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Improvement of Localization Effect on Region Based Covariance Localization Ensemble Kalman Filter Method using Dynamic Parameters

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Abstract: Region based covariance localization ensemble Kalman filter is a method that incorporating the information of region to ensure that the updated parameters honor the region models such as facies, flow unit, rock type model, etc. Since, the model updated under specified regions, the adjacent parameters would not maintain its spatial correlation if it is under different regions. Therefore, the algorithm could freely update the parameters within the region without considering the values in another region. This approach would fit best in history matching that target reservoir-wide area. On the contrary, the significance of the fluid dynamics rarely follows such regions. The affected areas that influenced the production data is governed by the physics of fluid flow which incorporate the fluid types, relation of rock-fluid properties and so on. Since, history matching use production data as a measurement data, the parameters should only occur in the areas that affected by fluid flow in reservoir. These areas usually smaller than the area provided by regions model. Thus, it could be used to improve localization effect. In this study, we explore the formulation of localization based on the behavior of pressure and fluid flow combined with region based covariance localization ensemble kalman filter. The results show that, the combination of both methods could improve the localization effect while maintaining the defined regions. This method could be useful to improve the area within the wells that affects directly to the production forecast.

Key words: Dynamic parameter, ensemble kalman filter, region based covariance localization, history matching, explore, improve the area

INTRODUCTION

The most important step in dynamic modeling workflow is history matching. In this step, the model is validated by using production data acquired from measurements. The main purpose of history matching is to minimize the differences between predicted and measurement data (Tavassoli *et al*., 2004). This is generally known as inverse problem. Usually, the target of history matching is single valued parameter such as ratio of vertical permeability and horizontal permeability, skin factor, etc. But, sometimes tuning these targets is not enough to reduce the error between predicted and measurement data. If these happens, one should look at the distribution of parameters in static model. Since, the distribution of parameters are generated randomly, it is possible that the selected realization is not perfectly accurate.

Ensemble Kalman Filter (EnKF) is designed to update a distribution of parameters to reduce the error in history matching. The algorithm is developed by combining the monte-carlo method and extended kalman filter to minimize error in a nonlinear model (Evensen, 2004). Since, its inception, the EnKF algorithm is already used in many fields of study (Jia and Brownb, 2009; Evensen, 1997; Evensen, 1994; Evensen, 2003). In static parameter history matching, the algorithm is successfully implemented to update porosity model by assimilating production data (Haugen *et al*., 2008).

The EnKF algorithm consist of prediction step and assimilation step. The prediction step is a modeling process which is done by reservoir simulation while the assimilation step is the correction phase that update the parameters based on the differences between predicted and measured data. The EnKF algorithm is summarize as follows. Prediction step:

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$$X_t^- = f(X_{t-1}) + N(O, W_t) \quad (1)$$

$$P_t^- = (X_t^- - \bar{X}_t^-)(X_t^- - \bar{X}_t^-)^T \quad (2)$$

Where:

X = The parameter ensemble
W_t = The covariance matrix that characterizes model error
N = The function that generates gaussian random which follows designated covariance matrix
P = The matrix denotes the covariance matrix for parameter X

Assimilation step:

$$Z_t^{'} = Z_t + N(0, V_t) \quad (3)$$

$$K = P_t^- H(HP_t^- H + V_t)^{-1} \quad (4)$$

$$X_t = X_t^- + K(Z_t^{'} - HX_t^-) \quad (5)$$

$$P_t = (X_t - \bar{X}_t)(X_t - \bar{X}_t)^T \quad (6)$$

Where:

Z = The measurement ensemble
V = The covariance matrix that characterizes measurement error
K = The Kalman gain
H = The transition matrix which maps the prediction in parameter ensemble into measurement ensemble

The assumption in ensemble kalman filter is the distribution of static parameters is spatially correlated (Naevdal *et al*., 2005). One of the equation used in defining spatial correlation is gaussian correlation model:

$$C = C_{ij} = \exp\left[-\left(\frac{S_{xi}-S_{xj}}{l_c}\right)^2 - \left(\frac{S_{yi}-S_{yj}}{l_c}\right)^2 - \left(\frac{S_{zi}-S_{zj}}{l_c}\right)^2\right] \quad (7)$$

Where:

C = The gaussian correlation matrix
s = The point at specified axis
l_c = The correlation length

From the gaussian correlation matrix, the initial covariance matrix P_o could be generated by multiplying variance to the covariance matrix P_o (Naevdal *et al*., 2005). Under RCL-EnKF method, initial covariance matrix is modified using region modifier matrix F (Ambia *et al*., 2017). The symbol represents hadamard product which is an element by element multiplication.:

$$F = f_{ij} = \begin{cases} 1, f_i = f_j \ \forall i, jE\{1, 2, ..., n\} \\ 0, f_i \neq f_j \end{cases} \quad (8)$$

$$P' = F \Theta P \quad (9)$$

MATERIALS AND METHODS

In this method, we explore the possibility of using dynamic parameters that directly affect the production data such as pressure and flux magnitude. Most of the reservoir simulation is done by using finite difference simulator that utilize IMPES algorithm to solve the fluid flow in porous media. Thus, the pressure and flow information is already calculated when the simulator solve the equation. This information is used to control which grid gets updated by modifying the kalman gain. For pressure formulation, it is important to maintain consistency for every possible pressure data. Therefore, the pressure needs to be converted into normalized pressure:

$$\forall t \in \{0, ..., T\text{-}1\}, \forall i \in \{0, ..., N\text{-}1\}$$
$$\rho = p_{D_{ij}} = \frac{\max_{i\in\{0, ..., N1\}}(p_{i,t}) - p_{i,t}}{\max_{i\in\{0, ..., N1\}}(p_{i,t}) p_{wf}} \quad (10)$$

Where:

p = The variable is a reservoir pressure
p_{wf} = The bottom hole pressure

Another method is using flux magnitude as a basis of localization. The flux magnitude is normalized using the following Eq. 11:

$$\forall t \in \{0, ..., T\text{-}1\}, \forall i \in \{0, ..., N\text{-}1\}$$
$$\rho = F_D = \frac{u_{fi,t} \ \min_{i\in(0,...,N-1)}(u_{fi,t})}{\max_{i\in(0,...,N-1)}(u_{fi,t}) - \min_{i\in(0,...,N-1)}(u_{fi,t})} \quad (11)$$

where, u is flux magnitude. The normalized model gives the consistency for every possible flow results. From the kalman gain modifier, ρ the new kalman gain is calculated The modified kalman gain then is used in EnKF algorithm:

$$K' = \rho k \quad (12)$$

RESULTS AND DISCUSSION

The algorithm is tested in reservoir simulation. Suppose there is a channelized reservoir model that have the properties shown in Table 1. The reservoir consists of two distinctive facies that is a channel and a levee as shown in Fig. 1. For each facies, the permeability is distributed evenly. The permeability on channel is substantially higher than the permeability in levee area. The channel area has permeability of 800 md while the levee has 300 md. The permeability in non-reservoir area is 50 md. The objective of history matching is to find the

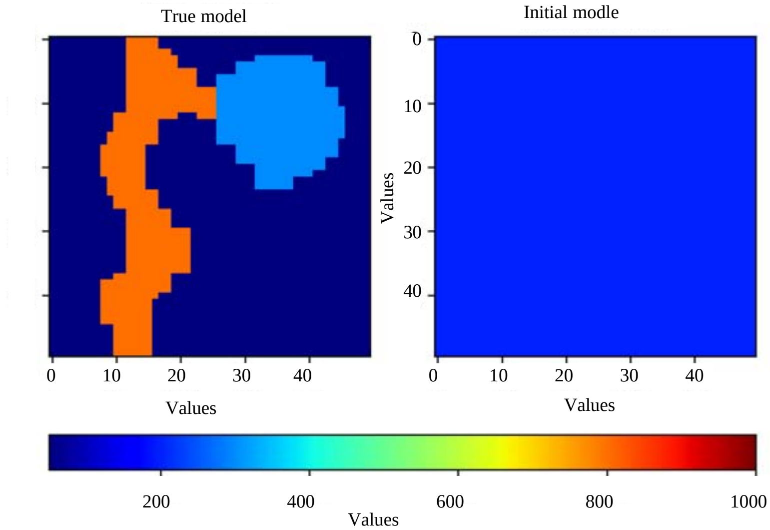

Fig. 1: The distribution of permeability in true model and the model that used as initial condition

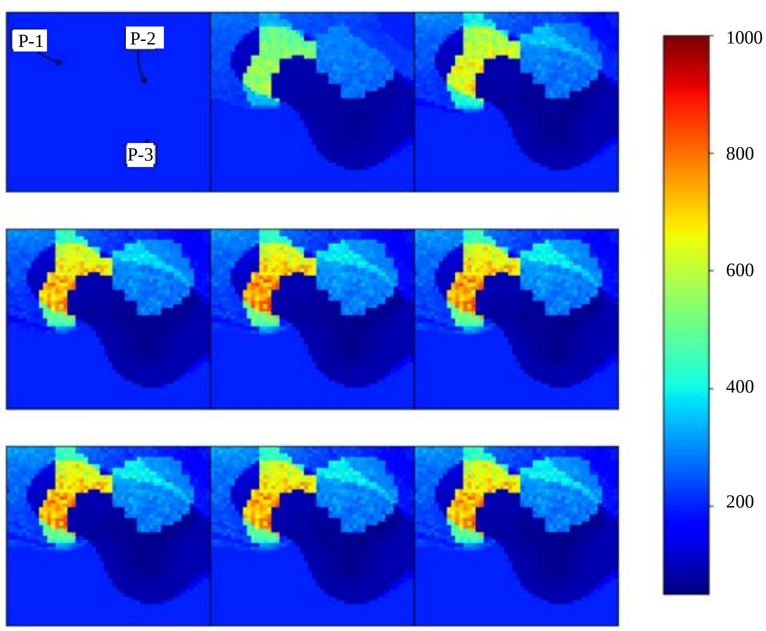

Fig. 2: The update of permeability distribution over time using pressure as an additional localization method. The facies model is preserved within the updated area

distribution of permeability that follows true model using homogenous model as an initial condition. The initial permeability is 100 md. The reservoir is produced from three production wells. There is no water and gas produced from the reservoir. We use standard RCL-EnKF from previous research as a baseline results (Ambia *et al*., 2017). The Root Mean Squared Error (RMSE) for permeability distribution is 42 md. The updated results using Eq. 10 is shown in Fig. 2. The updated area follows the pressure change distribution in reservoir. Notice that in the lower permeability area the pressure change reach farther ranges than in high permeability area. The effect is caused by in the high permeability area, the pressure change is higher, makes it depleted more rapidly. The RMSE for pressure based RCL-EnKF is 143 md. The histogram of permeability is shown in Fig. 3.

Another method that, we explore is flux oil magnitude based RCL-EnKF. In this method, we use Eq. 11 to

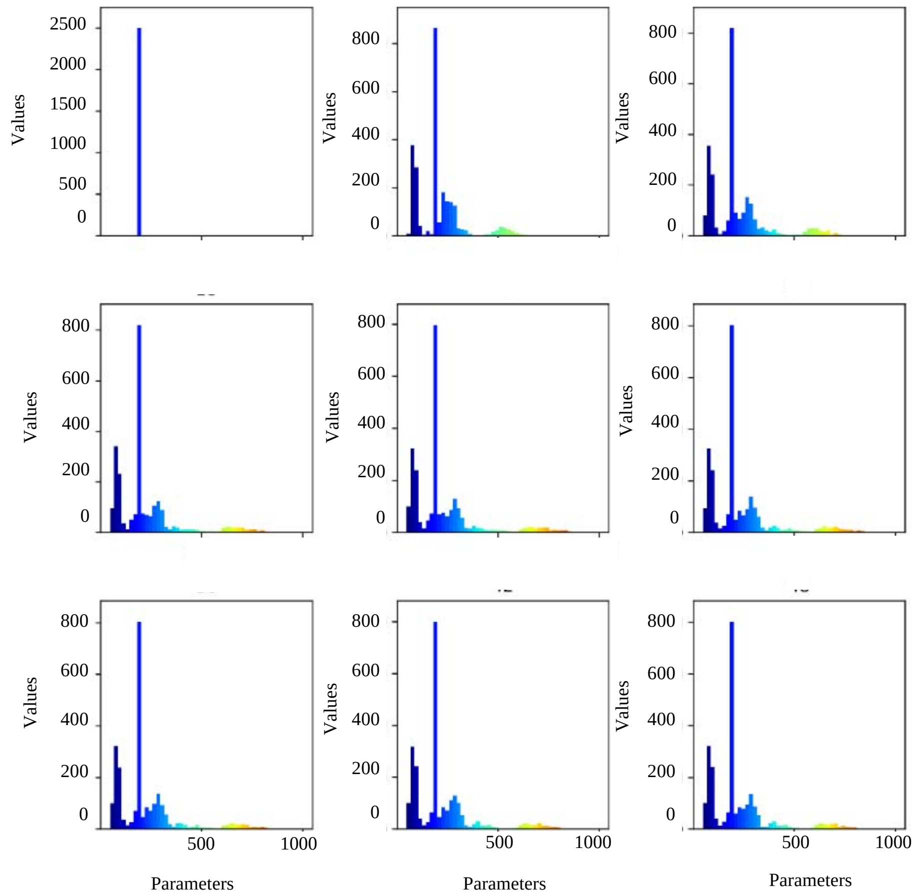

Fig. 3: Histogram of permeability distribution over time

Table 1: Properties in reservoir model

Parameters	Values
Grid size	50×50, 100 ft
Top depth	5000 ft
Thickness	100 ft
Initial pressure	2048 psi
Temperature	212 F
Porosity	10%
Oil density	20 API
Gas density	0.8

Table 2: Comparison of root means squared error for each method

Root mean squared error	Grid (md)	Oil rate (BOPD)
RCL EnKF	42	P-1: 73 P-2: 27 P-3: 44
Pressure based RCL-EnKF	143	P-1: 77 P-2: 30 P-3: 69
Flux oil magnitude based RCL-EnKF	190	P-1: 750 P-2: 226 P-3: 319

generate Kalman gain modifier matrix. The result is shown in Fig. 4. The updated area encloses a smaller area than pressure based kalman gain modifier. This phenomenon is caused by the area that have enough pressure difference to move the oil is smaller than the actual area that affected by pressure changes. From the histogram shown in Fig. 5 there are three separate facies in the model. Other than that, a lot of area is still unchanged because it is located outside of updated perimeter. This effect is expected since it means that, the localization method works as intended. The RMSE for flux oil magnitude based RCL-EnKF is 190 md. The comparison of RMSE for every method is shown in Table 2.

From comparison of RMSE, both methods give higher RMSE error than standard RCL-EnKF. The explanation is by increasing the localization method, the updated area is smaller compared to normal RCL-EnKF. Therefore, a lot of area is under initial condition. A comparison between both methods are fairer if, we select the permeability of the area within 200 ft from wells. The RMSE for pressure based RCL-EnKF is 247 md while the RMSE for flux oil magnitude is 82 md which is considerably lower than RMSE of normal RCL-EnKF at 168 md. The comparison of RMSE for every method is shown in Table 3.

From the comparison, the lowest error is obtained by flux oil magnitude based RCL-EnKF. This is also

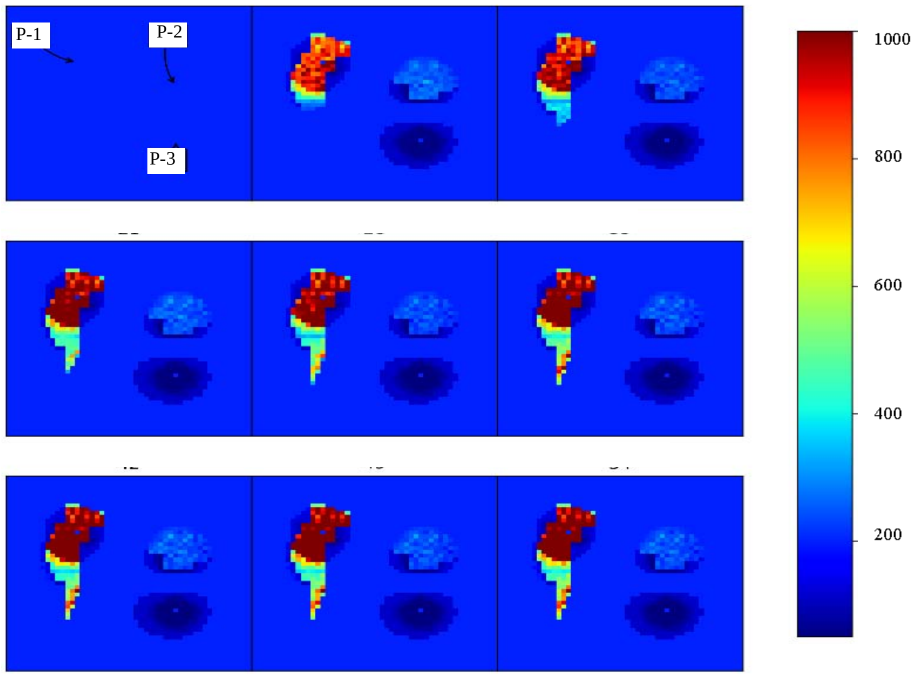

Fig. 4: Permeability distribution over time using flux oil magnitude as an additional localization method. The updated area is smaller than other methods

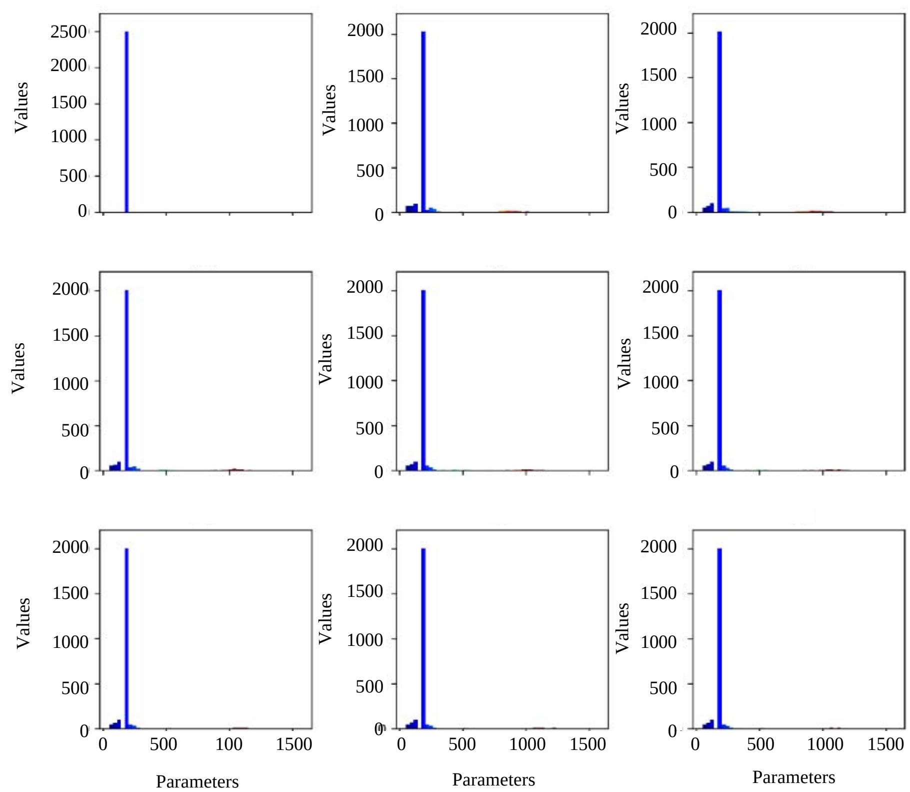

Fig. 5: Histogram of permeability distribution over time

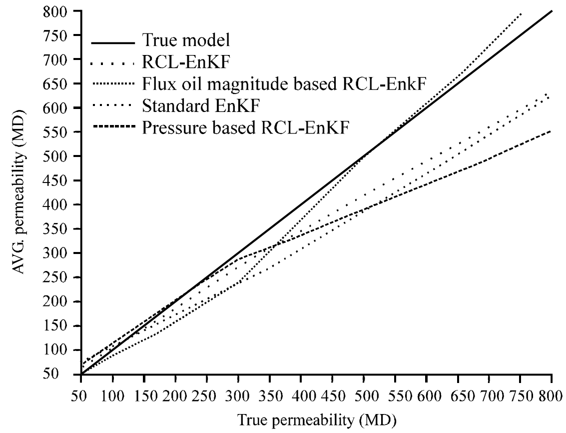

Fig. 6: Plot of permeability of true model vs. average permeability within 200 ft radius of wells

Table 3: Comparison of root means squared error within 200 ft radius of nearest well

Methods	P-1 (md)	P-2 (md)	P-3 (md)	RMSE (md)
True model	800	300	50	-
RCL-EnKF	635 (-21%)	272 (-9%)	64 (28%)	168 (-11%)
Pressure based RCL-EnKF	554 (-31%)	283 (-5%)	70 (40%)	247 (34%)
Flux oil magnitude based RCL-EnKF	855 (7%)	239 (-20%)	56 (12%)	82 (-56%)

confirmed from the plot of permeability from true model vs. predicted model within 200 ft of well radius Fig. 6.

CONCLUSION

The flux oil magnitude based RCL-EnKF gives the lowest error. This is caused by the algorithm only updates in much smaller area. Thus, the ratio between unknown variables and known equation is smaller than normal RCL-EnKF which makes it easier to solve the optimum solution. Even though, flux oil magnitude is the best method, the pressure based RCL-EnKF could be used to update the permeability in wider area. The decision depends on the available initial model, whether is good enough or far from true model.

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