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Optimal field synthesis for enhancing the modeling capabilities of reservoir/aquifer fields

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Abstract: One field identified by an inverse method is one of multiple candidate solutions those are independently obtained through a specific estimation technique. While averaging of optimized fields can provide a better description of the spatial feature of an unknown field, it deteriorates the flow and transport characteristics of the optimized fields. As a result, the averaged field is not suited for modeling aquifer performances. Based on genetic algorithm, an optimal field synthesis technique is developed, which combines diversely optimized fields into a refined group of fields. Each field in the population is paired, and a sub-region of each field is exchanged by crossover operation to create a group of synthesized fields of enhanced modeling capability. The population of the fields is evolved till the synthesized fields become sufficiently similar. Applications of the optimal field synthesis to synthetic cases indicate that the objective functions of the fields assessing the modeling capabilities are further reduced after the optimal field synthesis. The identified fields from various inverse techniques may yield a range of modeling results under varied flow situations. The uncertainty is narrowed down through the optimal field synthesis and the associated modeling results converge on that of the reference field. The developed inverse modeling facilitates the construction of a reliable simulation model and hence trustworthy predictions of the future performances.

1. Introduction

We often come to have multiple candidate fields for an unknown site of interest from various sources. In the case, there can be one reasonable approach to perform Monte-Carlo simulations with the multiple fields and obtain the corresponding multiple model performances of certain range of uncertainty (Vasco et al., 1997). In a certain case, we might be confronted with a situation when we should construct one best field using the multiple fields obtained through various ways. The multiple fields could be various estimations from different estimation methods such as geostatistical methods and seismic surveys, or solutions obtained by different inverse techniques. Even if the identified fields show similar accuracies of performances evaluated by an objective function, the fields may reveal diverse geological features. Therefore, it is of importance to adequately combine those fields and come up with one refined field by synthesizing the fields.

One possible way of synthesizing the fields could be simply averaging the fields in the gridblock-scale. However, that would deteriorate the capability of the synthesized field in simulating model performances such as a pressure computation and tracer transport modeling. In terms of optimization, the degradation of the model performances of the averaged field emerges as the increase of the objective function. Therefore, an optimal field synthesis technique is developed based on genetic algorithm for the purpose of enhancing the capability of modeling aquifer performances.

2. Optimal Field Synthesis

In the optimal field synthesis, the initial population is made up of the fields identified by various inverse techniques, i.e, stochastic optimization (SO), stochastic streamline calibration (SSC), and simulated annealing (SA) (Johnson and Rogers, 2001). Those fields have the similar level of the objective function so that they reproduce properties of the reference field at a similar level. However, the fields are not the same in the gridblock-scale and viewed as equi-probable ones showing equivalent performance.

Under the framework of genetic algorithm, offspring is typically created from the population of parents using evolutionary operators of crossover and mutation. Mutation is to perturb a solution in a stochastic way, yet it has been repeatedly incorporated in the inverse modeling from which the initial population originates. In other words, mutation has been already applied sufficiently in the precedent inverse modeling through the stochastic processes in the inverse modeling. Therefore, mutation is not adopted in the optimal field synthesis to avoid redundancy.

Each field in the population is paired, and part of each field is exchanged by crossover operation to create a group of offspring. Then new population is set up by selecting better solutions in the group according to the fitness of each offspring. The population of parents is now replaced by the new population established. The whole procedure is iteratively repeated and the population of solutions is evolved till a pre-specified stopping criterion is met. Fig. 1 presents a brief illustration of the optimal field synthesis proposed in this study.

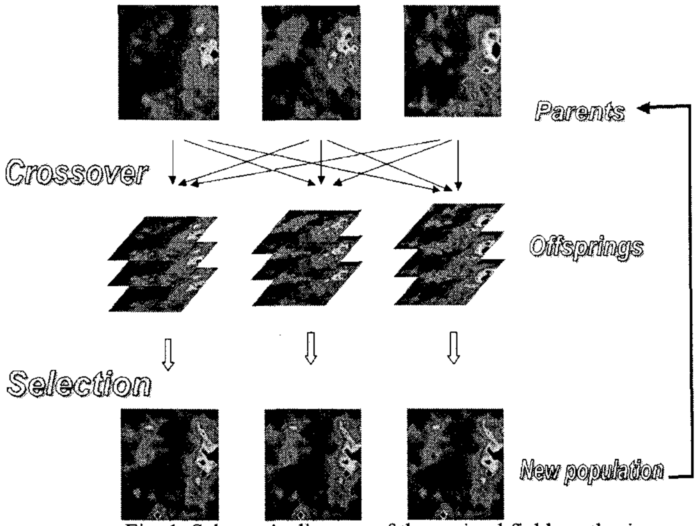


Fig. 1. Schematic diagram of the optimal field synthesis.

Assorted evolution

Consider a problem that begins with an initial population of three candidate fields, A, B, and C as shown in Fig. 2. By a crossover operation, we can come up with offspring of A, Ab, Ac, Ba, B, Bc, Ca, Cb, and C for instance. Here, A○ denotes an offspring generated by crossover between the parent of A and that of other fields. In the wholesale replacement of the population, three best fields would be selected and constitute the population. Provided that Ab, A, and Bc are the offspring of the highest fitness among the offspring, all the fields of C○ will be excluded permanently from the field synthesis process. It is not desirable because some good traits of C lose the chance of contributing to the construction of the synthesized field too early. Therefore, assorted evolution is implemented to prevent the hasty exclusion of candidate fields. For the case above, the offspring of the highest fitness is selected among each individual group and the population becomes composed of the selected offspring within the different groups of A○, B○, and C○. For instance, Ab, Bc, and C constitute the population and the process proceeds to the next stage. Through the assorted evolution, main traits of individual fields are inherited without being lost too hastily.

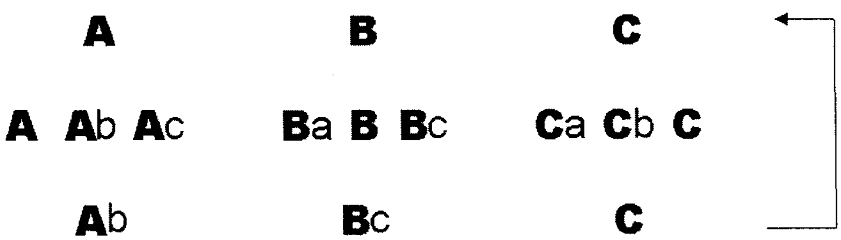


Fig. 2. Schematic diagram of the assorted evolution.

3. Results

The optimal field synthesis was carried out on the fields those have been already optimized to a considerable level by the various inverse techniques. The underlying fields underwent further calibrations by the optimal field synthesis and an improved field was yielded. The results of the optimal field synthesis were analyzed from diverse viewpoints and compared with those of conventional ensemble averaging.

Optimization by inverse techniques

Three fields were obtained from different inverse techniques of SO, SSC, and SA. The inverse process was performed in the form of minimizing an objective function, which three types of data are incorporated in as:

$$\begin{aligned} E &= E_k + E_p + E_T \\ &= w_k \sum_{l=1}^{L} (k_l^{obs} - k_l)^2 + w_p \sum_{l=1}^{L} (p_l^{obs} - p_l)^2 + w_T \sum_{ls=1}^{N_{SL}} (T_{ls}^{obs} - T_{ls})^2 \end{aligned} \tag{1}$$

where w is the weighting, L is the number of the observation points, k is the permeability, p is the pressure, T_{ls} is the breakthrough time of the $l$sth streamline, and N_{SL} is the number of the observed tracer breakthrough times. The first term describes misfit of permeability between observed value and computed value, second term is that of pressure, and the third term is that of tracer data. Pressure is obtained from the flow simulation and the breakthrough time of a streamline is obtained from streamline simulation (Jang and Choe, 2002).

Averaging of fields

The three fields by inverse modelling are displayed in Fig. 3 (b), (c), and (d). All the three fields have been optimized to a satisfactory level and represent similar values in the objective function as shown in Table 1. As a result, the global geological features of the fields are analogous to that of the reference field and so are the performances of the fields from the viewpoint of the flow and transport behaviors. Since the fields are acquired under the different inverse schemes, they show discrepancies in small-scale spatial patterns nevertheless.

Table 1. Objective functions of identified fields by the various inversions.

Field	Objective function
SO	49.83
SSC	35.68
SA	35.37

Ensemble mean can offer common trend in multiple fields (Wen et al., 2002). Fig. 3 (e) shows the ensemble mean field of the three optimized fields. The spatial patterns become more apparent in the ensemble mean field, and hence the field provides a better description of permeability distribution.

Deviations of permeability values of identified fields from those of the reference field are measured and denoted by mean residual errors. Mean residual error is given by:

$$MRE = \frac{\sum \left(\sqrt{(k_{ref} - k)^2} \right) / k_{ref}}{N_m} \tag{2}$$

where N_m is the number of gridblocks, k_{ref} is the reference permeability in a gridblock, and k is the corresponding permeability in the identified field. Fig. 4 shows the change of the objective function and the mean residual error after the ensemble averaging of the fields. Compared to the optimized fields, the ensemble mean field shows the reduction in the residual error (Fig. 4.(a)). It means that the geological similarity to the reference field is enhanced by the ensemble averaging of the identified fields. In spite of it, the objective function of the ensemble mean field is poorer than any of the three optimized fields as shown in Fig. 4.(b). That is, the capability of modeling flow and transport behaviors are not preserved but attenuated in the ensemble mean field. While averaging of optimized fields can provide a better description of the spatial feature of an unknown field, it deteriorates the flow and transport characteristics of the optimized fields. Therefore, the averaged field is not suited for modeling an aquifer performance.

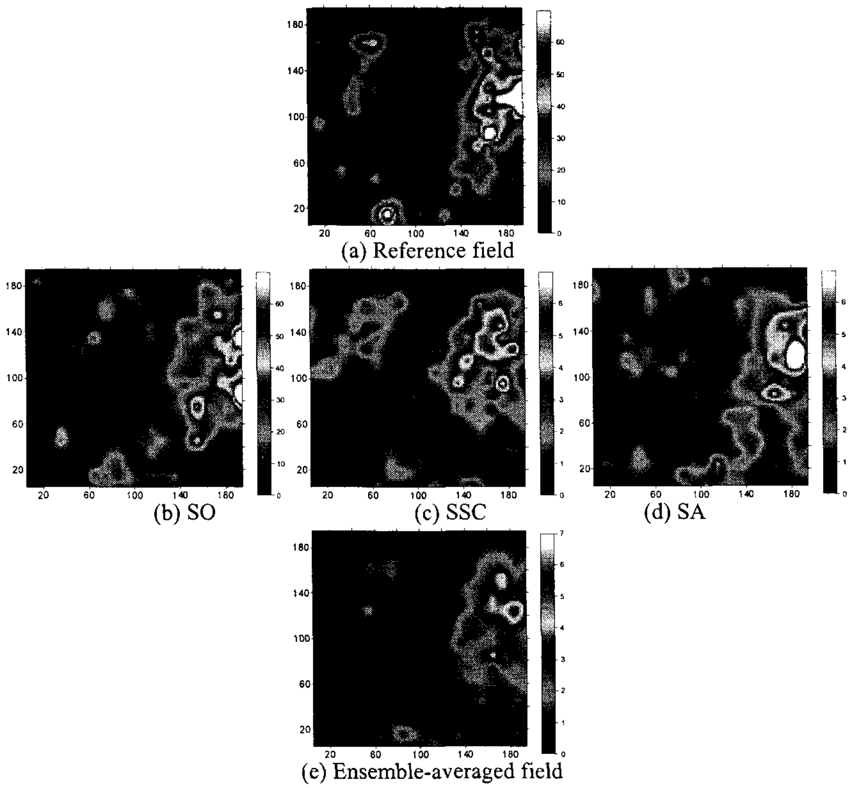
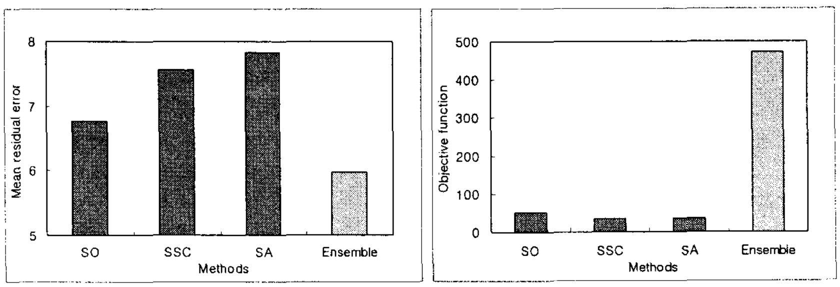


Fig. 3. Comparison of permeability fields. (a) reference field, (b, c, d) fields by the three cases of inversion, and (e) an ensemble average of the fields.



(a) Mean residual error (b) Objective function

Fig. 4. Variations of the objective function and mean residual error after ensemble averaging of the fields.

Optimal field synthesis

After the optimal field synthesis, the optimized fields and the synthesized fields are displayed together in Fig. 5. Though the improvement in the geologic similarity among the fields is not conspicuous, if we take a closer look at the fields, the three synthesized fields (d, e, and f) are transformed to be more similar with another, compared to the original fields before the field synthesis.

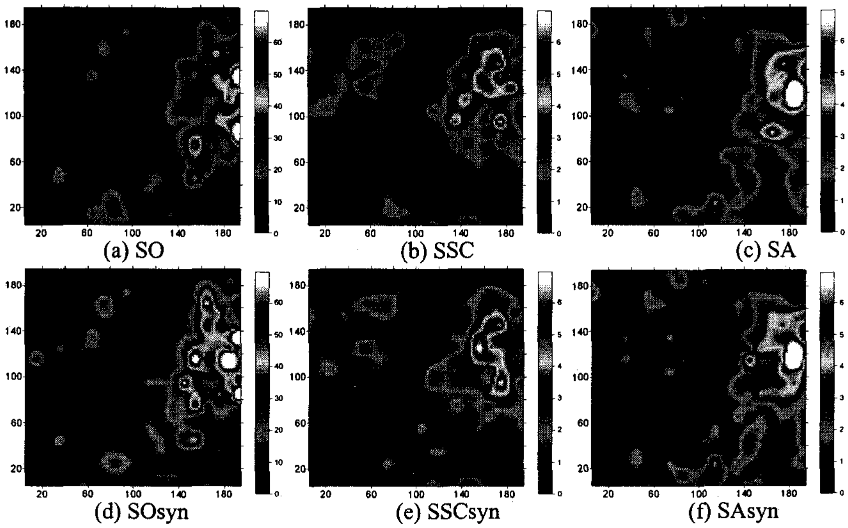


Fig. 5. Comparison of permeability fields between identified fields by the various inverse techniques and those after the optimal field synthesis.

At all the gridblocks, the variances of the permeability values among the synthesized fields were calculated and the averaged value of them is named as "field variance". The field variance of the fields by the inversions and the synthesized fields are compared by the histograms in Fig. 6. Compared to the fields by the inversions, the synthesized fields show lower field variance. It manifests increased similarity among the fields.

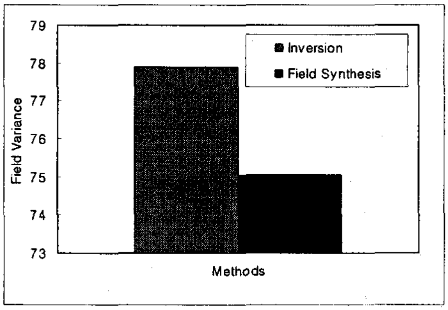
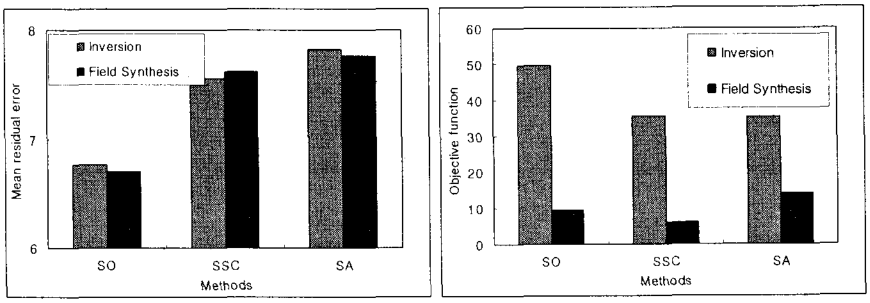


Fig. 6. Comparison of field variance before and after the optimal field synthesis.

Fig. 7 represents the change of the mean residual error and the objective function after the field synthesis. All the objective functions of the synthesized fields are noticeably reduced compared to the fields before the field synthesis as shown in Fig. 7(b). While ensemble mean simply averages permeability values at the gridblocks without taking into account the modeling capabilities of the fields, the field synthesis modifies the population of fields to generate optimally averaged fields. However, when it comes to mean residual error, no meaningful changes are perceived (Fig. 7(a)). Since the optimal field synthesis is designed to optimize fields in terms of an objective function, the mean residual error is not affected by it. As we know, the underlying objective function puts emphasis on the modeling capability regarding the flow and transport behaviors.



(a) Mean residual error (b) Objective function

Fig. 7. Variations of the mean residual error and the objective function after the optimal field synthesis.

5. Conclusions

While averaging of optimized fields can provide a better description of the spatial feature of an unknown field, it deteriorates the flow and transport characteristics of the optimized fields. Therefore, an averaged field is not suited for modeling an aquifer performance. On the other hand, the optimal field synthesis combines the optimized fields into refined fields to enhance the modeling capabilities of the fields in consequence. It is observed that the objective functions of the fields assessing the modeling capabilities are further reduced after the optimal field synthesis, while the similarity among the fields being increased. However, when it comes to the mean residual error, no meaningful changes are perceived. Since the optimal field synthesis is designed to optimize fields in terms of an objective function, the mean residual error is not affected much by it.

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