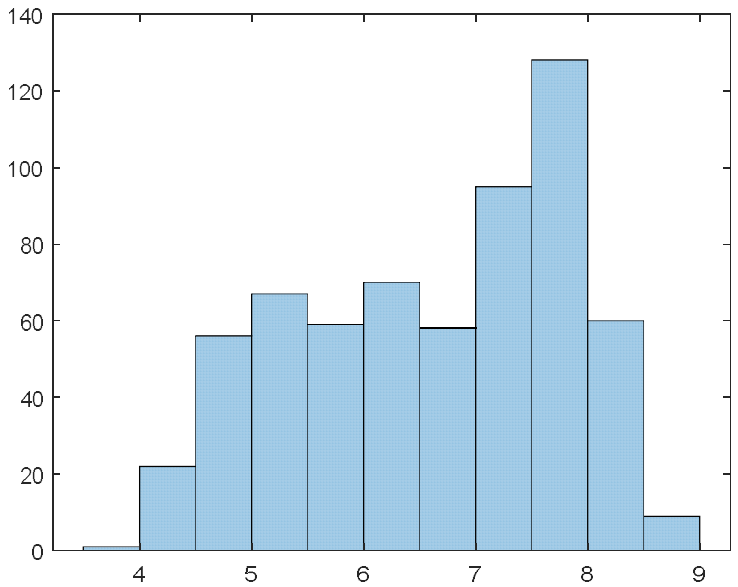


Fig. 3.13 Assimilated log-permeability histogram of the 100 selected models

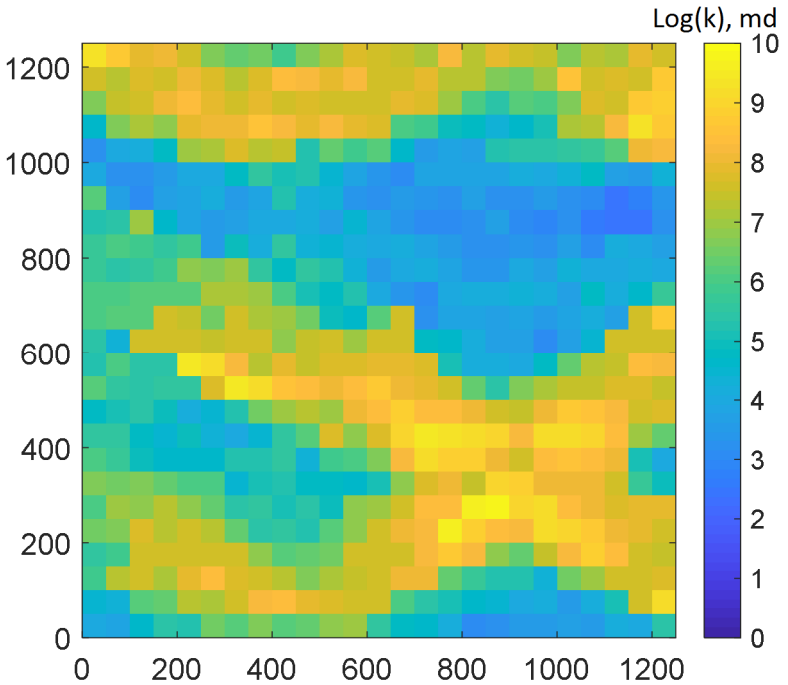


Fig. 3.14 Assimilated permeability of the proposed method

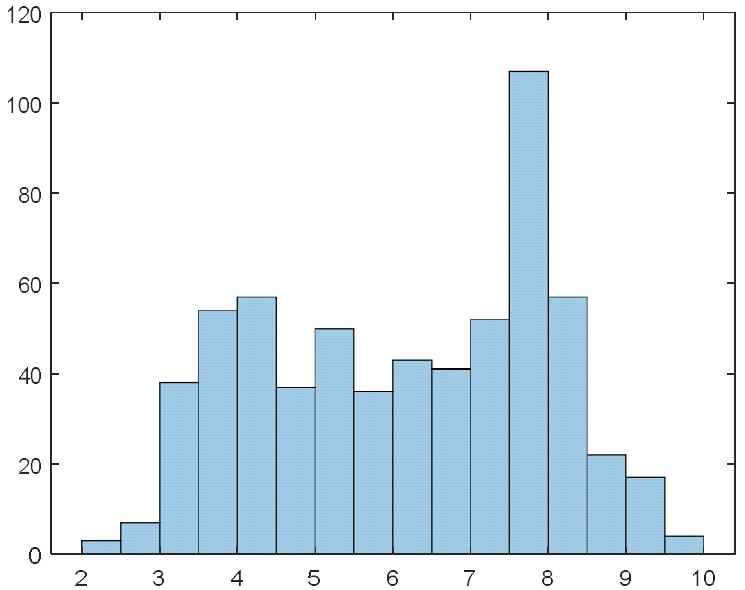


Fig. 3.15 Assimilated log-permeability histogram of the proposed method

3.3 Water and oil production rates

Figs. 3.16, 3.17, and 3.18 show the WOPR and WWCT prediction results of 400 ensemble models, 100 selected models, and the proposed method, respectively. The grey lines are updated ensemble models. The blue lines are the mean of the all ensemble models. The red lines are the behavior of the reference field. In reality, we do not know the true production performance. Thus it is important that simulation models should cover the true line with reasonable uncertainty range.

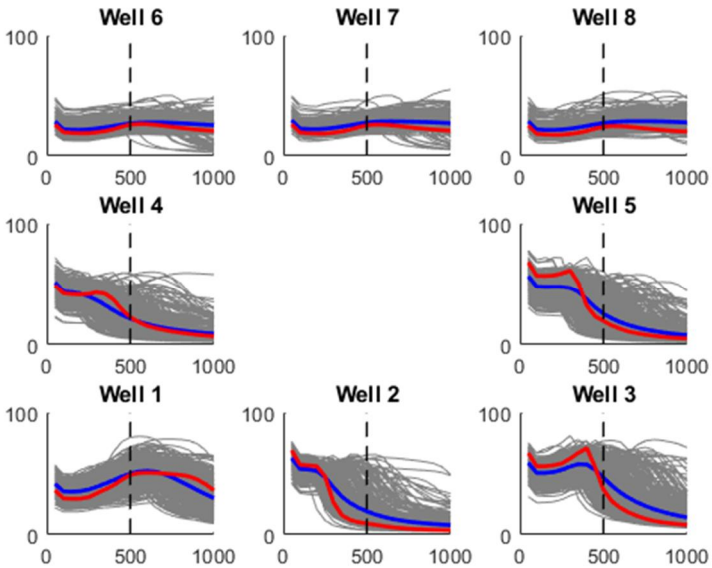
The first case has extremely huge range of uncertainty in both oil and gas production results. WOPR results of well P3 are far from the true model rate. In some production wells like P1-P4 the average results of WWCT do not follow the reference ones. It is difficult to say that reliable estimation of future prediction can be received from the 400 ensemble members.

The second case displays better results of WOPR and WWCT compared to the those with the 400 ensemble models, because more reliable models have been selected before the assimilation steps. Even though the predicted oil rates and water cut are mostly quite reliable, the prior part, observed values are quite different. The average value of P1 and its uncertainty range do not match the reference one complitely. Wells P3, P4, and P5 have different behavoirs due to overshooting problems. Moreover, the mean WWCT values of wells P1 and P4 are deviated from the reference values.

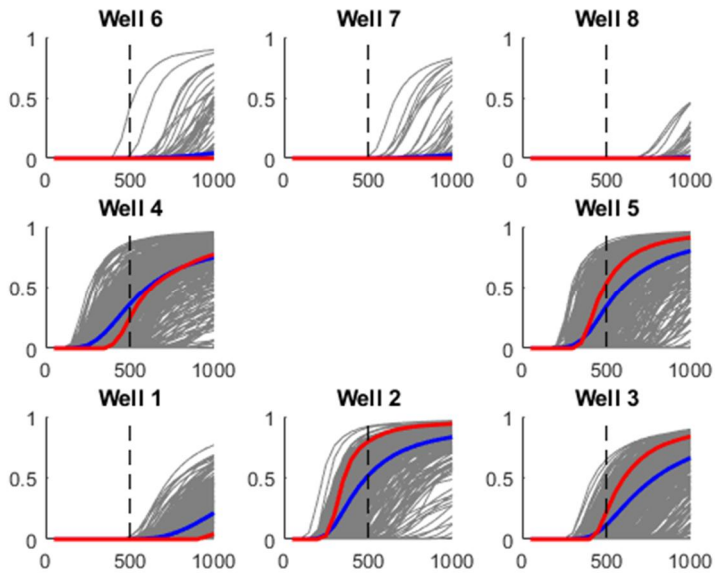
The last case shows the results of WOPR and WWCT. By the proposed method the behaviors of wells P1, P3 to P5, after excluding

meaningless data, have become closer to the reference one, and they provide reliable prediction for the true model. Also the uncertainty ranges are suitably reduced in the most wells. The proposed method represents the best estimation of reservoir performance by having the narrower uncertainty and following the true ones.

——	Reference	——	Mean of ensemble	——	Each ensemble member

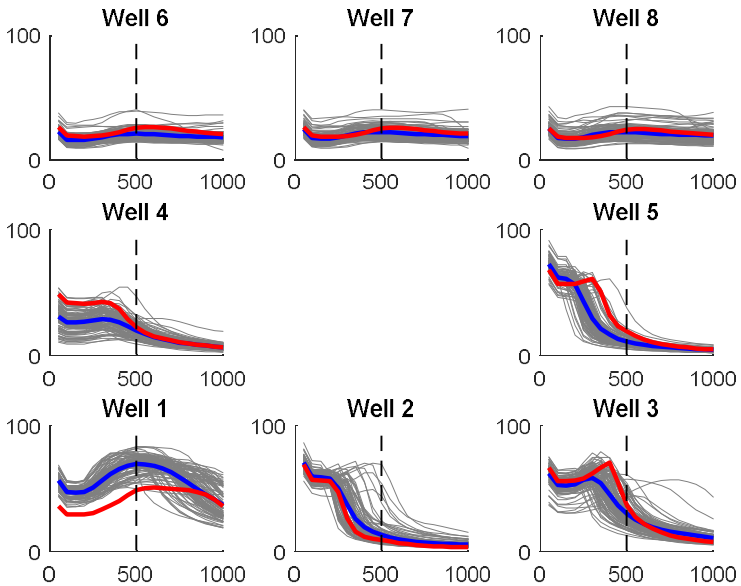


(a) Oil production rate of each well

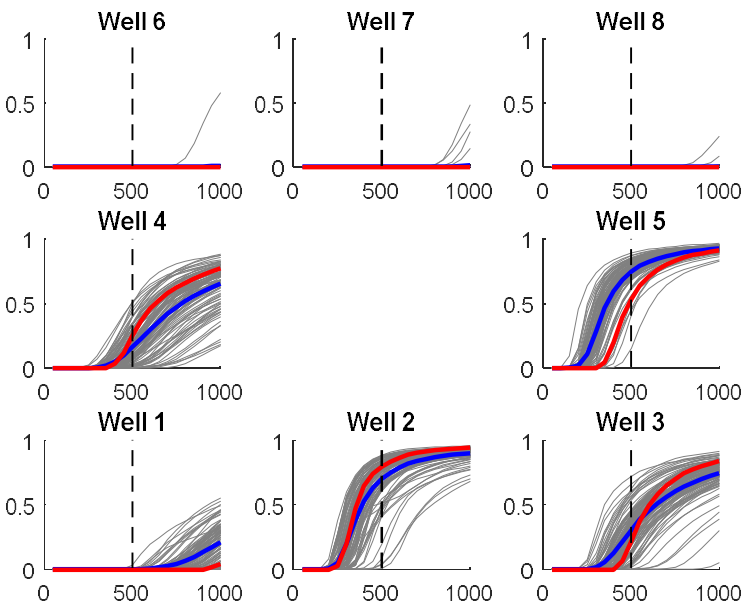


(b) Water production rate of each well

Fig. 3.16 WOPR and WWCT of the 400 selected models

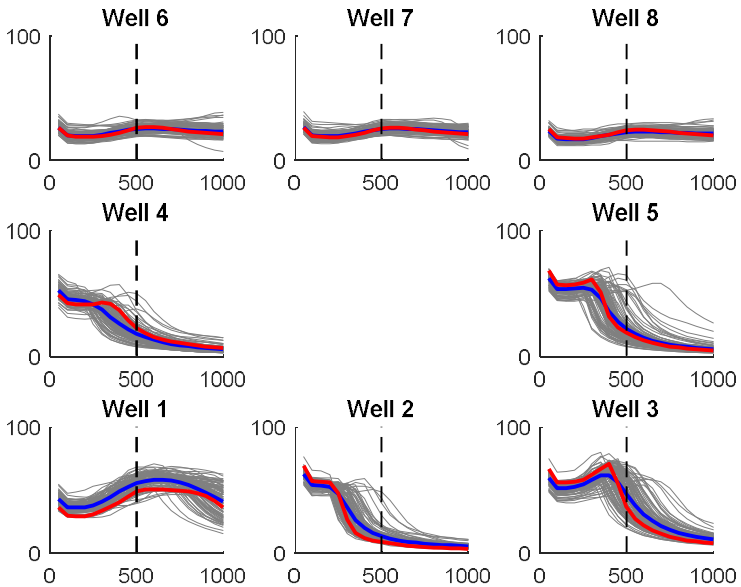


(a) Oil production rate of each well

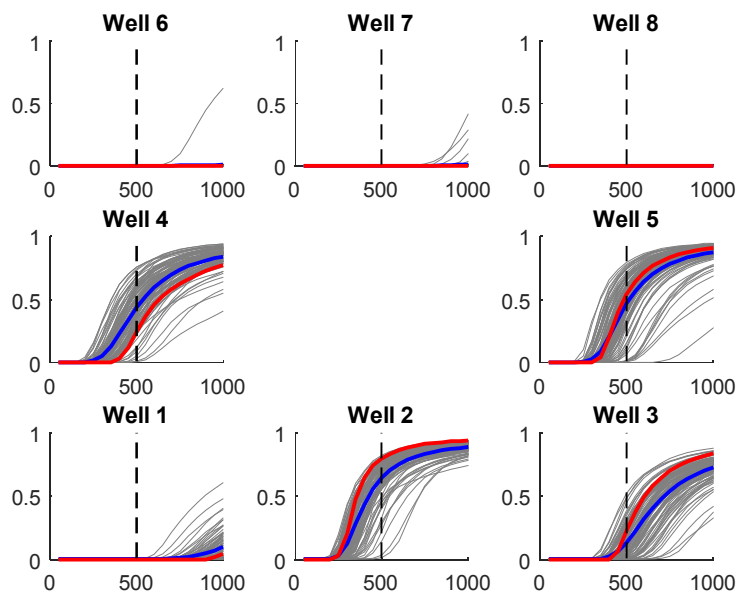


(b) Water production rate of each well

Fig. 3.17 WOPR and WWCT of the 100 selected models



(a) Oil production rate of each well



(b) Water production rate of each well

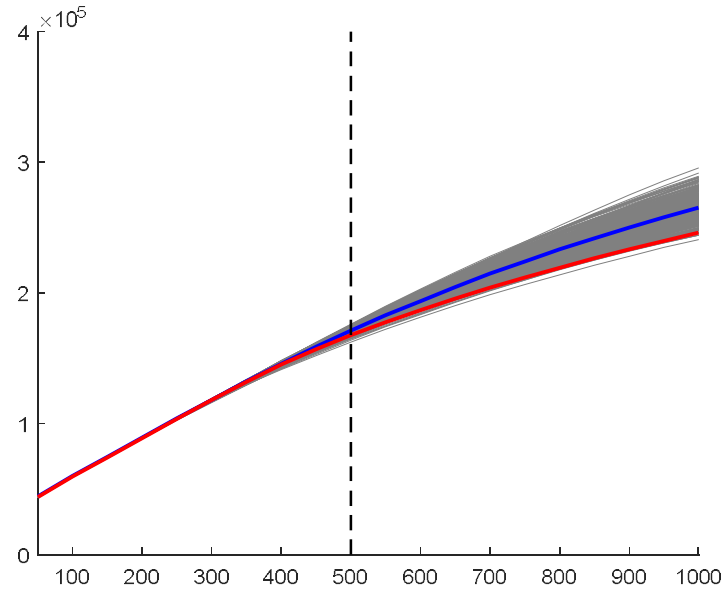
Fig. 3.18 WOPR and WWCT of the proposed method

3.4 Total oil and water productions

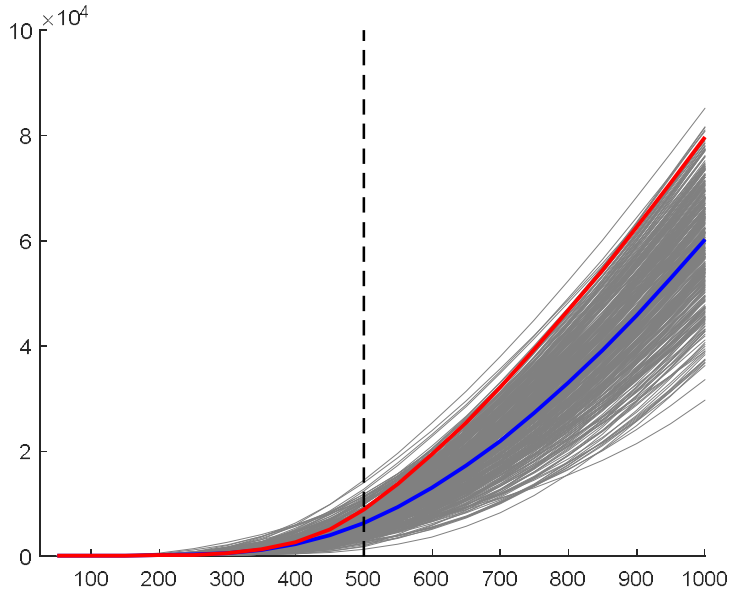
Fig. 3.19 shows total oil and water productions of the initial ensemble. The red line means cumulative oil and water productions from the reference field. The blue line is the mean values of the ensemble models, which are marked by grey lines. The total oil production has quite reliable trend till observed data. However, it does not follow the true model afterwards. The total water production has huge uncertainty and the reference field is close out of the bandwidth of the ensemble.

On the contrary, after selecting the 100 initial ensemble models, the mean of total oil of production shows similar trend to the true prediction of the reference field, as seen in Fig. 3.20. Moreover, the range of uncertainty in water production is greatly decreased. However, the trend is still different from the true one, because water flow is highly affected by permeability distribution.

Fig. 3.21 presents a case by the proposed method. The uncertainty of oil and gas productions is lowered and the means of the predicted productions match up with the true productions properly.

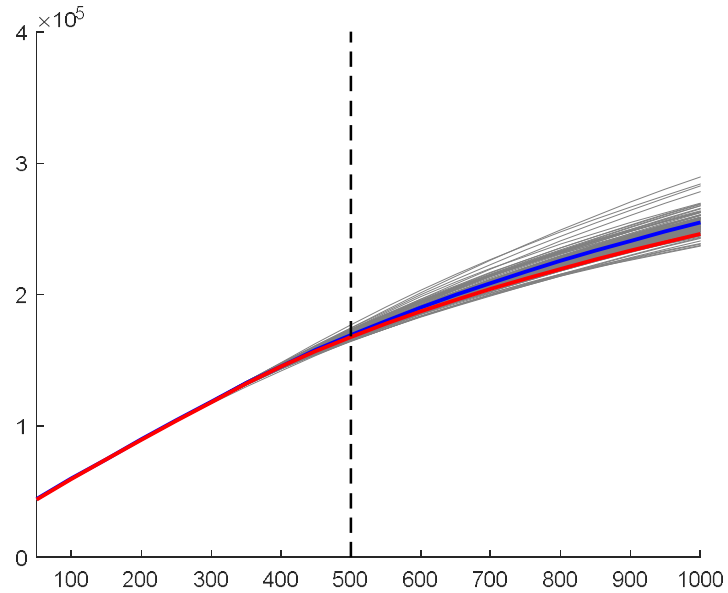


(a) Field Oil Production Total

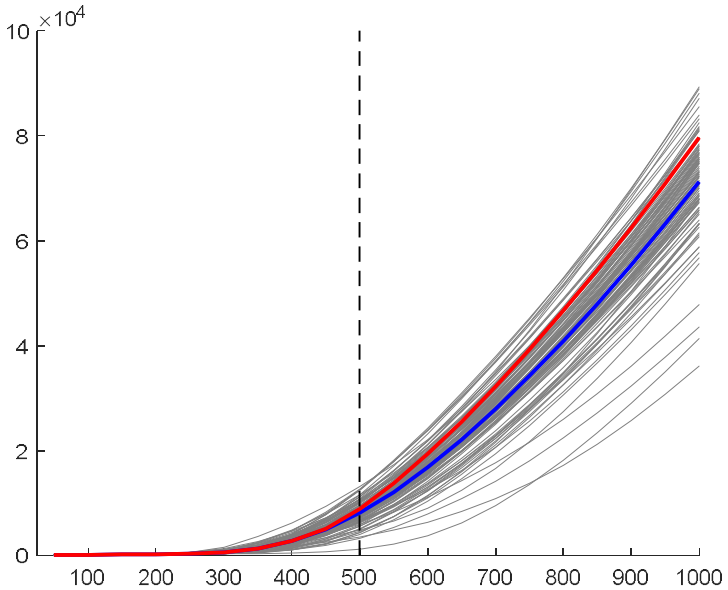


(b) Field Water Production Total

Fig. 3.19 Total oil and water productions predicted by the 400 ensemble models

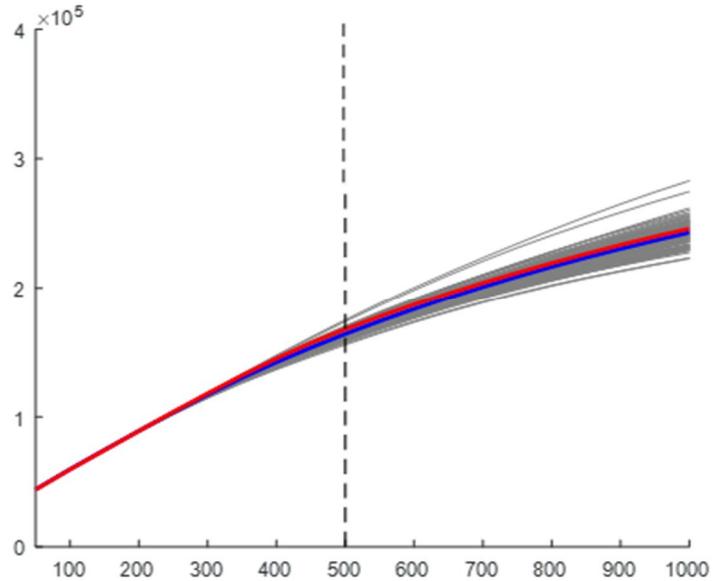


(a) Field Oil Production Total

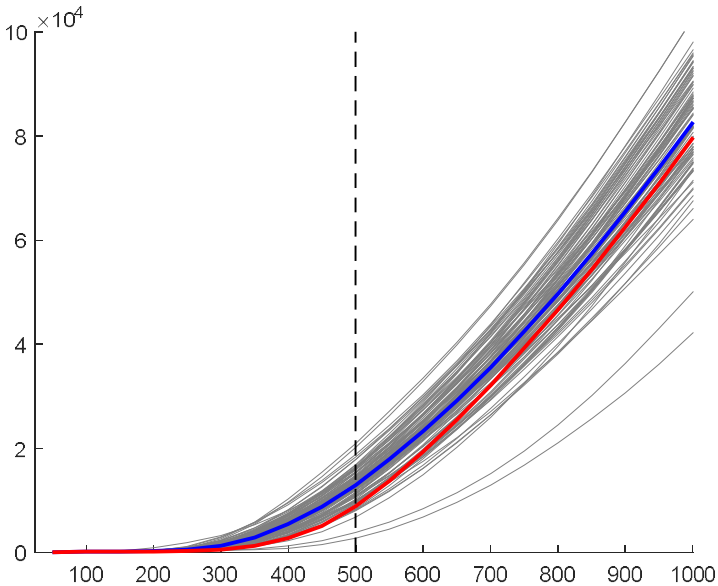


(b) Field Water Production Total

Fig. 3.20 Total oil and water productions predicted by the 100 selected ensemble models



(a) Field Oil Production Total



(b) Field Water Production Total

Fig. 3.21 Total oil and water productions predicted by the proposed method

Conclusions

Characterization of channel reservoirs is essential to make reliable future performances. Due to high uncertainty, the methodology of estimating channel properties should be used properly. Using only conventional ES method is not enough to get credible performance results for 2D channel reservoirs due to its limitations. Thus, it is absolutely necessary to utilize an additional scheme to reduce its instability with possible overshooting of parameters and distorting of parameters' distribution. In this research, the ES with selective measurement data based on water breakthrough for each well has been proved as a reliable characterization method for channel reservoirs. Also the method of reducing initial models has been suggested to get good models and reduce computational time. From the study, the following conclusions can be obtained.

1. The standard ES with all data does not work due to typical overshooting and filter divergence problems. Estimated performances give poor trends with high uncertainty ranges.

2. ES with 100 selected ensemble models may provide good future performances, but its results strongly depend on the initial ensemble members. It cannot provide reasonable uncertainty quantification of future performance in some cases.

3. The selective use of measurement data for each well can

properly overcome the limitations of the standard ES and conserve the channel connectivity. It is very effective for improving ES because the ensemble-based methods cannot interpret the physical characteristic of water breakthrough. It also manages high uncertainty ranges and gives the best reservoir characterization results and shows the reliable future performance estimations.

Bibliography

Aanonsen S.I., Naevdal G., Oliver D.S., Reynolds A.C., & Valles B., 2009. The Ensemble Kalman Filter in reservoir engineering - a review. SPE Journal 14(3). pp. 394-412.

Chen, Y. & Oliver, D.S., 2014. History matching of the norne full-field model with an iterative Ensemble Smoother. SPE Journal 17(2). pp. 244-256.

Evensen G., 1994. Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. Journal of geophysical research 99(C5). pp. 10143-10162.

Evensen G., Hove J., Meisingset H.C., Reiso E., Seim K.S., & Espelid O., 2007. Using the EnKF for assisted history matching of a North Sea reservoir model. Paper SPE 106184 presented at the SPE Reservoir Simulation Symposium, Houston, Texas, USA, February 26-28. pp. 13.

Hyne N.J., 2012. Nontechnical guide to petroleum geology, exploration, drilling, and production, second edition. Tulsa, Oklahoma: PennWell. pp. 73-84.

Jafarpour B. & McLaughlin D.B., 2009. Reservoir characterization with the discrete cosine transform. SPE Journal 14(1). pp. 182-201.

Jeong D., Jeong K, Baik H., & Choe J., 2013. Uncertainty analyses of basement fracture reservoir performances using proxy models with high-quality history matching. Energy exploration &exploitation 31(3). pp 395-410.

Jeong H., Ki S., & Choe J., 2010. Reservoir Characterization from insufficient static data using gradual deformation method with Ensemble Kalman Filter. Energy Sources, Part A: Recovery, Utilization, and environmental Effects 32(10). pp. 942-951.

Jung H., Jo H., Kim S., Lee K., & Choe J., 2017. Recursive update of channel information for reliable history matching of channel reservoirs using EnKF with DCT. Journal of Petroleum Science and Engineering 154. pp. 19-37.

Kalman R.E., 1960. A new approach to linear filtering and prediction problems. ASME - Journal Basic Engineering 82. pp. 35-45.

Kang B. & Choe J., 2017. Initial model selection for efficient history matching of channel reservoirs using Ensemble Smoother. Journal of Energy Resources Technology 152. pp. 294-308.

Kang B., Yang H., Lee K., & Choe J., 2017. Ensemble Kalman Filter with principal component analysis assisted sampling for channelized reservoir characterization. Journal of Energy Resources Technology 139 / 032907-1.

Oliver D.S. & Chen Y., 2011. Recent progress on reservoir history matching: A review. Computational Geosciences 15(1). pp. 185-221.

Park K. & Choe J., 2006. Use of ensemble Kalman filter to 3-dimensional reservoir characterization during waterflooding. Paper SPE 100178 presented at the SPE Europe/EAGE Annual Conference and Exhibition, Vienna, Austria, June 12-15. pp. 1-8.

Peters E., Wilschut F., Leeuwenburgh O., Van Hooff P., & Abbink O., 2011. Intergrated workflow for computer assisted history matching on a channelized reservoir. Paper SPE 141659

presented at the SPE Middle East Oil and Gas Show and Conference, Manama, Bahrain, September 25-28.

Lee K., Jung S.P., Shin H., & Choe J., 2014. Uncertainty quantification of channelized reservoir using ensemble smoother with selective measurement data. Energy Exploration & Exploitation 32(5). pp. 805-816.

Lee K., Jung S., Lee, T., & Choe J., 2016. Use of clustered covariance and selective measurement data in Ensemble Smoother for three-dimensional reservoir characterization. Journal of Energy Resources Technology, 139(2), 022905.

Nævdal G., Mannseth T., & Vefring E.H., 2002. Near-well reservoir monitoring through ensemble Kalman filter. Paper SPE 75235 presented at the SPE/DOE Improved Oil Recovery Symposium, Tulsa, Oklahoma, USA, April 13-17. pp. 9.

Potter P.E., 1962. Late mississippian sandstones of Illinois. Circular 340. Urbana, Illinois: Technical Report Series, Illinois State Geological Survey.

Scheevel, J.R., Payrazyan, K., 2001. Principal component analysis applied to 3D seismic data for reservoir property estimation. SPE Reservoir Evaluation Engineering 4(1). pp. 64-72.

Skjervheim J.A., Evensen G., Hove J., & Vabo J. G., 2011. An Ensemble smoother for assisted history matching. Paper SPE 141929 presented at the SPE Reservoir Simulation Symposium, The Woodlands, Texas, USA, February 21-23. pp. 15.

Van Leeuwen P.J. & Evensen G., 1996. Data assimilation and inverse methods in terms of a probabilistic formulation. Monthly Weather Review 124(12). pp. 2898-2913.

Wikipedia. http://en.wikipedia.org/.

Yeo M., Jung S.P., & Choe J., 2014. Covariance matrix localization using drainage area in an ensemble Kalman filter. Energy Sources, Part A 36(19). pp. 2154-2165.

Zafari M. & Reynolds A.C., 2007. Assessing the uncertainty in reservoir description and performance predictions with the ensemble Kalman filter. SPE Journal 12(3). pp. 382-391.

Zhang Y., Song C., & Yang D., 2016. A damped iterative EnKF method to estimate relative permeability and capillary pressure for tight formations from displacement experiments, Fuel 167. pp. 306-315.

국문초록

선택적 물 돌파자료를 이용한 앙상블스무더의 채널저류층 특성화

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저류층특성화란 불확실성이 존재하는 지질모델에서 정적자료와 동적자료를 통합하여 더 좋은 지질모델을 얻는 과정이다. 그 중 앙상블스무더(ES)는 다수의 모델들을 이용하고 관측데이터를 활용한 한번의 교정으로 저류층 특성화를 수행한다. 이 방법은 빠르지만 오버슈팅 현상이 생길 수 있으며 저류층 유체투과율 분포를 왜곡시킬 수 있다.

본 연구에서는 잘못 해석될 수 있는 관측데이터를 제외하고 각 유정의 물돌파와 관련된 중요한 데이터를 선택적으로 사용하는 방법을 제안한다. 각 유정에 대해 물돌파시간 이전에는 유정오일생산율, 이후에는 유정물생산율을 관측데이터로 사용한다. 또한 좋은 신뢰할 수 있는 초기 저류층 모델을 선정하였다. 참조모델과 유사한 시뇌할 수 있는 초기 모델들을 선택하기 위해 PCA (주성분 분석) 및 K-평균 군집 분석을 사용하였다.

결과의 우수성을 확인하기 위해 본 연구에서 세 가지 방법을 2D 합성 채널저류층에 적용하여 비교한다. 모든 모델과 관측데이터를 사용한 ES; 선택된 100개의 초기모델들과 모든 데이터를 사용한 ES; 선택된 100개의 초기모델들과 관측자료를 선택적으로 사용한 ES의 세 가지 경우에 대해 지질 모델들의 불확실성, 참조모델과 유사성을 비교하였다.

제안 방법은 기존 앙상블스무더의 한계를 극복하였고 채널 연결성 또한 찾아낼 수 있었다. 그리고 제안 방법은 불확실성을 적절히 감소시키면서 가장 좋은 저류층 특성화 결과를 보였으며 신뢰할 수 있는 미래 거동 예측 결과를 나타내었다.

주요어: 저류층 특성화, 관측데이터의 선택적 사용, 물돌파, 앙상블스무더

학번: 2016-26588