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Integration of the Production Logging Tool and Production Data for Post-Fracturing Evaluation by the Ensemble Smoother

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Abstract: A post-fracturing evaluation is essential to optimize a fracturing design for a multi-stage fractured well located in unconventional reservoirs. To accomplish this task, a production logging tool (PLT) can be utilized to provide the oil production rate of each fracturing stage. In this research, a practical method is proposed to integrate PLT and surface production data into a reservoir model. It applies the ensemble smoother for history-matching to integrate various kinds of dynamic data. To investigate the validity of the proposed method, three cases are designed according to the frequency of PLT surveys. Each fracture half-length calibrated by PLT data is similar to the true value, and the dynamic behavior also has the same trend as true production behavior. Integration with PLT data can reduce error ratios for fracture half-length down to 48%. In addition, it presents the applicability of reserve prediction and uncertainty assessment. It has been proven that the more frequently PLTs are surveyed, the more accurate the results. By sensitivity analysis of PLT frequency—a cost-effective strategy—a combination of only one PLT survey and continuous surface production data is employed to demonstrate this proposed concept.

Keywords: post-fracturing evaluation; history-matching; ensemble smoother (ES); multi-stage fracturing; unconventional reservoir; production logging tool (PLT); stochastic optimization

1. Introduction

Recent advances in technology and accumulated experiences in unconventional reservoirs have made for the rapid increase of oil production, but eventually, these advancements have led to a collapse in the price of oil [1]. However, the low oil price is the main reason why many unconventional players have made efforts to reduce the break-even price for unconventional oil—to ensure survival [2]. A drop in the commodity has also caused a reduction in the break-even price, but efforts for effective production are more influential. These efforts, which enable survivors to maintain their competitiveness even in times of low oil prices, can be categorized into two groups: reservoir quality, and completion quality [3]. Identification of a sweet spot in reservoir quality is one of the most important aspects. This, combined with more effective completions, is the ultimate goal in order to deliver higher production performance after selecting drilling targets.

Before the price of oil collapsed, unconventional reservoirs were developed in a region in a monotonous, repetitive, and factory-like way [4]. Once a completion method was optimized in each region, it was applied to other wells across the region without considering the local properties of each fracturing stage. Instead, focus was on cost reduction by standardizing well design and operation. However, this type of practice is not suitable anymore in the current environment; thus, there are many research efforts on reservoir characterization for re-fracturing and effective fracturing design customized by reservoir properties [5–8].

A post-fracturing evaluation is essential for diagnostics, to reveal how much each fracture of the multi-stage fracturing generates and contributes to oil production [9]. It can be categorized with direct and indirect methods [10]. A direct method includes any method used to acquire fracture information directly from the reservoir, and can be accomplished through radioactive tracers, temperature logging, production logging, borehole image logging, tilt mapping, microseismic mapping, and other techniques [11–13]. Indirect methods, whilst measuring fracture information directly, calculate fracture properties through interpretation of the production rate, bottom-hole pressure, and other responses. Reservoir modeling, pressure transient test, and production analysis are representatives of indirect methods [8,14,15]. The majority of direct methods have limitations in that they cannot adequately predict production profiles and estimate the ultimate recovery of a reservoir. They are only capable of identifying properties of hydraulic fractures. Among the previously mentioned methods, reservoir modeling can identify fracture properties from history-matching using production behavior and predicting an estimated ultimate recovery (EUR) of a reservoir at the same time. However, it should be noted that the reservoir model needs to be created with accurate static data and calibrated with other observations for reliable forecasts.

Many studies that have applied integrated reservoir modeling with direct methods have been published [16–21]. A chemical tracer is widely used for hydraulic fracture diagnosis. A combination of tracer tests and production data can estimate fracture half-length and fracture conductivity in a multi-stage fractured reservoir [16,17]. Tarrahi et al. illustrate the applicability of integrating Distributed Temperature Sensing (DTS) with production data for hydraulically fractured reservoir characterization [18]. A thermal model calibrated with DTS observations can estimate fracture initiation points, number of created fractures, and distribution of stimulation fluid [19,20]. However, the tracer tests can only reflect production data in the early stage and DTS requires additional capital expenditure. For these technical and commercial reasons, they cannot be widely applied to an actual field site. However, the production logging tool (PLT) can be considered as an alternative. As a good indicator of effective fracture properties, it can be applied to targeted wells whenever needed. For a naturally fractured reservoir, it was shown that PLT data integrated with a simulation model can characterize the size of natural fractures effectively [21].

This research proposes a methodology integrating a reservoir model with PLT observations for post-fracturing evaluation. Several scenarios of history-matching are considered to confirm the effectiveness of the proposed concept for a reservoir completion characterization. The history-match for unconventional reservoirs is conducted by inverse modeling. In this model, permeability and porosity are used as model parameters, and production data from the PLT and surface are used as dynamic observations. Sensitivity analysis of PLT frequency will be performed to derive the best strategy to apply this proposed concept. In addition, this research will present the applicability of reserve prediction and its uncertainty assessment.

2. Methodology

2.1. Ensemble Smoother

The algorithm for integrating PLT data with surface production data in this study is the ensemble smoother (ES). It has several advantages in the reservoir characterization as an ensemble-based method. It maintains the advantages associated with the ensemble Kalman filter (EnKF), such as real-time assimilation, uncertainty assessment, and applicability, and has an advantage over the EnKF in computing time [22]. The EnKF is a recursive filter; thus, assimilation and prediction with forward simulation should be conducted whenever observation data is acquired. It spends the majority of its computing time predicting production behaviors by running simulations for every ensemble member at every timepoint. However, the ES assimilates all available dynamic data at the same time [23]. As such, it only needs to run forward simulation one time after the latest production data is observed.

The ES procedures are initialization, forecasting, and data assimilation as presented in Figure 1. The main frame of the ES is a state vector. Generally, the state vector consists of model variables "m" and dynamic data "d". Model variables to be calibrated are static properties for reservoir characterization and also function as input data for a reservoir simulation. Dynamic data refer to responses of the reservoir simulation and are often acquired from PLT observations in the downhole or gauges in the wellhead.

The state vector includes model variables and dynamic data. In ES, dynamic data are constructed for all timepoints. The state vector of the k-th ensemble member can be set up as:

$$\mathbf{x}_k = \begin{pmatrix} \mathbf{m}_k^{\mathrm{T}} & \mathbf{d}_{k,t}^{\mathrm{T}} \end{pmatrix}^{\mathrm{T}},\ t = 1, \ldots, N_t \tag{1}$$

where, N_t is the total assimilation at a given timepoint.

The observation vector, $\mathbf{z}_k$, is defined as the measured dynamic vector added by the measurement noise of $\mathbf{v}_k$:

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \tag{2}$$

where $\mathbf{H}$ represents the matrix operator, which consists of either 0 or 1, to extract observation components from the state vector.

The estimate error covariance, $\mathbf{P}_k$, is defined as the expected errors for each state vector ($\mathbf{e}_k$), and can be expressed as:

$$\mathbf{P}_k = \mathrm{E}\left[\mathbf{e}_k \mathbf{e}_k^{\mathrm{T}}\right] = \frac{1}{N_e - 1} \sum_{j=1}^{N_e} \mathbf{e}_{k,j} \mathbf{e}_{k,j}^{\mathrm{T}} \tag{3}$$

The definition of Kalman gain is a weight factor to minimize the estimate error covariance [24], and can be obtained as follows:

$$\mathbf{K} = \mathbf{P}\mathbf{H}^{\mathrm{T}} \left(\mathbf{H}\mathbf{P}\mathbf{H}^{\mathrm{T}} + \mathbf{R}\right)^{-1} \tag{4}$$

Finally, the assimilated state vector can be obtained as follows:

$$\mathbf{x}_k = \mathbf{x}_k^- + \mathbf{K}\left(\mathbf{z}_k - \mathbf{H}\mathbf{x}_k^-\right) \tag{5}$$

where, the superscript "−" of the state vector is the initial state vector.

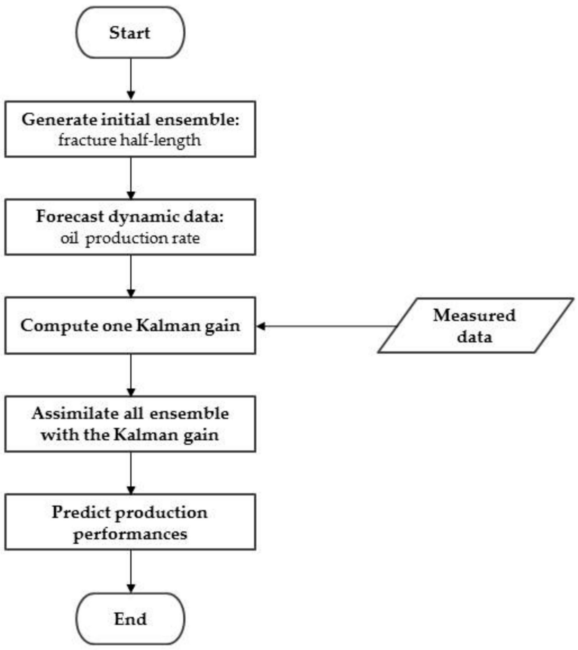


Figure 1. Flowchart of the proposed ensemble smoother (ES) scheme for history-matching.

2.2. Reservoir Model Description

The proposed method is applied for characterization of hydraulic fractures. A reference field, of which parameters are known, is necessary to verify this methodology. For this research, a synthetic model for an unconventional oil field was generated. Production data, which should be observed from a real field, was generated by simulating the reference field. The parameters and production data of the reference field are assumed as "true" values for verification. The dimension of the field is described in Table 1. A single horizontal well with multi-stage fracturing is considered for the half-section reservoir. The length of its horizontal section is 3600 ft with a total of seven fracturing stages, and the spacing of each fracture is 600 ft. A simulation for unconventional reservoirs needs fine grids close to the well and the hydraulic fractures for numerical stability. Figure 2 indicates fine grids in the grid block with a hydraulic fracture and both adjacent grid blocks.

Table 1. Dimensions of the model.

Model Dimension	Value
Grid number (x, y, z)	(43, 43, 1)
Grid block size (dx, dy, dz)	(120 ft, 40 ft, 10 ft)
Reservoir length	5160 ft
Reservoir width	1720 ft
Reservoir height	10 ft
Horizontal well length	3600 ft

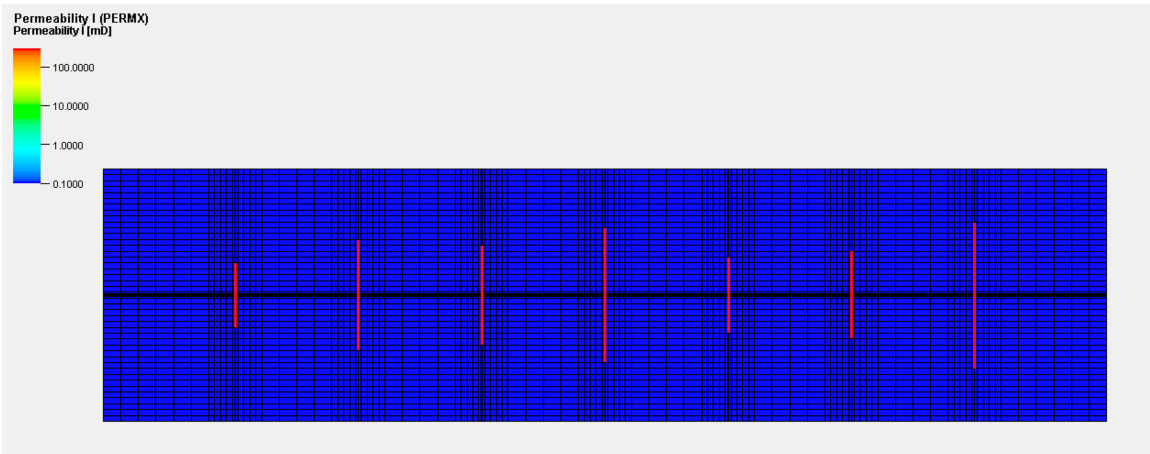


Figure 2. Synthetic model configuration with seven stages of hydraulic fracturing.

Reservoir properties are summarized in Table 2. Matrix properties are assumed to be homogeneous and of constant porosity and permeability. It also shows fracture properties, such as fracture permeability, fracture porosity, and fracture width. Fracture half-length is the target parameter to characterize in this research.

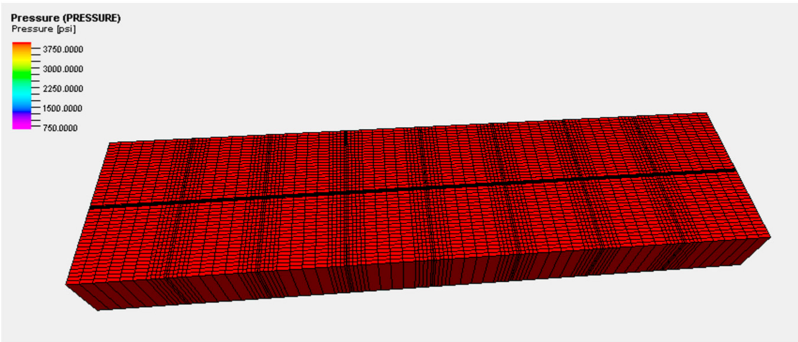
Table 2. Reservoir properties.

Reservoir Property	Value
Matrix permeability	0.01 md
Matrix porosity	2.5%
Fracture half-length	220–550 ft
Fracture width	2 ft
Fracture permeability	300 md
Fracture porosity	30%
Initial pressure (@ 7150 ft)	4000 psi
Initial water saturation	30%

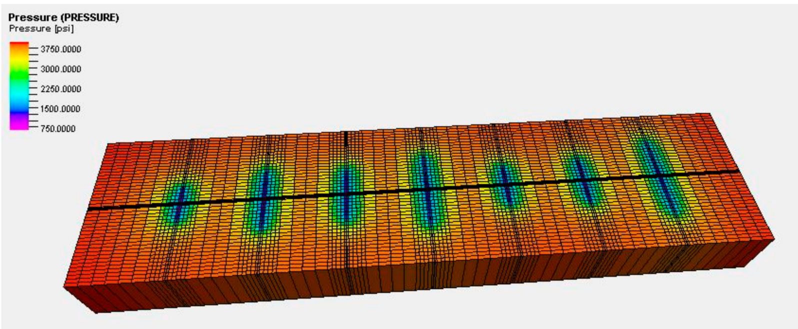
The "true" fracture properties of the reference field are assumed to be as in Table 3. The half-length of each fracture stage is randomly generated. The reference model is run using ECLIPSE, the reservoir simulation software of Schlumberger. The results showing the evolution of the pressure distribution, are represented in Figure 3. A typical pressure behavior can be observed in that the pressure decline near an individual fracture during early timepoints is propagated to the whole reservoir as time passes. Assuming these "true" fracture properties are unknown, I attempted to identify the half-length of each fracturing stage by solving an inverse problem with only production behaviors.

Table 3. Fracture half-length of each fracturing stage in the reference field.

Stage	#1	#2	#3	#4	#5	#6	#7
Half-length (ft)	220	380	340	460	260	300	500



(**a**)



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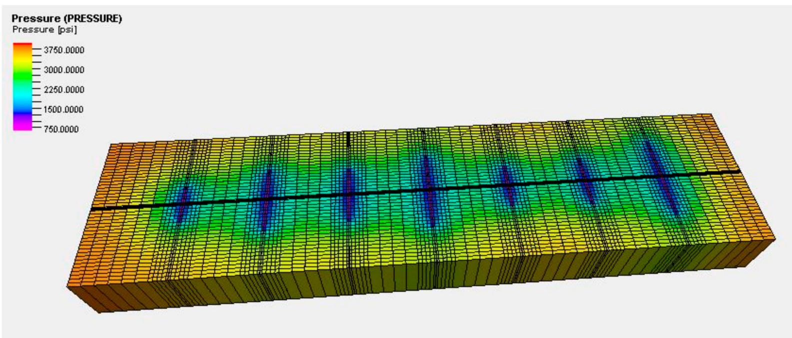

(**c**)

Figure 3. Evolution of reservoir pressure distribution during production: (**a**) initial pressure distribution, (**b**) pressure distribution after 1 year production, (**c**) pressure distribution after 6 years production.

2.3. Sensitivity Analysis of History-Matching with PLT and Production Data

Production data, such as production rate, wellhead pressure, watercut, and other measurable information on the surface, is regularly observed and collected in a database. This database is used for history-matching to calibrate a more reliable reservoir model. Downhole data can improve results of history-matching, but needs additional investments due to the need for expensive tools and the operational difficulties encountered. Nevertheless, to identify each fracture property in unconventional reservoirs with multi-stage fracturing, it is essential to allocate the total production rate to each fracture based on downhole measurements. A PLT is an effective tool when investments have not been made in permanent downhole tools. However, PLT surveys are charged according to the number of surveys conducted; therefore, a minimum number of surveys should be conducted.

Considering these backgrounds, three case studies were designed to verify a proposed method for post-fracturing evaluation as seen in Figure 4. Case 1 is a control experiment for history-matching using only production data measured from the wellhead. Cases 2 and 3 are designed to quantify the effects of the PLT frequency on history-matching. Each case uses production data that incorporates PLT data surveyed three times, and once, respectively. The assimilations for all the cases are conducted three times at the 1st, 2nd, and 12th month.

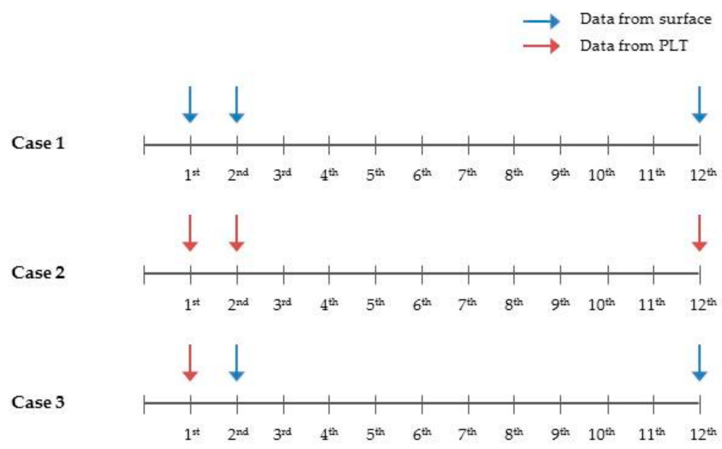

Figure 4. Clarification for cases with different assimilation time and data.

3. Results and Discussion

The oil production rates calibrated by history-matching for Case 1 are shown in Figure 5. The graph located in the bottom right indicates the entire oil production from the target well, and other graphs describe oil production rates from each fracturing stage. The red line indicates the "true" value from the reference field. The grey and blue lines indicate oil production rates from ensemble members, and their average, respectively. The estimate of oil production tends to be well-matched to the reference in the entire well aspect. However, in each fracturing stage aspect, the production behavior is significantly different to the reference field. The difference is reasonable in that history-matching for Case 1 is conducted using only production data from the entire well. Comparing permeability distributions between the reference field and the calibrated model, and in Figure 6a,b, it is found that the calibrated model does not represent the characteristics of hydraulic fractures at all. The reason is that it calibrates the model by only focusing on the entire oil production, and therefore, allocates total oil production to each fracture arbitrarily.

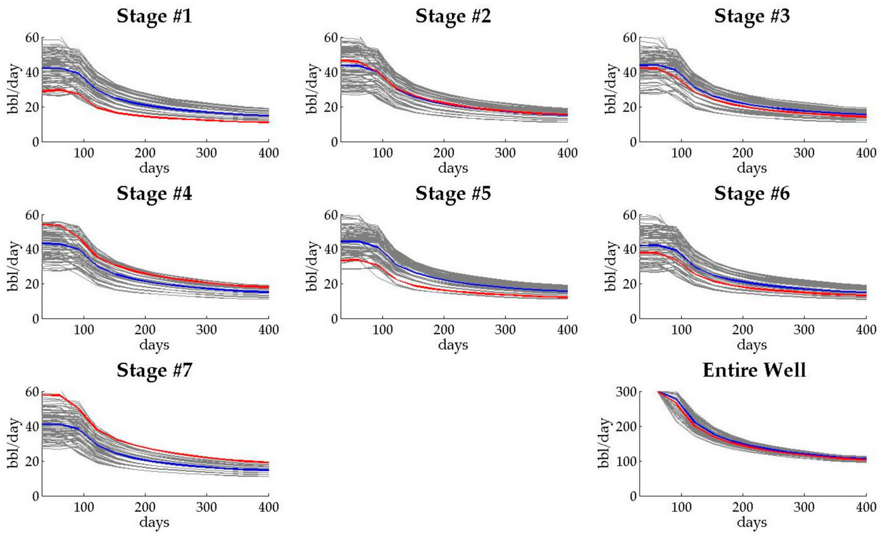

Figure 5. Comparison of reservoir performance between the "true" and ensemble production rates calibrated by surface production data only, Case 1. The red line corresponds to the "true" production rates from the reference field, and the grey lines and blue line correspond to the production rates from ensemble members, and their average, respectively.

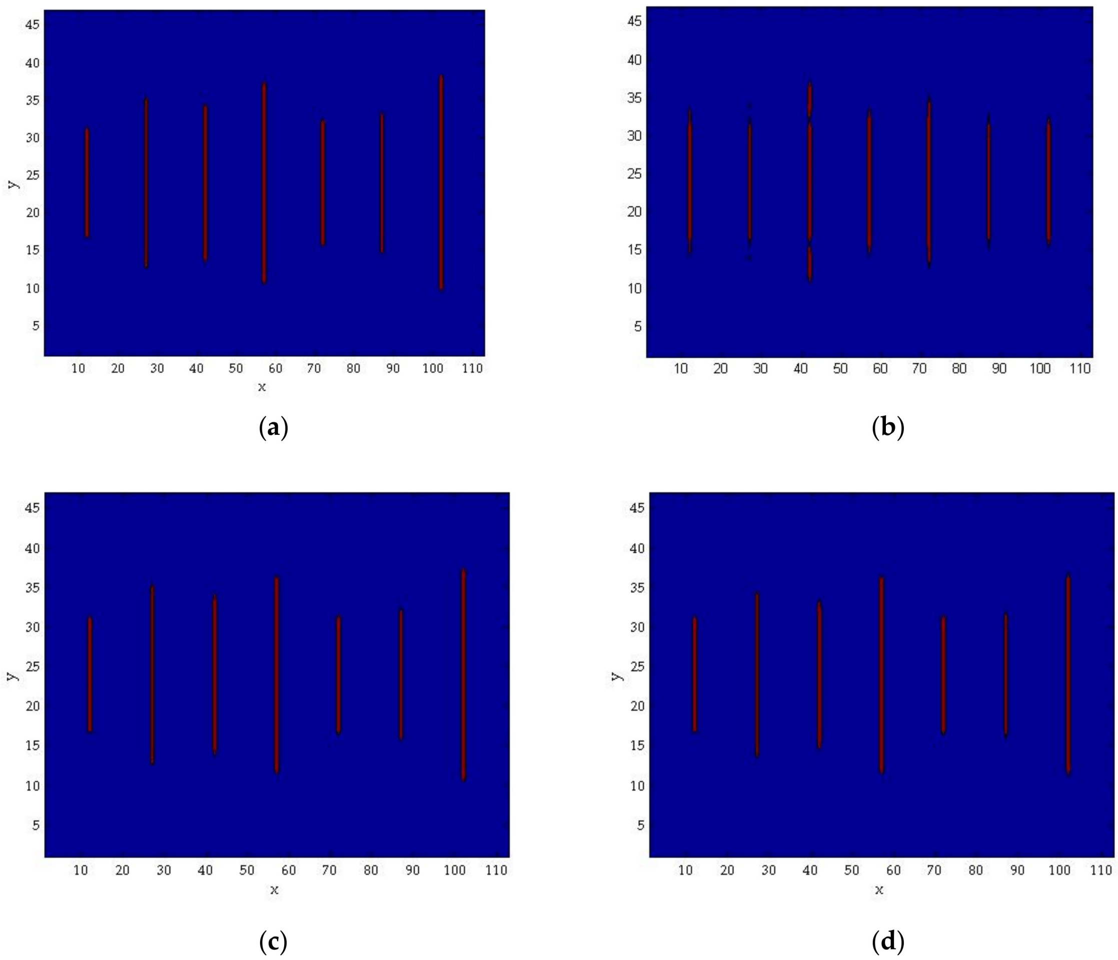

Figure 6. Comparison of fracture half-length between the "true" and calibrated models: (**a**) reference field, (**b**) Case 1, (**c**) Case 2, and (**d**) Case3.

A contribution from each fracture to oil production is required to overcome these obvious limitations. PLT surveys enable us to acquire the information of each fracture through direct measurements of the downhole. In Case 2, it is assumed that history-matching with three PLT surveys is conducted at the commencement of the 1st, 2nd, and 12th months of production. Oil production rates of each fracture and the entire well, which are generated by the calibrated model, have similar decline trends to the reference field, as seen in Figure 7. Upon closer analysis, only two production profiles at stages #1 and #5 are lower than the reference field. However, in the two stages, they maintain similar trends to the reference and the quantity of the gap is negligible; likewise, the history-matching is implemented with good performance.

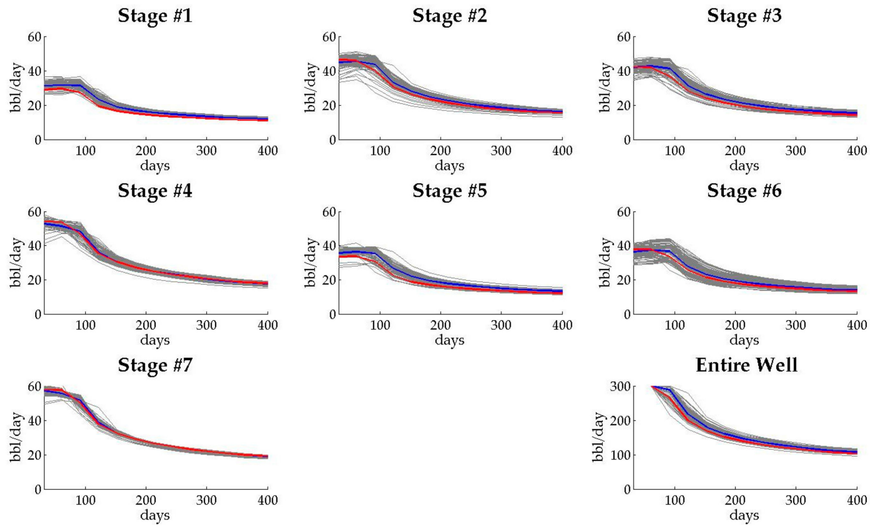

Figure 7. Comparison of reservoir performance between the "true" and ensemble production rates calibrated by the production logging tool (PLT) data only, Case 2. The red line corresponds to the "true" production rates from the reference field, and the grey lines and blue line correspond to the production rates from ensemble members, and their average, respectively.

In addition, the fracture half-length of each stage calibrated by history-matching represents a similarity to the reference field. As shown in Figure 6c, the relative size between each half-length has a sufficient accordance with the reference, the characteristics of which are the longest fractures at stages #4 and #7, and the shortest fractures at stages #1 and #5. The proposed scheme can be effective for post-fracturing evaluation.

Despite satisfactory results, this scheme cannot be widely applied to actual fields. That is why frequent PLT surveys can curtail the project's economics. The key point of this study is to find a practical scheme, which should concurrently possess both reliable accuracy and economic feasibility. To complement the scheme, I propose another scheme that calibrates the model with a PLT survey during the early production period, and afterwards, the entire production data from the wellhead. Case 3 is designed to thoroughly reflect this concept. The history-matching is conducted using PLT data at the 1st month, and the entire production rate of the well at the 2nd and 12th month. Figure 8 represents the results of the history-matching in Case 3. The production rate of each fracture shows similar decline trends to the reference field similar to the preceding Case 2. It shows the typical declining characteristics of oil production in unconventional reservoirs, which peaks during the initial period, and thereafter, a rapid drop in the production rate is observed. Additional results by history-matching and the fracture properties of each stage are demonstrated in Figure 6d. By comparing these results to the reference field, it is confirmed that the calibrated model can also identify how much each fracture is developed. The results achieved here are not so different than those achieved in Case 2.

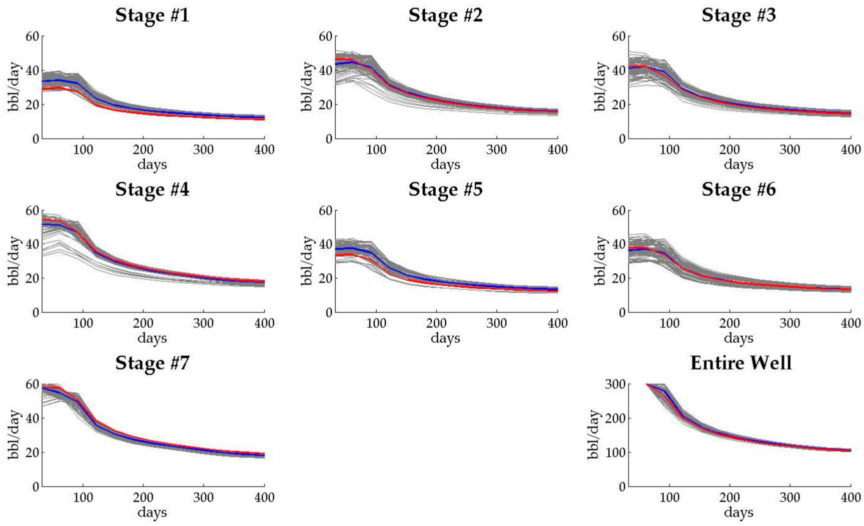

Figure 8. Comparison of reservoir performance between the "true" and ensemble production rates by the production logging tool (PLT) and surface production data, Case 3. The red line corresponds to the "true" production rates from the reference field, and the grey lines and blue line correspond to the production rates from ensemble members and their average.

To investigate the accuracy of the results more precisely, similarity to the reference is quantified numerically by calculating the sum of squared errors (SSEs), as shown in Table 4. In the table, the ratio of each case to Case 1 is also indicated in parentheses. SSEs of static and dynamic parameters are calculated using permeability and oil production rates, respectively. Both SSEs of static and dynamic data for Cases 2 and 3 are significantly reduced in comparison with Case 1. This indicates that history-matching with PLT data can improve accuracy for calibrated models. The more timepoints of PLT data that are used, the more accurately the model is calibrated. However, the quantity of improvement is insignificant, with only 10 percentage points. This comparative study implicates that the scheme of Case 3, which calibrates the model with PLT data at one timepoint and production data afterwards, is the most effective scheme, from an economical and engineering standpoint.

Table 4. Comparison of sum of squared errors (SSEs) for history-matching results.

Case	SSE of Static Data		SSE of Dynamic Data	
1	1619	-	147	-
2	780	(48%)	35	(24%)
3	958	(59%)	48	(33%)

In addition to fracture characteristics, this indirect method of reservoir simulation has another capability that can be used to predict the production profile and consequent EUR. To examine the accuracy of prediction, EURs of the cases are calculated through reservoir simulations. Generally, the definition of EUR is the amount of oil and gas expected to be economically recovered from a reservoir or field by the end of its production lifecycle. In this study, for convenience, EUR is assumed as a quantity recovered over 10 years. Oil production volume after 10 years constitutes a minor portion of the EUR because the production rate declines very rapidly for unconventional reservoirs. EURs of various scenarios are displayed in Figure 9 as a box plot. By comparing these EURs to the reference field, an accuracy of reserve predictions can be quantified. The box plot provides comparative information about distributions of ensemble members. The red line is the median of ensemble members, and the bottom and ceiling of blue boxes are the first, and third quartile of the ensemble members, respectively.

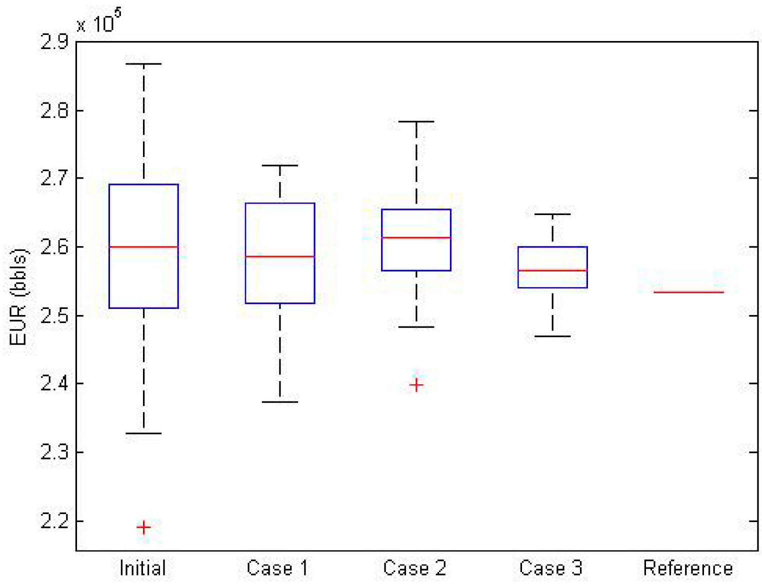

Figure 9. Box plots of the estimated ultimate recovery (EUR) predictions. The red line corresponds to the mean, and the bottom and top sections of the blue boxes correspond to 25%, and 75%, of cumulative distribution function (CDF) within the EUR range, respectively.

The ranges of EUR predictions for all the cases contain the "true" value, which is an EUR of the reference field. However, a prediction about the initial case has a huge range of uncertainty; thus, it does not have significant meaning as an estimate. The distribution of the initial case is symmetric based on the axis of the median. Fracture half-lengths of the initial ensemble are generated at random; thus, EURs calculated from the initial ensemble are distributed symmetrically.

However, history-matching for Case 1 produces EUR estimates with a lower dispersed distribution than the initial case. This improves the accuracy of EUR prediction slightly, but there is still high uncertainty regarding the prediction. The range between EUR estimates is about 34,496 bbls, and it accounts for 13.6% of the "true" value. A history-matching for Case 2 shows a satisfactory performance for EUR prediction. It estimates a EUR for the field with a smaller range, unlike Case 1. The distance between the first and the third quartile is significantly decreased to 8992 bbls. In particular, Case 3 records the highest confidence level; its ensemble members are distributed within a range of 17,752 bbls. In addition, the median of predicted EURs for calibrated ensembles is very close to the reserve of the reference field—the difference is merely 1.3%.

Although this proposed method shows feasibility and applicability, it has limitations. It is assumed that a field consists of a homogenous matrix and hydraulic fractures. When a hydraulic fracture is connected to a network of natural fractures, the estimated fracture half-length can be overestimated, due to the effects of natural fractures.

4. Conclusions

In this study, the proposed method proves to have high potential for successful evaluation of each of the fracture properties in multi-stage fractured reservoirs. The main idea of the method is to integrate a reservoir model with PLT and production data. Through PLT data, which provides oil production rates for each fracturing stage of the downhole, the reservoir model can be calibrated similarly to the reference field with hydraulic fracturing. The calibrated reservoir model has almost the same characteristics of fracture half-length at each stage. This feature can expand the applicability of the scheme to optimize the design and operational practices of hydraulic fracturing.

In addition to post-fracturing evaluation, it can be utilized as a reserve estimation tool. The ES shows good performance with respect to history-matching with PLT and well production data.

This ensemble-based approach enables an uncertainty assessment through analyzing an EUR distribution from ensemble members.

This study shows that PLT surveys improve the accuracy of fracture characterization and reliability of reserve predictions. A single PLT survey reduced the error ratio for fracture half-length drastically: down to 59%. By contrast, an additional two PLT surveys reduced the error ratio for fracture half-length by 11 percentage points. From the results, it can be concluded that the proposed scheme—only one PLT survey instead of several—is practical and effective for evaluating multi-stage fracturing in unconventional reservoirs.

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