Reparameterization of Complex Geological Models Using Neural Style Transfer

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Abstract

In the field of reservoir engineering, lower dimensional reparameterization for complex geological models is an important but challenging problem. Properties for complex geological models such as facies are non-Gaussian, characterized by multipoint spatial statistics. Traditional reparameterization method such as principal component analysis (PCA) only works well for Gaussian models that can be characterized by two-point spatial statistics [8]. The recently developed optimization-based PCA (O-PCA) is shown to provide better performance for non-Gaussian models [9]. However, O-PCA relies on hard data at well locations. The performance of O-PCA for unconditional models is not satisfactory. In this study, we explore the application of neural style transfer [1] for the reparameterization of non-Gaussian geological models. The neural style transfer algorithm is firstly introduced for transferring photographs to new images that resembles the styles of famous artworks, and extended to more applications such as video style transfer [4]. Our idea is to use the neural style transfer algorithm as a post-processing step after traditional PCA transformation. PCA transforms the original non-Gaussian model into Gaussian-like models. The purpose is to apply the neural style transfer algorithm to transfer the Gaussian-like PCA model to match the style of the original non-Gaussian model. We will perform both O-PCA and neural style transfer to preprocess same PCA models. Visual inspection will be performed to evaluate the results, in terms of matching style of the original model and geological realism.

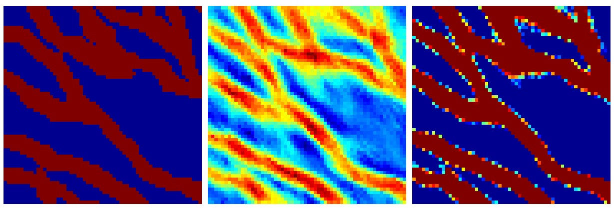
1. Introduction

This study is in the field of oil and gas reservoir engineering. We are dealing with a special kind of "photo". In our case, it is the permeability map of a subsurface oil and gas reservoir. Permeability describes how easily fluid can flow through the porous rocks in the reservoir. Larger permeability values means fluid flows through the porous rocks more easily. For example, Fig. 1 (a) represents the permeability map of a hypothetical 2d reservoir. Red color represents high permeability rocks such as sandstone, while blue color represents low permeability rocks such as shale. This model represents a channelized reservoir, we can see the high permeability sandstone follows some paths like river-channels.

Because oil and gas reservoirs are deeply underground, we can not measure the permeability map for the whole reservoir. In practice, we only have measurement data at few locations where we drill wells, and these measurement data are referred to as hard data. To accurately quantify the uncertainty of such system, we need to generate a very large amount of different permeability maps. However, it is very difficult for this type of channelized reservoirs, since a permeability map is often high dimensional and have strong spatial correlation.

Traditionally, we use PCA to reduce the dimension and to allow us generate large amount of permeability maps. For example, one example is shown in Fig. 1 (b), but we can see PCA models kind of smooths out the sharp constrast between high and lower permeability values shown in this permeability map. Traditionally, what we do is to introduce postprocess step on the PCA permeability map to get back the sharp contrast. One popular approach is the so-called optimized-based-PCA (O-PCA) which is essentially a pixelwise histogram transformation. The O-PCA result for this PCA permeability map is shown in Fig. 1 (c), we can see that we do get back the sharp contrast, however, the connectivity of the channels is somehow destroyed.

In this study, we use the neural style transfer algorithm to postprocess the PCA permeability map. We will first describe the problem in the language of reservoir engineering. As shown in Fig. 1(a), the original model is permeability of a channelized reservoir defined on a 60×60 grid. The original model is binary, meaning permeability is either of type 1 (red), representing high permeability sand, or of type 0, representing low permeability mud. The corresponding PCA approximate model, as shown in Fig. 1(b), captures the location of sand and mud. However, the PCA model is no longer binary. The problem is to postprocess the PCA model to generate a new model that is approximately binary, consistent with the original model. O-PCA is one solution to this problem. The idea of O-PCA for this binary model is similar to simply snapping PCA values to 0 and 1, but in a more sophisticated way based on optimization that preserves some intermediate values and renders the mapping differentiable. The corresponding O-PCA model is shown in Fig. 1(c). O-PCA works well for this model because the PCA model is reconstructed from the original model. Its performance deteriorates when we deal with randomly generated PCA models.



(a) Original model (b) PCA model (c) O-PCA model

Figure 1: PCA and O-PCA transformation for a binary model.

This problem can be viewed as an image style transfer problem. The facies distribution defined on the 60×60 grid can be viewed as an image with 60×60 pixel, each gridblock being one pixel. The facies values on each gridblock can be mapped to RGB values. The original model has a binary style, with only red and blue color. The PCA approximate model captures the content of the original image. Here content means the close-to-red stripes and close-to-blue patches, and their locations in the image. But the style of the PCA approximate differs from the binary style. Therefore, we can formulate the problem as transfer the PCA model into the style of the original image.

To fit the problem in the neural style transfer algorithm, we take the PCA model as the input content image, and the original model as the target style image. We will use the an PyTorch implementation of the original neural style transfer algorithm [10], based on a pre-trained VGG model [6].

2. Related Work

In this section, we will describe traditional approaches for lower dimensional reservoir reparameterization including PCA and O-PCA.

2.1. PCA

The application of principal component analysis (PCA) to parameterize reservoir models or production data has been discussed by many authors; see, e.g., [5, 8, 7]. First, a set of N_r reservoir model realizations is generated using geostatistical toolbox [3], and each realization comprises a column of the following data matrix

$$X_c = [\mathbf{m}_1 - \bar{\mathbf{m}} \quad \mathbf{m}_2 - \bar{\mathbf{m}} \quad \dots \quad \mathbf{m}_{N_\mathrm{r}} - \bar{\mathbf{m}}], \tag{1}$$

where $\mathbf{m}_i$ is a geological realization of dimension $N_c = 3600$, and $\bar{\mathbf{m}}$ is the mean of all N_r realizations. Performing singular value decomposition of the matrix $X_c/\sqrt{N_r - 1}$ gives

$$X_c = \sqrt{N_r - 1} U \Sigma V^T = \sqrt{N_r - 1} \Phi V^T, \tag{2}$$

where Φ is the so-called basis matrix. Given this basis matrix, the PCA realizations can be generated through application of

$$\mathbf{m} = \Phi \boldsymbol{\xi} + \bar{\mathbf{m}}, \tag{3}$$

where $\boldsymbol{\xi}$ is a low-dimensional vector drawn from standard normal distribution. One example of the randomly generated PCA model is shown in Fig. 4(a).

2.2. O-PCA

Optimization-based PCA is essentially a post-processing method [8], that seeks to transform the value of each parameter/pixel assisted with the target histogram. In the case binary models (e.g., channelized system), the O-PCA result is obtained by minimizing the following objective function

$$\mathbf{m} = \underset{\mathbf{x}}{\operatorname{argmin}} \Big\{ ||\Phi \boldsymbol{\xi} + \bar{\mathbf{m}} - \mathbf{x}||_2^2 + \gamma \mathbf{x}^T (\mathbf{1} - \mathbf{x}) \Big\}, x_i \in [0, 1], \tag{4}$$

where x_i indicates an element of $\mathbf{x}$, and γ is the weight of the regularization term. See [8] for detailed discussions and explanations. We can see from Eq. **??** that O-PCA modifies the value of each parameter independently, the correlations between different parameters are not considered.

3. Method

In this section, we will describe the key methods in this study. We will start with a brief description to the neural style transfer algorithm [1] and the fast neural style transfer algorithm [2]. Then we will introduce the procedure of applying the neural style transfer algorithm for reparameterization. We name the procedure CNN-PCA since it combines PCA and CNN-based neural style transfer algorithm. Next we will introduce additional loss term to handle hard data constraint. Hard data refers to the measurements at well locations that need to be preserved during the reparameterization process.

3.1. Neural Style Transfer

The neural style transfer algorithm developed in [1] takes two images: an input image and a reference image. Denote the input image/model as I, reference image S and output image O. The output image is generated by minimizing the following objective function

$$L_\mathrm{t} = \sum_{l=1}^{L} \alpha_l L_\mathrm{c}^l + \lambda \sum_{l=1}^{L} \beta_l L_\mathrm{s}^l, \tag{5}$$

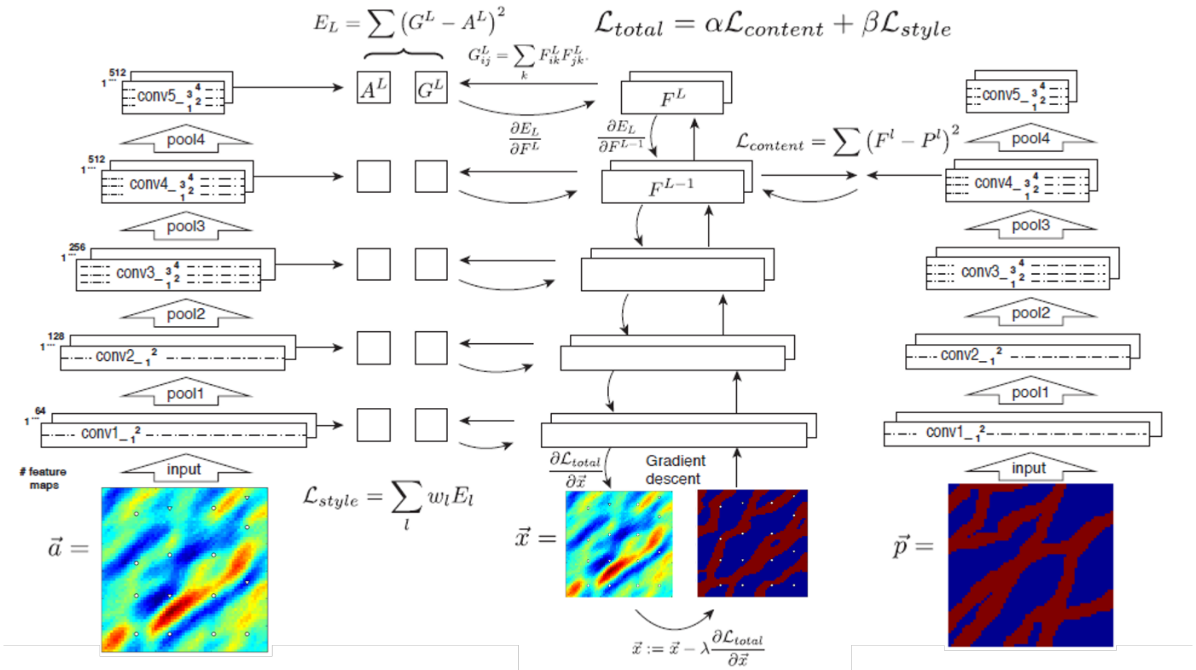


Figure 2: Neural style transform for reservoir reparameterization, modified from [1].

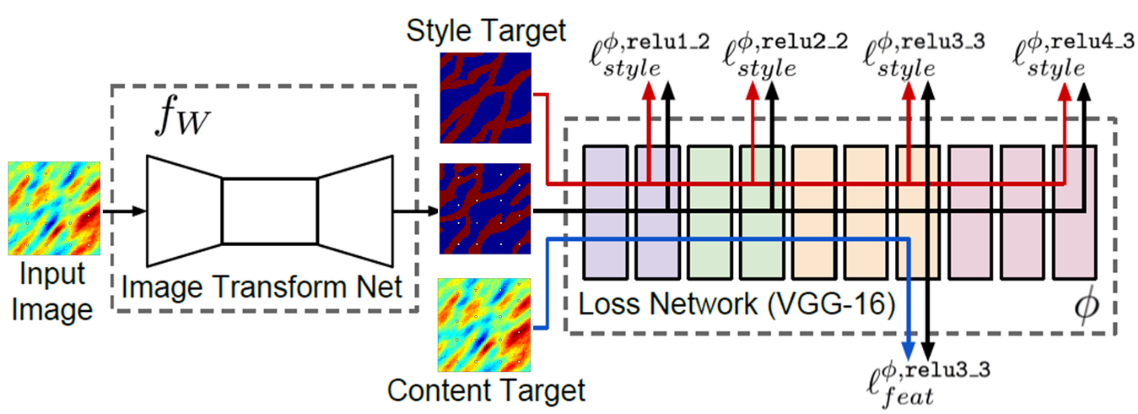


Figure 3: Fast neural style transform for reservoir reparameterization, modified from [2].

where

$$L_{\mathrm{c}}^{l} = \frac{1}{2N_l D_l} \sum_{ij} (F_l[O] - F_l[I])_{ij}^2, \tag{6}$$

$$L_{\mathrm{s}}^{l} = \frac{1}{2N_l^2} \sum_{ij} (G_l[O] - G_l[S])_{ij}^2. \tag{7}$$

$$L_{\mathrm{h}} = \sum_{ij} h_{ij} (I - O)_{ij}^2. \tag{8}$$

Here L denotes the total number of convolutional layers and l indicates the l-th convolutional layer. $F_l[\cdot] \in \mathbb{R}^{N_l \times D_l}$ and $G_l[\cdot] = F_l[\cdot] F_l[\cdot]^T \in \mathbb{R}^{N_l \times N_l}$ represent the feature matrix and Gram matrix. λ is a weight that represents the tradeoff between the input and reference images. See [1] for detailed explanations of the algorithm. In this study, we simply use the pre-trained model from [1].

3.2. CNN-PCA

To apply the neural style transfer algorithm for reparameterization, we first use PCA to transform the permeability map $\mathbf{m}$ to lower dimensional variable $\boldsymbol{\xi}$ using Eqs. 1 to 2. Sampling $\boldsymbol{\xi}$ from the standard normal to allow us generate multiple realizations of the permeability map. These permeability maps are not binary. So we apply the neural style transfer algorithm to post-process the PCA realizations. Each PCA realization of the permeability map is taken as the content image. The original binary permeability map is taken as the style image. As illustrated in Figs. 2 and 3, both slow neural style transfer algorithm and the fast neural style transfer algorithm can be applied. This procedure is named as CNN-PCA.

3.3. Hard Data Constraint

Hard data are measurement data of the permeability values at well locations. In the process of reparameterization, we need to ensure that the output permeability maps have the correct permeability value at well locations. The PCA models will always honor hard data. However, the direct application of CNN-PCA does not guarantee that hard data are honored. Therefore, we introduce an additional hard data loss term in the neural style transfer algorithm,

$$L_{\mathrm{t}} = \sum_{l=1}^{L} \alpha_l L_{\mathrm{c}}^l + \lambda \sum_{l=1}^{L} \beta_l L_{\mathrm{s}}^l + \omega L_{\mathrm{h}}, \tag{9}$$

where

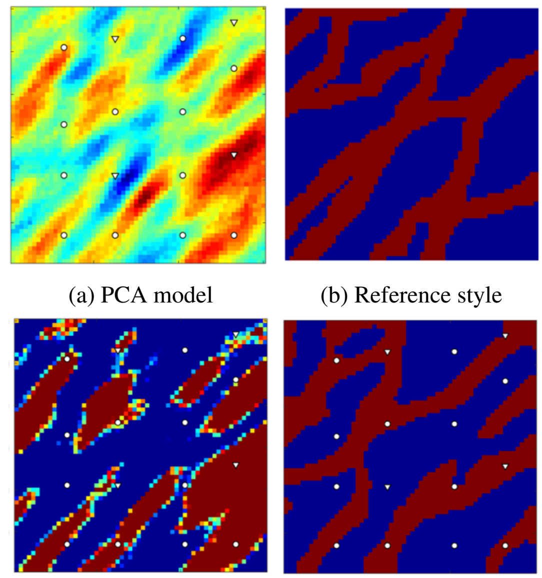
$$L_{\mathrm{h}} = \sum_{ij} h_{ij} (I - O)_{ij}^2 \tag{10}$$

is the hard data loss. Here h_{ij} is the hard data indicator, with $h_{ij} = 1$ meaning there is hard data at location (i, j). And ω is the hard data weight, which is set to a large value to enforce the hard data constraint.

4. Results

4.1. Unconditional Models

Figure 4(a) presents a 2D PCA reservoir model, which is of size 60 × 60. Figure 4(b) plots a reference geological model that is binary channelized system. Our target is to post-process the PCA model such that the resulted model is as realistic as possible. Here realistic models represent those that have the binary channelized features as in Fig. 4(b). The O-PCA result is shown in Fig. 4(c). It is evident that the O-PCA result display better binary feature in comparison with the original PCA model. However, the connectivity, which represents large-scale correlation, of channels in the O-PCA result is poor, in comparison with the apparent connectivity shown in the reference model (Fig. 4(b)). The resulted poor connectively in O-PCA result is due to the lack of large-scale correlation constraint in the O-PCA formulation shown in Eq. 4. Figure 4(d) shows the result using neural style transfer (CNN-PCA). We can see that both the binary feature for each parameter/pixel and the channel connectivity show significant improvement compared with the PCA model. This result demonstrates that the application of neural style transfer is capable of capturing the large-scale correlation and high-order geological statistics.



(a) PCA model (b) Reference style

(c) O-PCA result (d) CNN-PCA result

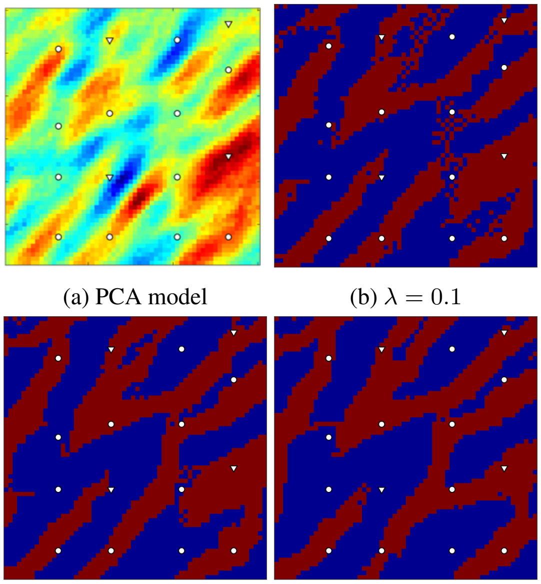
Figure 4: Reparameterization of PCA model using O-PCA and neural style transfer (Case 1).

Figure 5 shows the neural style transfer results with different value of the weighting parameter λ. From Eq. 9, the larger λ is, the more weight is on the reference style image. This effect is obvious when looking at the middle-right channel in the transferred results. In the original PCA model, there are indications of a very thick channel; however, in the result with $\lambda = 5$ (Fig. 5(d)), the width of the channel becomes much narrower. In the cases with smaller λ (Figs. 5(b) and 5(c)), the corresponding channels stay relatively thick. It is expected that the narrowing of channels is resulted from the reference-style model shown in 4(b), in which all channels width are consistently narrow. In this study, we use $\lambda = 5$ for cases considered.

4.2. Conditional Models

Figure 6 shows a similar comparison study for a different case. The PCA model is shown in Fig. 6(a). In this case, the pixel value at the 12 wells' (white dots and triangles) locations are known, and therefore, the post-processed model must honor the measured well data (hard data) at these locations. To achieve this goal, we added a hard data loss in the total loss function in Eq. 9. The weight assigned to the hard data component (w) is specified to be a very large value to ensure the honor of hard data during the neural style transfer procedure.

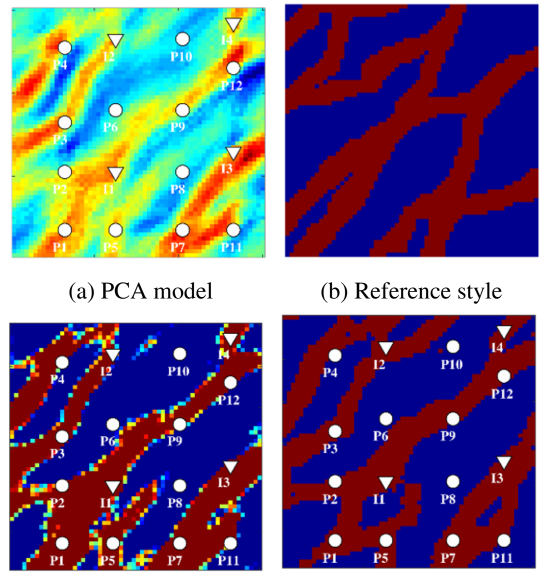
The reference model (Fig. 6(b)) used is the same as in



(a) PCA model (b) $\lambda = 0.1$

(c) $\lambda = 0.5$ (d) $\lambda = 5$

Figure 5: Neural style transfer results with different λ parameters.



(a) PCA model (b) Reference style

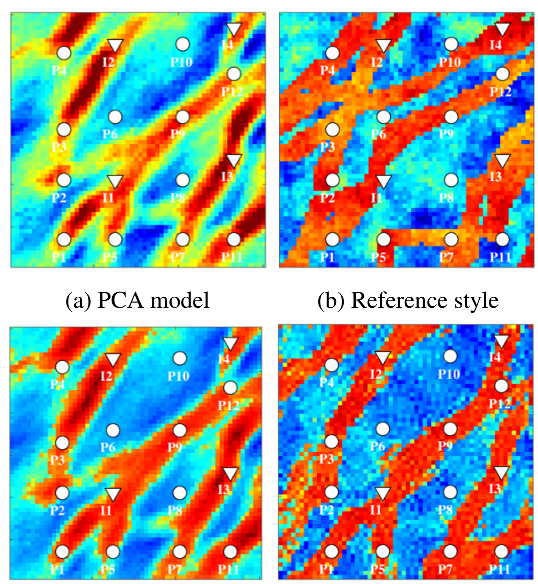
(c) O-PCA result (d) CNN-PCA result

Figure 6: Reparameterization of conditional PCA model using O-PCA and neural style transfer (Case 2).

Case 1. It is interesting to see the comparison of the results at the lower-left corner, where the O-PCA result shows very wide channel, while the CNN-PCA result displays relatively narrow channel. From the reference model, we can see that the channel width is relative consistent and narrow. Therefore, the CNN-PCA result actually preserves the reference style, which is what we want, even when the original PCA model display non-desirable feature (wide channel at the lower-left corner). This result clearly demonstrates the capability of CNN algorithm to capture the high-order features in the reference model and impose those to transferred model. It is, therefore, of great interest to further investigate the application of CNN, particularly neural style transfer, for reservoir parameterization.

4.3. Bimodal Models

We now extend the application of CNN-PCA to a more challenging case. The reference model is shown in Fig. 7(b). Within each faces (sand and shale), the permeability values are also uncertain. Again, it is apparent that the CNN-PCA results display better channel features in comparison with the O-PCA results. For example, all channels at the lower-left corner (Figs. 7(a) and (c)) terminate at the well location, which indicates the poor quality of both PCA and O-PCA models, as the channel length is generally long when looking at the reference model. However, in the CNN-PCA model, we can see that the lower-left channels are naturally extended toward the boundary of the system. It is, however, notable that, in the CNN-PCA result, the distributions of permeability values within each face are less smooth compared with the distributions shown in the reference style. It is of interest to address this non-smoothness of CNN-PCA results in bimodal cases as of future work.



(a) PCA model (b) Reference style

(c) O-PCA result (d) CNN-PCA result

Figure 7: Reparameterization of bimodal PCA model using O-PCA and neural style transfer (Case 3).

4.4. Comparison of Flow Statistics

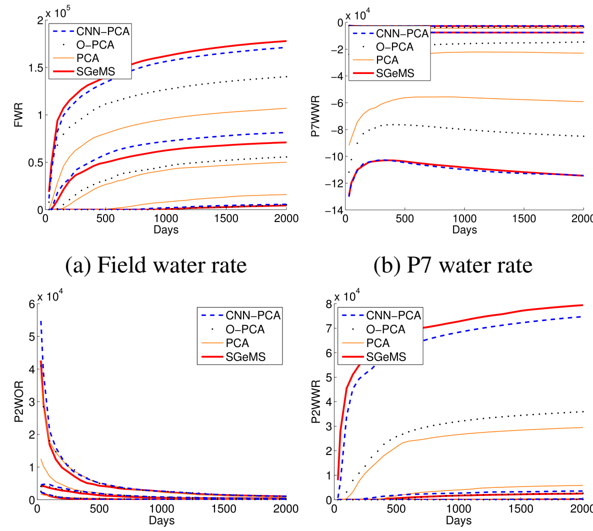
Once reservoir models (e.g., Figs 4 and 6) are generated, we evaluate the potential of water injection rate, water and oil production rate from the wells, which are the quantities of most interest, drilled throughout the reservoir. The production rates can then be used to evaluate the performance of the system. The well patterns considered in this work are shown in Fig. 6(a), with white triangles representing injectors (which inject water into the reservoir), and round circles producers (which produce oil and water). The production rates are obtained through traditional numerical reservoir simulator. Because of the uncertain nature of subsurface reservoir properties, therefore are infinite number of possible reservoir models. In this study, we generated an ensemble of 200 models for both the conditional (Fig. 4) and unconditional (Fig. 6) cases. These ensemble of models are then used to obtain the simulated well flow rates.

Figure 8 shows the flow statistics (P10, P50, and P90) computed from the ensemble of flow rates corresponding to the unconditional case. Figure 8(a) shows P10, P50, and P90 curves for field water production rate corresponding to SGeMS, PCA, O-PCA, and CNN-PCA models. Here SGeMS models provide the reference results to benchmark with. The total simulation time is 3000 days. It is clear that the CNN-PCA flow statistics results (dashed blue lines) match closely with the reference results (solid red lines), and display significant improvements compared with the O-PCA results (dashed black lines) and PCA results (dashed yellow lines). Figure 8(b) plot the water rate from P7, which is an injector and therefore shows negative production rate. Again, it is evident that the CNN-PCA results agree well with the reference results, and show significant improvements compared with the PCA and O-PCA results. Similar observations hold for the P2 oil production rate (Fig. 8(c)) and water production rate (Fig. 8(d)).

Figure 9 shows the flow statistics corresponding to the conditional systems shown in Fig. 6. In this case, because of the availability of well hard data, the O-PCA results match reasonably well with the reference results, except for the P4 water rate shown in Fig. 9(b)). While the CNN-PCA results display much closer match with the reference results for all the well rate statistics shown in Fig. 9. The results shown in Figs. 8 and 9 demonstrate the CNN-PCA is indeed useful for the reparameterization of complex binary geological models, at least in the cases considered.

5. Conclusion

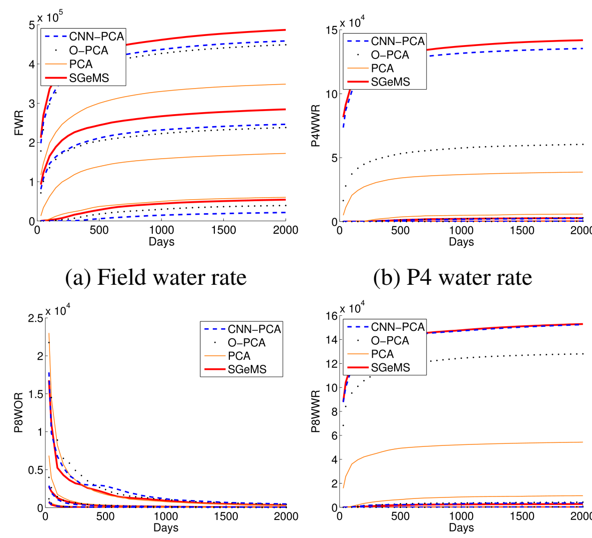
We applied a neural-style transfer algorithm for the post-processing of unconditional and conditional binary (facies) channelized models, and also for bimodal channelized system. The transferred models are referred as CNN-PCA models. In comparison with the traditional popular



(a) Field water rate (b) P7 water rate

(c) P2 oil rate (d) P2 water rate

Figure 8: Flow statistics (P10, P50, and P90) for unconditional channel model shown in Fig. 4.



(a) Field water rate (b) P4 water rate

(c) P8 oil rate (d) P8 water rate

Figure 9: Flow statistics (P10, P50, and P90) for conditional channel model shown in Fig. 6.

approach, optimization-based PCA (O-PCA), CNN-PCA models clearly display better connectivity of the channels, and also the sharp contrast between different facies. The CNN-PCA models also provide better prediction of the well rate flow statistics in comparison with the O-PCA models for the binary geological cases. The reason for this improvement is that spatially correlations of geological models are considered by the CNN-PCA algorithm with multiple convolutional layers, while, in O-PCA approach, essentially only pixel-wise histogram transformation is applied. However, there are some issues with the CNN-PCA results, particularly for the bimodal cases, in which the CNN-PCA models display rougher distribution of permeability values within each geological facies. In the future work, we will add some smoothness constraints in the loss function for CNN-PCA, which is possible to help address the non-smoothness issue.

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