Conditioning a hybrid geostatistical model to wells and seismic data

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ABSTRACT

Hybrid geostatistical models imitate a sequence of depositional events in time. By considering sedimentation processes, these algorithms produce highly realistic subsurface structures from a variety of environments. However, since depositional events are forward-modeled, they cannot be directly conditioned to data. Therefore, conditioning requires solving a possibly expensive inverse problem. In this study, an optimization scheme is developed that allows conditioning turbidite simulation to thickness information and boreholes data. The methodology is based on the addition of a noise to the lobes' surface, which is perturbed until data are satisfactorily matched. The process is made more efficient by dividing the optimization problem into similar steps, allowing decreasing the number of parameters to consider at a time. This methodology is applied to a realistic dataset to demonstrate the validity of the method.

1.Introduction

Recently developed hybrid geostatistics models (Leiva 2009; Michael et al. 2010) are an important contribution to reservoir characterization. They create realistic subsurface structures by reproducing the interaction of topography, sediment transport, erosion and deposition. However, their practical usage is still limited due to the difficulties associated to conditioning. Indeed, since depositional events are forward-modeled, conditioning such models is challenging. Direct conditioning as performed with traditional geostatistics cannot be universally applied. Existing conditioning methods present several shortcomings (Michaels et al., 2010; Zhang, 2009). We propose a different approach where conditioning is addressed through the application of an inverse modeling scheme. In numerical stratigraphy, such approaches have extensively been studied (Charvin et al., 2009) . However those methods do not focus on fitting efficiently data at the reservoir scale and, therefore, cannot be applied to a typical reservoir modeling workflow. The aim of this work is then to reformulate the inverse scheme as an optimization problem tailored to consider log data and thickness information. In this paper, we first present a review of hybrid geostatistical modeling and the associated challenge of direct conditioning. Then we discuss the implementation of an optimization problem for conditioning to well and thickness data. Finally, a realistic example is presented and explained. The concluding discussion focuses on the computational performance of the optimization algorithm.

2.Hybrid geostatistical models concept

a)Review of hybrid geostatistical modeling

Hybrid models are tailored to reproduce the effect of erosion and deposition, as would do a process-based method, but in a more computationally efficient way. Contrary to process based models, hybrid geostatistical algorithms do not simulate physical processes but model directly the sedimentary architecture by moving predefined geological object like lobes or channels. This paper focuses on algorithms modeling turbidite systems (Pyrcz and Deutsch, 2004; Michael et al., 2010; Leiva, 2009; Zhang, 2009). The general methodology of hybrid modeling can be divided in four main steps depicted in fig. 1.
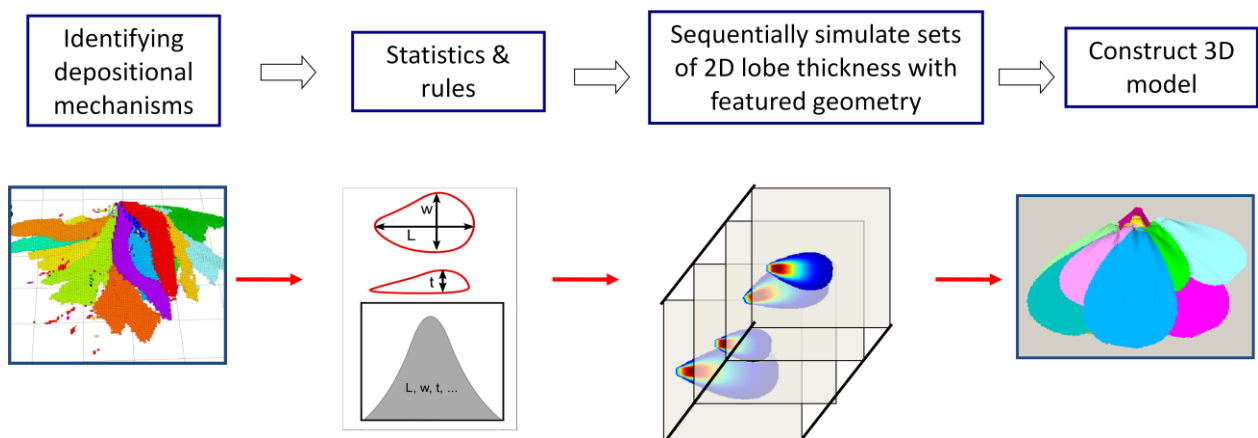
Figure 1: Basic methodology for hybrid geostatistical modeling. The first step consists in analyzing the depositional environment. The second one is to develop some rules reproducing the mechanism and geobodies observed in the depositional environment. Following those rules, the geobodies are then simulated and stacked sequentially on top of each other. The last step consists in building the 3D model from the geometry of the geobodies.

Analysis of the depositional environment
The first step aims at understanding the sedimentation mechanisms occurring in the depositional environment, and identifying the resulting geological structures (called geobodies). This study is generally based on outcrop observations, reservoir analogs or process-based models.
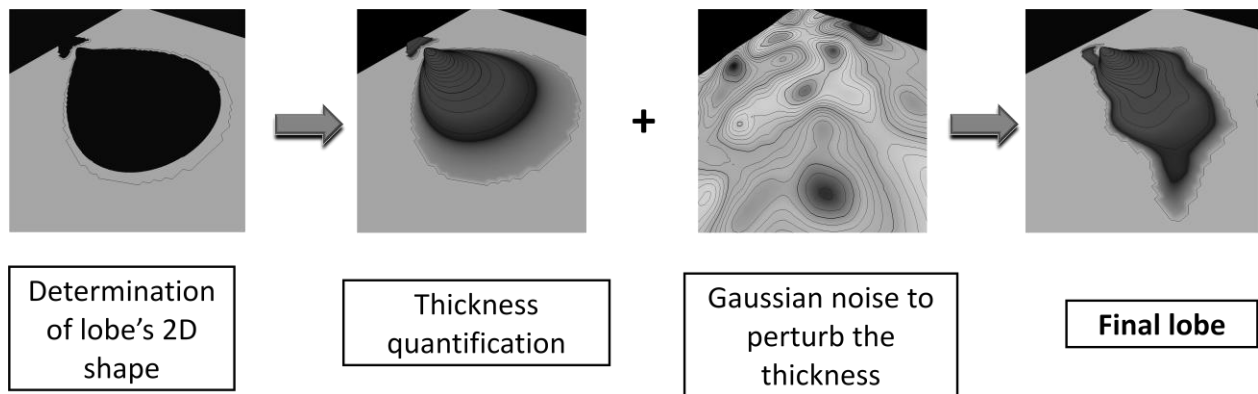
Definition of the geological rules and geobodies
Once geological rules have been determined and understood, the following step is to model them numerically. For turbidite systems, those rules of deposition are often controlled by the underlying topography and previously deposited geobodies. In general, they aim at reproducing the compensational stacking patterns by placing lobes in topographic depressions. For example Leiva (2009) uses the D8 algorithm (O'Callaghan et al, 1984) to model the sediment flow and deposition to find the lobe location in accordance to the topography. In Michael et al. (2010), the approach is different. Statistics about migration and progradation between lobes are inferred from a process based model. Then, these statistics (PDF) are used during the simulation to draw a lobe location in accordance to the previously simulated one.

Erosion is the second important mechanism to consider because it can create some connectivity paths by eroding flow barriers. In Leiva (2009), the process is simulated accounting for flow direction. Topographic gradient and curvature are used to give erosion values at a given point in the topography under a lobe deposition. This erosion will modify the thickness of the underlying lobes. The intensity of erosion is more important in high gradient regions. In Michael et al (2010), the geometry of the removed materials is directly associated with each geobody.

Simulation of the geobodies

In a hybrid approach, the object is simulated by using a predefined geometry (fig.2). The parameterization of the geobodies consists of defining a template shape and size. In general, a two dimensional shape is created by using a mathematical function. Based on this shape, a thickness property is interpolated such that the center of the lobe reaches a predefined maximum thickness, creating 3D structures of the lobe (Leiva, 2009). This thickness is stochastically perturbed by adding a Gaussian correlated noise (generated with a sequential Gaussian simulation, Goovaerts 1997). The noise aims at reproducing the small scale variability of the lobes' structures, making them more realistic (fig. 2). Those noises are important components of the model behavior since the placement of lobes is mainly controlled by the topography. The added noise modifies the topography, hence influence directly the simulation of lobes (fig. 3). Note that the method is not restricted to the simulation of simple lobes. In the following examples, channels can are appended to the lobes to produce structures such as those present in turbiditic environments.

| Determination of lobe's 2D shape | Thickness quantification | + | Gaussian noise to perturb the thickness | **Final lobe** |

Figure 2 Methodology to define the geometry of a lobe. The first step determines the 2D shape of the object. Then, the thickness profile is interpolated. The last step is to add a Gaussian noise to perturb the thickness of the lobe.
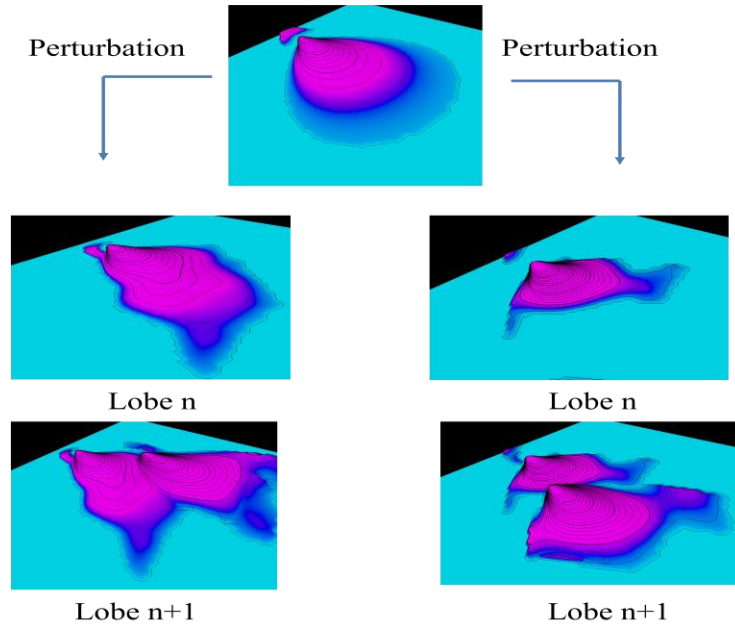
Figure 3. The lobe n is perturbed with two different noises. The first noise creates a low topography on the right of the lobe. The following lobe is logically filling it (left pictures). The opposite happened in the other case (right). This example shows the importance of the noise in the placement of the lobes.

Stacking of the lobes

Following the previously defined rules, the geometry, thickness and location of each lobe is sequentially computed. It is represented as 2D property maps (figure 3).

3D model output

The result of the simulated lobes is a set of 2D thickness maps. For each of the 2D map, we can create the boundaries surface of the lobe. Then, stacking these lobes all on top of each other produces the final 3D model. The output does not represent a grid, but a purely geometric representation composed of surfaces (fig. 4). Faulting and folding also need to be considered before gridding these structures for flow simulation.
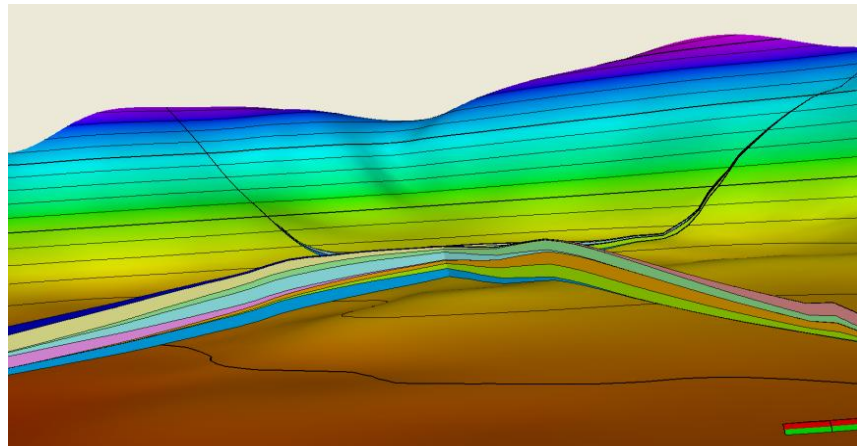
Figure 4. 3D surfaces created with a hybrid geostatistical models.

b) Challenge of direct conditioning

Conditioning lobe thickness from well data

The thickness of a lobe is first defined by the quantity of sediments deposited during the sedimentation process. Then, this thickness can be modified by a possible erosion event. Without erosion, conditioning to well data requires that the algorithm simulates a precise thickness at the data location. In our model, that thickness is determined only by the deposition rules, controlled by the initial paleotopography and previously simulated geobodies. Hence, the structural match with well data cannot be ensured (fig. 3). Modifying locally the lobe geometry to ensure a fit is not a solution because it does not preserve the geological consistency of the object as defined by the model. Erosion adds complexity in the conditioning because it requires considering how much material has been removed. How much a lobe is eroded depends on the nature and location of the geobodies simulated on top of it, and there is no direct ways to forecast this except by simulating the entire process. Some work has been done for well conditioning. Michaels et al. (2010) proposes a method using well interpretation. Each of the lobes recorded in the wells has to be associated with one of the depositional event of the sequence. However, correlating wells is time consuming and very uncertain. The approach based on interpolation between logs used by Zhang (2009) necessitates a large amount of wells, which is unrealistic in deep offshore development, where only a couple of them are in general drilled.

Thickness data conditioning

An important data source in turbidite reservoir development is seismic data, especially thickness information derived from it (whether exact or inexact). However, conditioning to such data is difficult because it requires controlling the algorithms such that the total thickness of the simulated geobodies match a thickness defined all over the field (or up to a certain precision if the inexactitude of the seismic data is accounted for). Contrary to wells, those data do not allow defining the location of some lobes neither provides information about the sequence of deposition in time (stacking of the lobes along the well does). Conditioning as explained previously where the location of the lobe is known and just the thickness needs to be modified would be inefficient. The use of a servo-system is limited because the constraint of thickness is not effective before the lobes start to reach the top of the reservoir, when it is too late to perform an efficient match. The sequential simulation can indeed be seen as a Markov process, the location and shapes of the first lobes can have an influence on the final thickness of sediments.

3. Development of an optimization scheme

a) Challenge in developing an optimization scheme

Hence, a solution for conditioning is to find efficiently the right set of inputs parameters matching data. This approach requires solving the inverse problem through optimization, which is a challenge for the following reasons:

- The number of inputs parameters is very large.
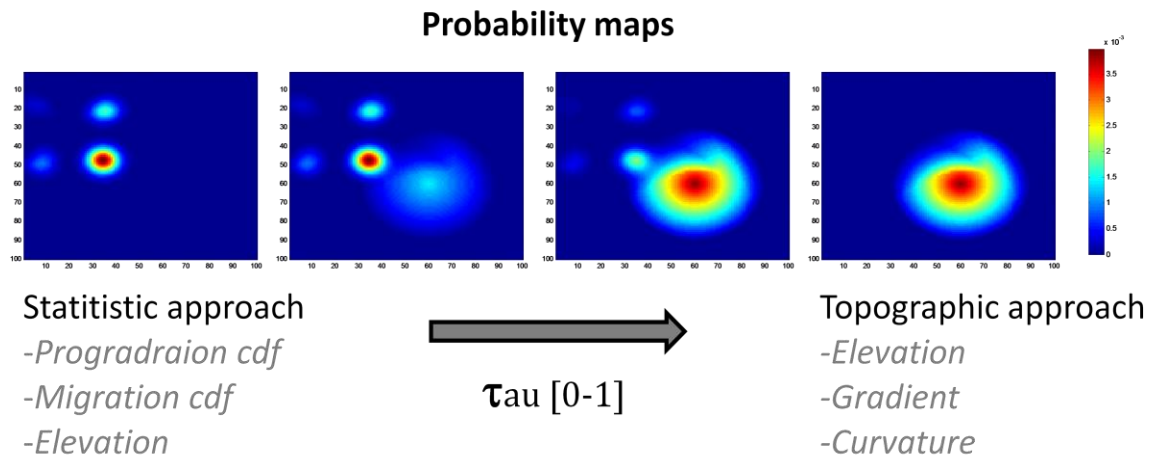- The input parameters interact with each others in a non-linear way.

- The model can display great sensitivity to small perturbation of inputs parameters.

b) *Inputs parameters selections*

Indeed, those algorithms require a high degree of parameterization to produce realistic models. However, some parameters have more influence on the algorithm's behavior than others. A sensitivity analysis is then required to determine the parameters to include in the optimization scheme. Such analysis has been performed on Leiva's hybrid geostatistical algorithm (Leiva 2009; Bertoncello and Caers, 2010). The study determined that the noise added on top of the lobe and the model of deposition are the most influencing parameters.

Model of deposition

In the hybrid model used in this work, two different depositional models are used. The first one is based on migration and progradation statistics and elevation inferred from the Exxon model (Michael et al., 2010). The second model is based only on topographic features (Leiva, 2009). Each of the models generates a probability map. These two maps are then combined using the tau model (Journel, 2002), and the resulting map is used to draw the location of the lobes. The variation between 0 and 1 of the tau values emphasizes more or less on one of the models (fig. 5). With the statistics approach, the distance between a new lobe and the previously simulated one is partly controlled by the statistics; they tend to be closely gathered. With the second model, the distance between the two lobes is only function of the topography leading to a higher degree of freedom in the lobe placement. The optimization aims at finding the best Tau value so that the resulting model matches the data.

Probability maps

Statitistic approach
-Progradraion cdf
-Migration cdf
-Elevation

τau [0-1]

Topographic approach
-Elevation
-Gradient
-Curvature

Figure 5 .Each of the deposition models produces different probability map of lobe location. Using the Tau model, it is possible to combine them. Depending on the value of the tau, one the model is more or less considered.

Generation of the Gaussian noise.

The Gaussian noise added to the surfaces of the lobes is the second very important components to consider. The spatial characteristics of the noise are controlled by a variance, a covariance and a seed controlling the stochastic components of the algorithm. To develop an efficient optimization approach, it

is important to be able to modify the noise gradually and smoothly. For a same seed, small perturbation in the variance and covariance leads to small perturbation in the resulting Gaussian noise. However, small perturbations in the seed dramatically change the spatial structure of the noise. This behavior is not suitable for optimization because it leads to discontinuity in the objective function. To address this issue, an algorithm based on the gradual deformation (Hu, 2000) has been developed in which a small perturbation of the seed results in small perturbation of the noise.

Seed = 101   Seed =102   seed = 103   Seed = 104
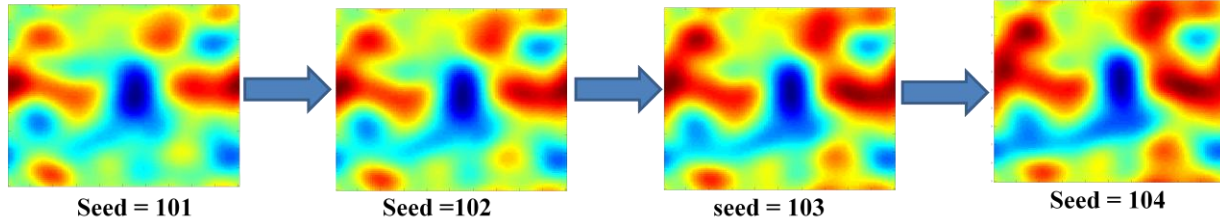
Figure 6. Based on the gradual deformation, an algorithm has been developed to gradually in which a small perturbation of the seed results in small perturbation of the simulated noise.

c) Optimization framework

Even after the sensitivity analysis, the number of parameters remains an issue. Indeed, the SA in Bertoncello and Caers (2010) determined that the depositional models and the Gaussian noise are the most impacting parameters. In terms of optimization, this requires perturbing one parameter for the depositional model and three for each lobe (variance, covariance and seed), resulting to $p = 3N_{lobes} + 1$ parameters. For 15 lobes, it adds to 46 parameters to optimize which is still a very expensive model. To speed up the process, the problem is then divided in N_{lobes} steps (fig .7) and the following sequential optimization strategy is employed:

Initial step: The same noise is added to all the N_{lobes} lobes. As a result, only four parameters need to be optimized: the seed, variance and covariance of the noise and the tau value for the depositional model. The tau value obtained from this initial step is used in the following steps to ensure a depositional consistency between lobes.

Second step: At the end of the initial step, the first lobe of the sequence of deposition is frozen. Its geometry is added to the initial paleotopography. Hence, one realization requires simulating only $N_{lobes} - 1$ lobes. The previously optimized noise is added to the remaining $N_{lobes} - 1$ lobes as an initial guess. The three parameters controlling this noise are then perturbed and optimized.

For the i step, the $i - 1$ lobe is frozen and added to the previous paleotopography. For a simulation $N_{lobes} - i+1$ are simulated. The noise added to the lobes as an initial guess is the one obtained after the $i - 1$th step.
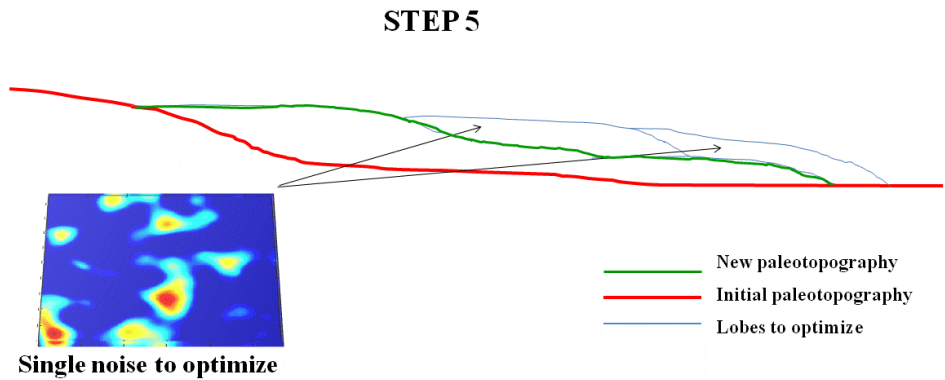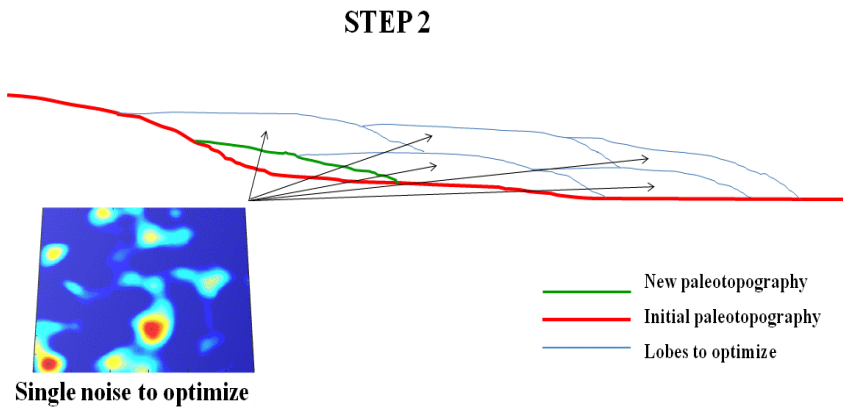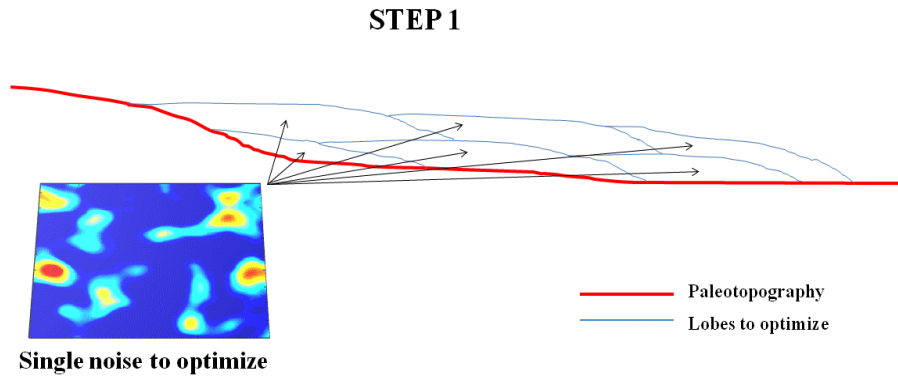
Figure 7. For the first step of the optimization workflow, a similar noise is added to the six lobes. The model of deposition, the covariance, variance and seed of the noise are then optimized, meaning that four parameters are being perturbed at this step. For the second step, the first lobe of the sequence is integrated to the topography to decrease the number of lobe to simulate, reducing the computation time. A similar noise is added to the five remaining lobes and optimized. The model of deposition used in this phase is the one obtained step 1. For the fifth step, the fourth lobe is added to the topography. A similar noise is added to the two remaining lobe and optimized. At the end of the processes, all the lobes have different optimized noise.

This approach allows simplifying the inverse problem by dividing it into similar steps. For each step, the optimization problem is easier to solve because only one similar noise is being perturbed. This approach is called greedy (Cormen et al. 1990) because it divides the problem in similar phases.

Updating the paleotopography after each step improves the efficiency of the algorithm. The computational cost of one realization with N_{lobes} is $O(N_{lobes})$. The lobes are indeed sequentially deposited; the complexity of the problem increases linearly with the number of lobes. For a traditional optimization approach, the cost of iterating is $N_{iterations}O(N_{lobes})$. With our approach, the problem is divided in $N_{steps} = N_{lobes}$. For a same total number of realizations, the number of iterations per step is $N_{iterations}/N_{steps}$. The resulting computational cost of the scheme is:

$$\text{Cost} = \sum_{i=1}^{\#step} \frac{N_{iterations}}{N_{steps}} O(N_{lobes} - i + 1)$$

$$\text{Cost} = \frac{N_{iterations}}{N_{steps}} N_{steps} O(\frac{1}{2}N_{lobes}) = N_{iterations} O(\frac{1}{2}N_{lobes})$$

For the same CPU time, our approach allows performing twice as much iterations as a typical optimization approach.

d) Selection of an optimization algorithm

The model does not respond linearly to small variation of the input parameters. The resulting evaluation function is then non-smooth and discontinuous (fig. 8). A derivative-free optimization algorithm is required. In this work, the Nelder-Mead approach is chosen because of its simplicity and its robustness for problems with discontinuities (Nelder and Mead, 1965).
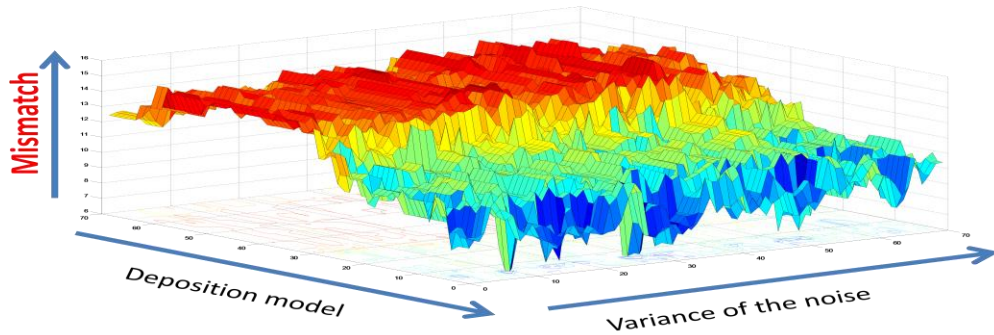
Figure 8 Mismatch values with respect to the reference top surface. The deposition parameter is varying in the range [0 1] and the variance of the noise is varying in the range [0.2-1.5]. The evaluation function is clearly non-smooth, presenting several local minima. Gradient based methods are not applicable for this family of problems.

The Nelder-Mead approach is a simplex-based method aimed at finding a local minimum of a function of several variables. For two variables, the simplex is a triangle, and the method is a pattern search that compares function values at the three vertices of a triangle. The worst vertex, where the value of the function is the largest, is rejected and replaced with a new vertex. A new triangle is formed and the search is continued. The process generates a sequence of triangles (which might have different shapes), for which the function values at the vertices get smaller and smaller. The size of the triangles is reduced and the coordinates of the minimum point are found (fig .9).

Nelder Mead Algorithm

1. *Selection of **n+1** points in the n dimension space, creating a geometric object called simplex. A simplex is the generalization of a triangle in n dimension.*
2. *Ordering of the vertices according to their values $f(X_1) < f(X_2) < \cdots < f(X_{n+1})$*
3. *Computation X_o the center of gravity of all the point except X_{n+1}*
4. ***Reflection***: *computation of the reflected point $X_r = X_0 + (X_o - X_{n+1})$. If $(X_1) \leq f(X_r) < f(X_n)$, a new simplex is created by replacing the worse point X_{n+1} by X_r and go to step 2*
5. ***Expansion***: *if $f(X_r) \leq f(X_1)$ meaning that the reflected point is the best point so far, then compute the expanded point $X_e = X_0 + 2(X_o - X_{n+1})$.*
   a. *If the expanded point is the best so far $f(X_e) \leq f(X_r)$, a new simplex is created by replacing the worse point X_{n+1} by X_e and go to step 2*
   b. *Else new simplex is created by replacing the worse point X_{n+1} by X_r and go to step 2.*
6. ***Contraction***: *if $f(X_r) \geq f(X_n)$, compute the expanded point $X_c = X_o + \frac{1}{2}(X_o - X_{n+1})$.*
   a. *If the contracted point is better than the worst point $f(X_c) \leq f(X_{n+1})$, a new simplex is created by replacing X_{n+1} by X_c*
   b. *Else go to step 7*
7. ***Reduction***: *For all but the best point, replace the point with*
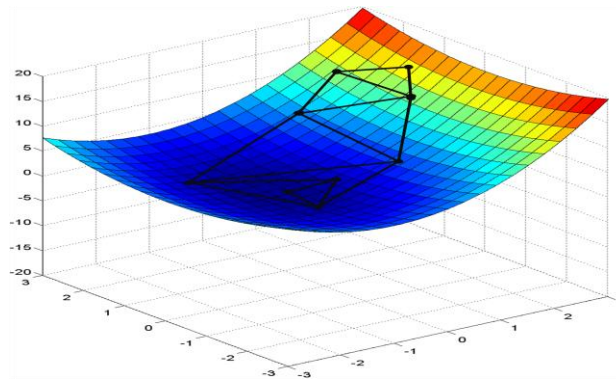   a. *$X_i = X_1 + \frac{1}{2}(X_i - X_1)$ go to step 2*

Figure 9. The sequence of triangles converging to the minimum for the Nelder-Mead method.

4.Application to a real data set

a) The Exxon II reservoir

The workflow is applied to a realistic turbidite lobe reservoir termed Exxon II (fig. 10 and fig 11). The paleotopography, shaped as a "mini-basin", comes from a real dataset. From this topography, the reservoir has been filled using a process based model. The simulated structures present a high degree of accuracy, exceeding the geological realism of the hybrid geostatistical model. The size of the reservoir is 20 Km by 11 Km and 50 meters thick. The data used in this study are composed of a bottom surface (initial paleotopography), a top surface and three wells with information about lobes thicknesses. The aim of the study is to fill the reservoir accounting to the top surface (i-e thickness information) and wells.
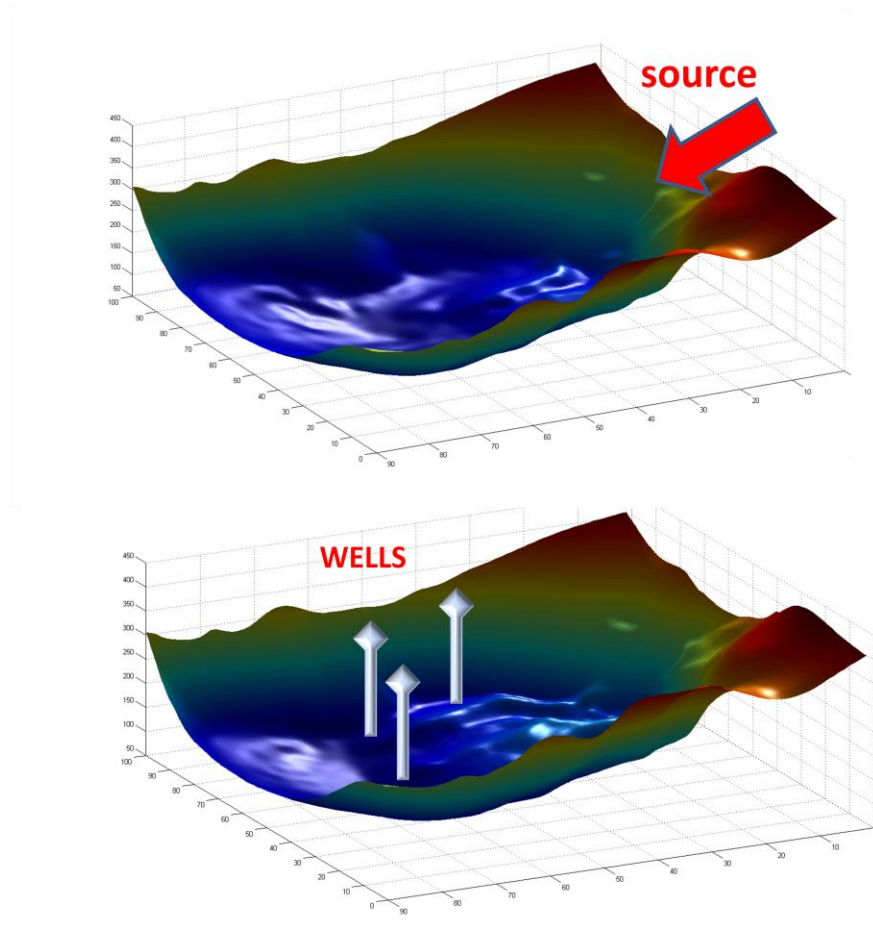
Figure 10 on the right: Initial Paleotopography of the reservoir. On the left, top surface of the reservoir with the location of the wells. The flux of sediments and the related erosion from the source create a channel and large levee.

On the top surface, we can observe a channel structure created by the flux of sediments from the source and the resulting erosion (fig 10 and fig.11). The deposited sediments are mainly located around this structure. Further offshore, the sedimentation is almost inexistent. Matching this data set requires first

simulating a sediment package with a correct thickness. It also requires honoring the location with no deposition. Producing regions with both sedimentation and no sedimentation is more challenging than just stacks lobes all over the topography because it involves a higher degree of precision in the control of the algorithm. In the following examples, the Gaussian noise is generated with a range varying between 1000 to 7000 m. The variance is chosen such that the thickness perturbation varies between 0 and 10 meters.

| Elevation of the initial topography | Elevation of the top of the reservoir | Thickness of sediments |
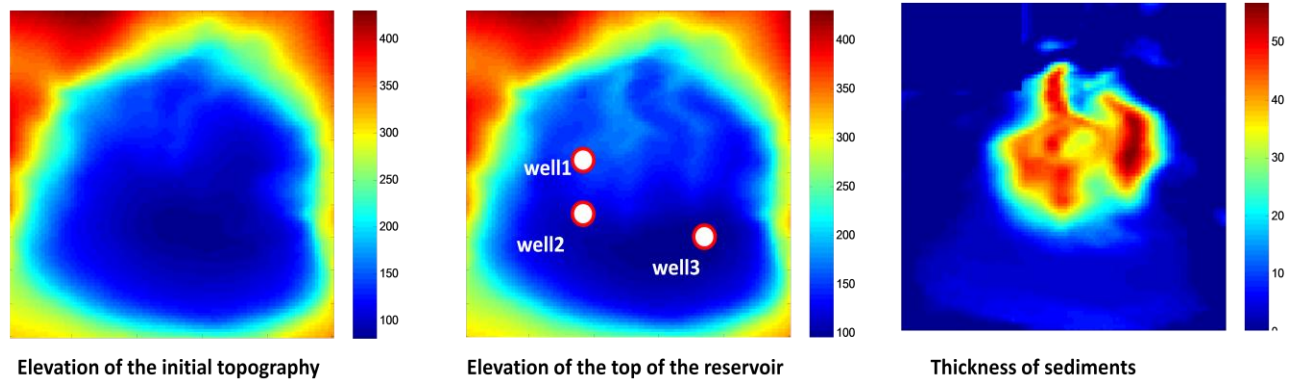
Figure 11 Initial elevation of the paleotopography, elevation of the top of the reservoir and thickness of the deposited sediment package. The sediments are not deposited all over the reservoir initial topography. They are mainly located around the channel.

b) Results with only thickness information

In this example, only thickness data are considered. The algorithm stops when the volume of simulated lobes is equal to the volume of sediments present in the dataset. The objective function is the pixel-wise absolute difference between the reference and simulated to surfaces. 50 iterations of Nelder-Mead are performed for each step of the optimization methodology.

The optimized model is composed of 14 lobes, meaning that the total number of iterations is 50x14=700. The resulting model displays the features present in the reference. The shape of the sediments package matches the reference one, and the high and low deposition areas are respected (fig 12-13). A canyon is also visible in the optimized model. From the error map, we can see that most of the mismatch is located in the channel area. The way the hybrid geostastical model computes the erosion is probably not realistic enough to accurately model the creations and fill of such complex structures. At the end, the average error is 1.7 feet.. The methodology enables producing models matching thickness information from seismic data.
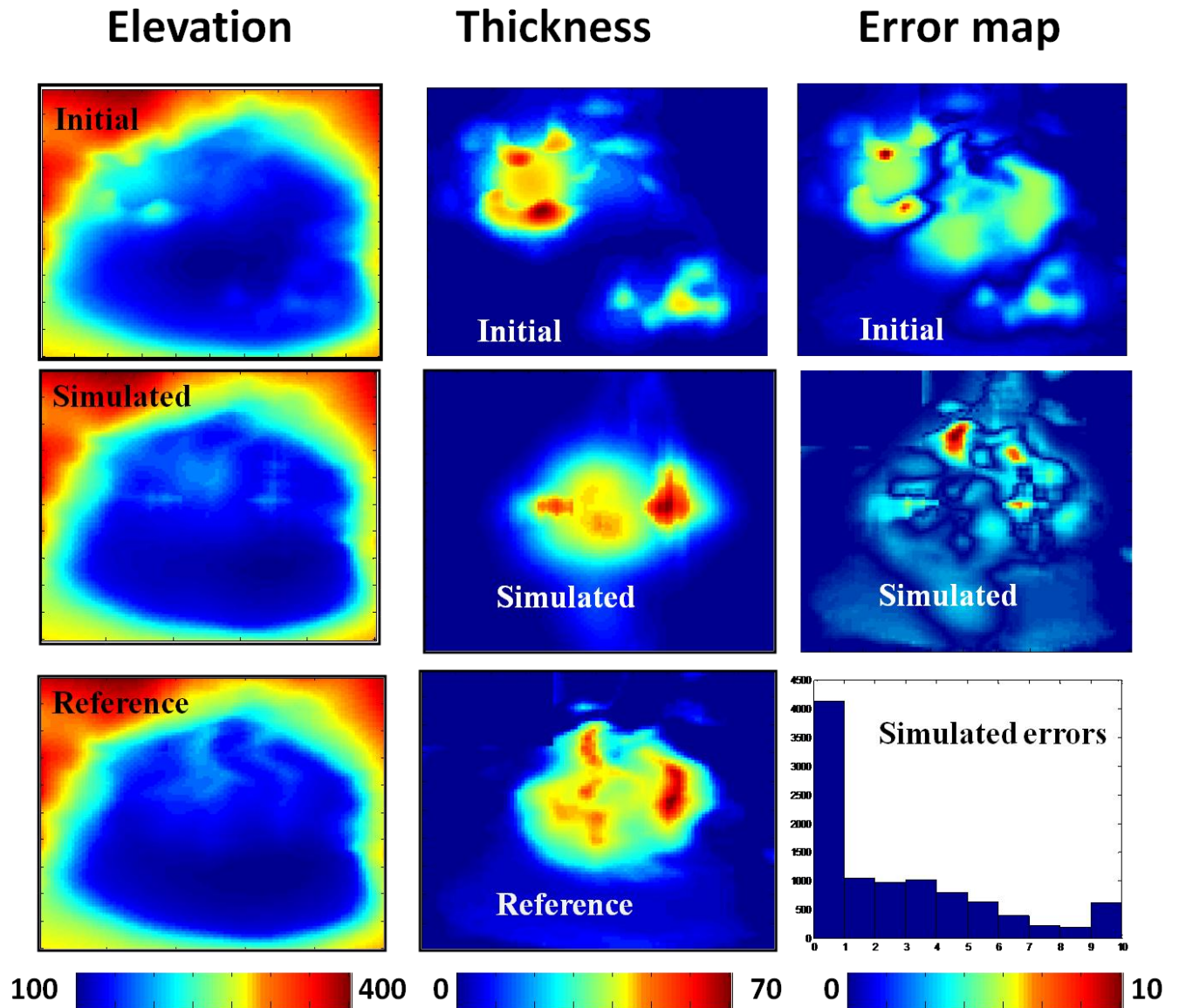
Elevation   Thickness   Error map

Figure 12. On the left, the elevation maps of both simulated sediments and the reference one. In the middle, maps of the thickness of sediments. On the right, the map and histogram of the errors between the simulation and reference. The main errors are located near the source, where the erosion is very pronounced. The erosion model is not able to reproduce such complex features.
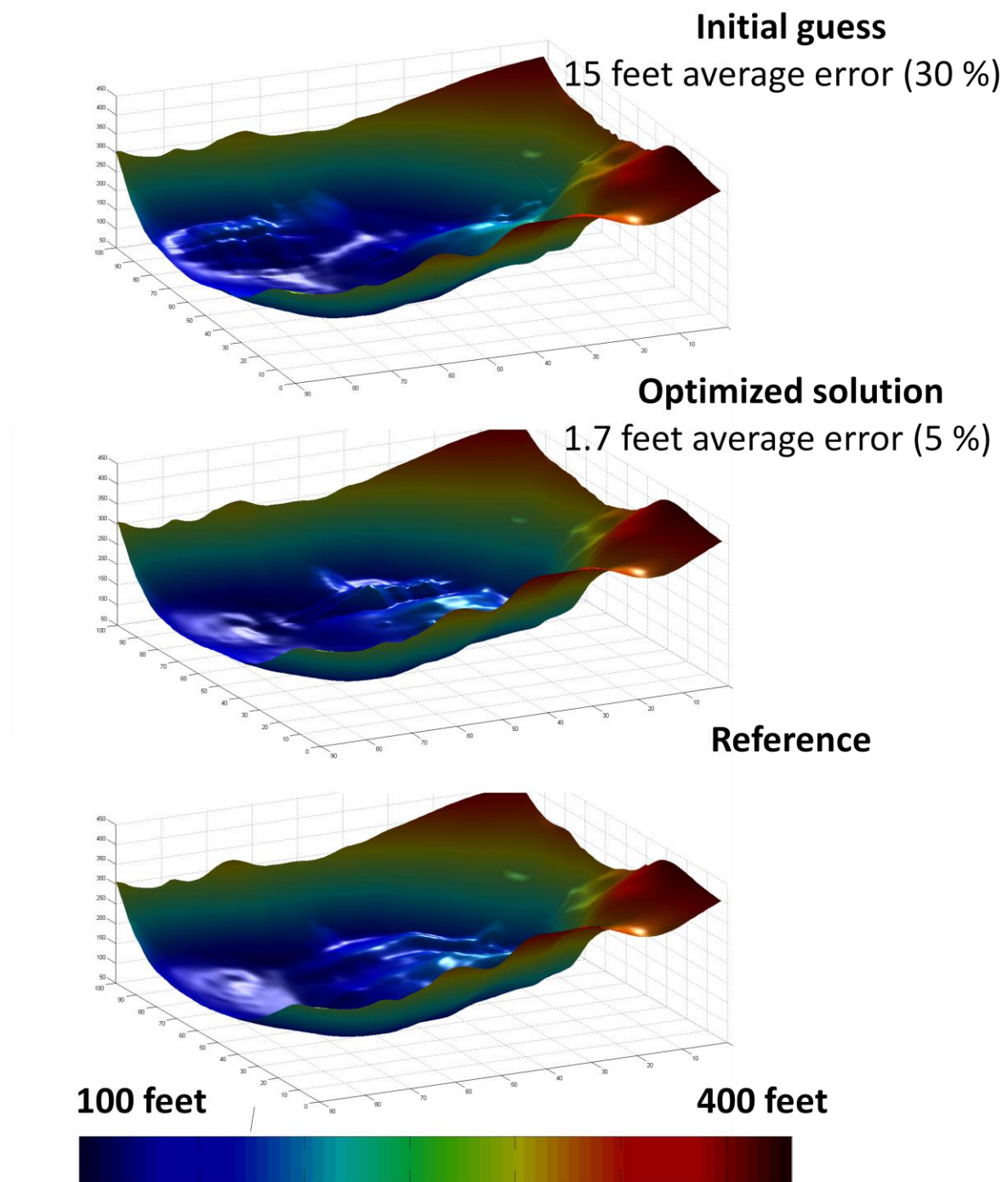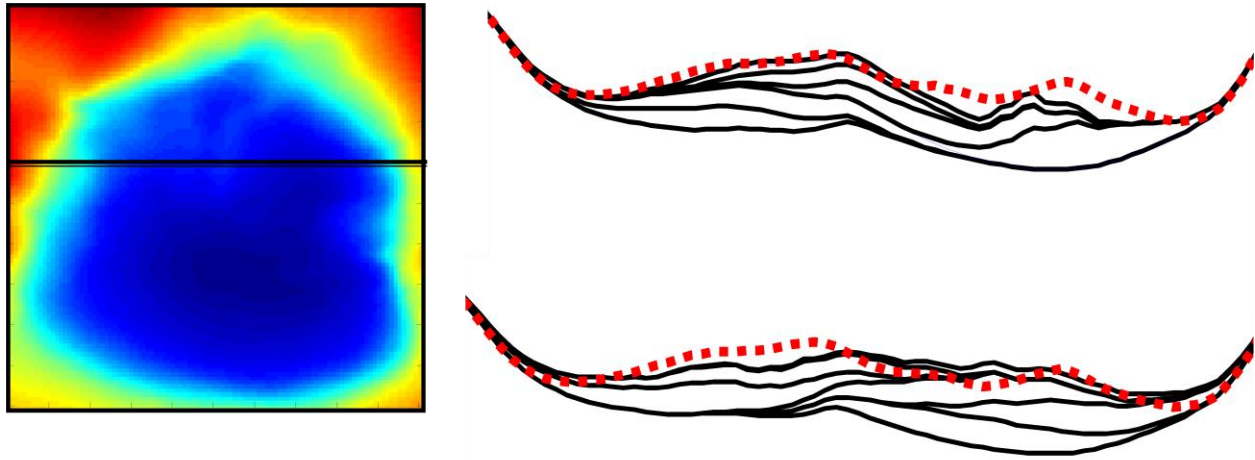
Figure 13. Comparing initial matched and reference top surface. The channel structure is reproduced in the optimal solution. The result is obtained after 700 iterations.

Figure 14. Cross section of two matching models. The internal structures are in black and the reference top surface in red.

## c) Results with log data and thickness information

Logs data and seismic are now being considered jointly. Three wells are drilled in the model (fig. 11). Two of them are located in high depositional area (well 1 and well 2) and a third one in a low depositional area (well 3). The goal is to study the ability of the algorithm to simulate accurately a sequence of lobes (well 1 and well 2) but also to study the ability to reproduce regions with low sedimentation (well 3). Conditioning to a low number of wells adds an additional complexity to the problem, because there is not enough information to completely drive the behavior of the algorithm as would do a larger number of wells.

The objective function is defined by the mismatch at the end of the simulation between the top surfaces and by the mismatch of the lobe thicknesses at the well location. This approach does not require any well to well interpretation/correlation. Note that matching a lobe thickness requires to model a correct combination of deposition and erosion. Indeed, the boundary between lobes recorded in the log data can be an erosion surface.

The optimized model is composed of 14 lobes, meaning that the total number of iterations is 700. The simulated top surface in this example is matching the reference with an accuracy of 2.8 feet. It displays also the canyon features and the high and low depositional areas are honored (figs. 15-16). The number of lobes simulated at the wells locations always matches the reference number (fig. 17). In addition, they fit with an average error of 1.1 feet per lobe. The variability of the lobe thicknesses is less for the model than for the reference. The inability of the model to reproduce the same high variability in lobe thicknesses is probably due to the use of Gaussian distribution to model thickness distribution that may poorly reproduce the actual variability. To address this issue, one needs to modify the statistics about the lobes thickness. Another solution can be to change the erosion model. For example, a high variability in the

lobes size can mean high variability in erosion intensities. Lastly, we notice that the depth at the bottom of a well can differ between realizations, due to erosion. Erosion intensity differs in accordance to the location of the lobe on top of it, hence the initial topography can be more or less modified.

As a conclusion, the hybrid geostatistical model is able to produce realizations matching at the same time well data and thickness information.
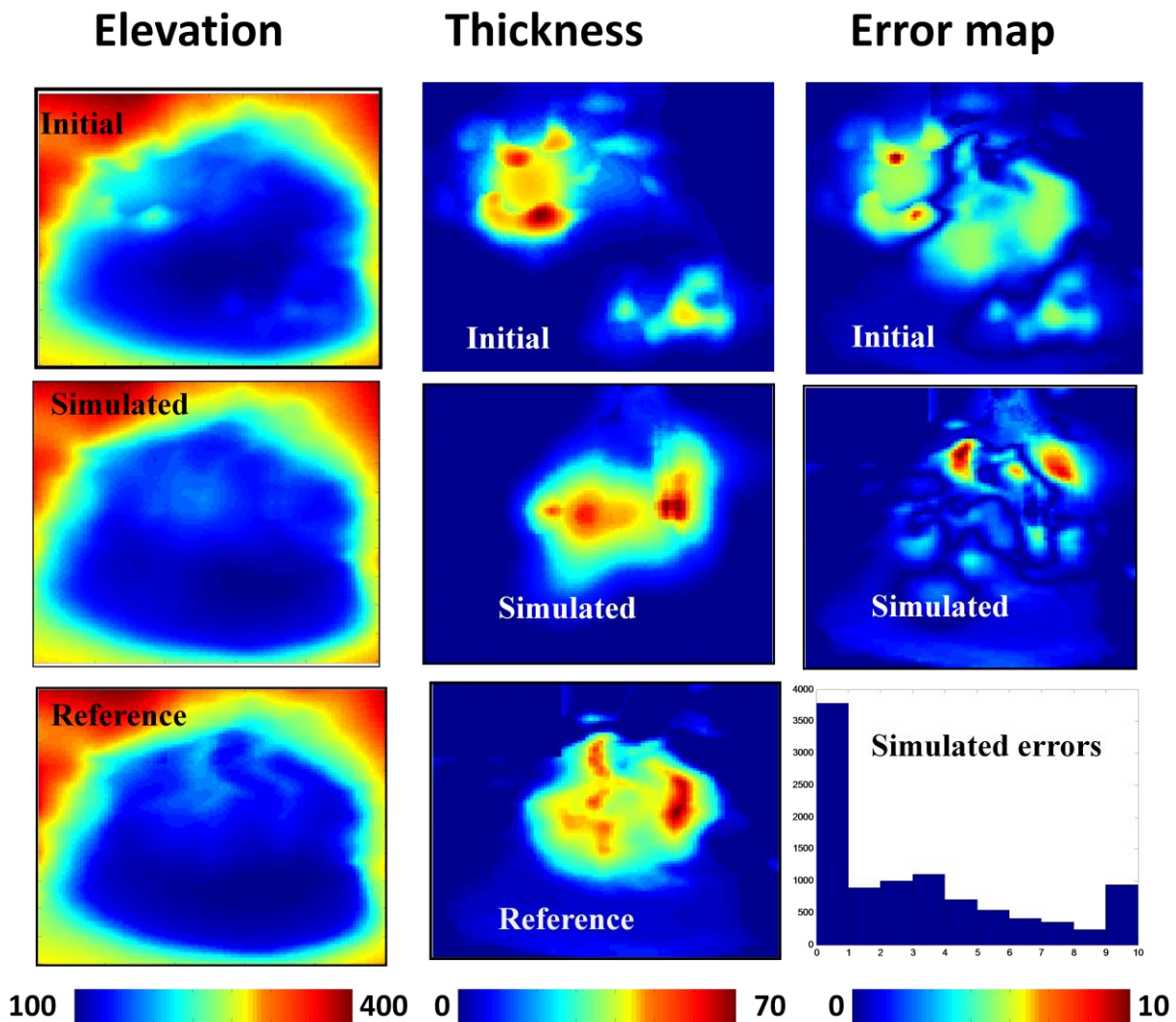
Figure 15 On the left, the elevation maps of both simulated sediments and the reference one. In the middle, maps of the thickness of sediments. On the right, the map and histogram of the errors between the simulation and reference. Like the previous example, the main errors are located near the source, where the erosion is very pronounced. The erosion model is not able to reproduce such complex features.

Initial guess
15 feet average error (30 %)

Optimized solution
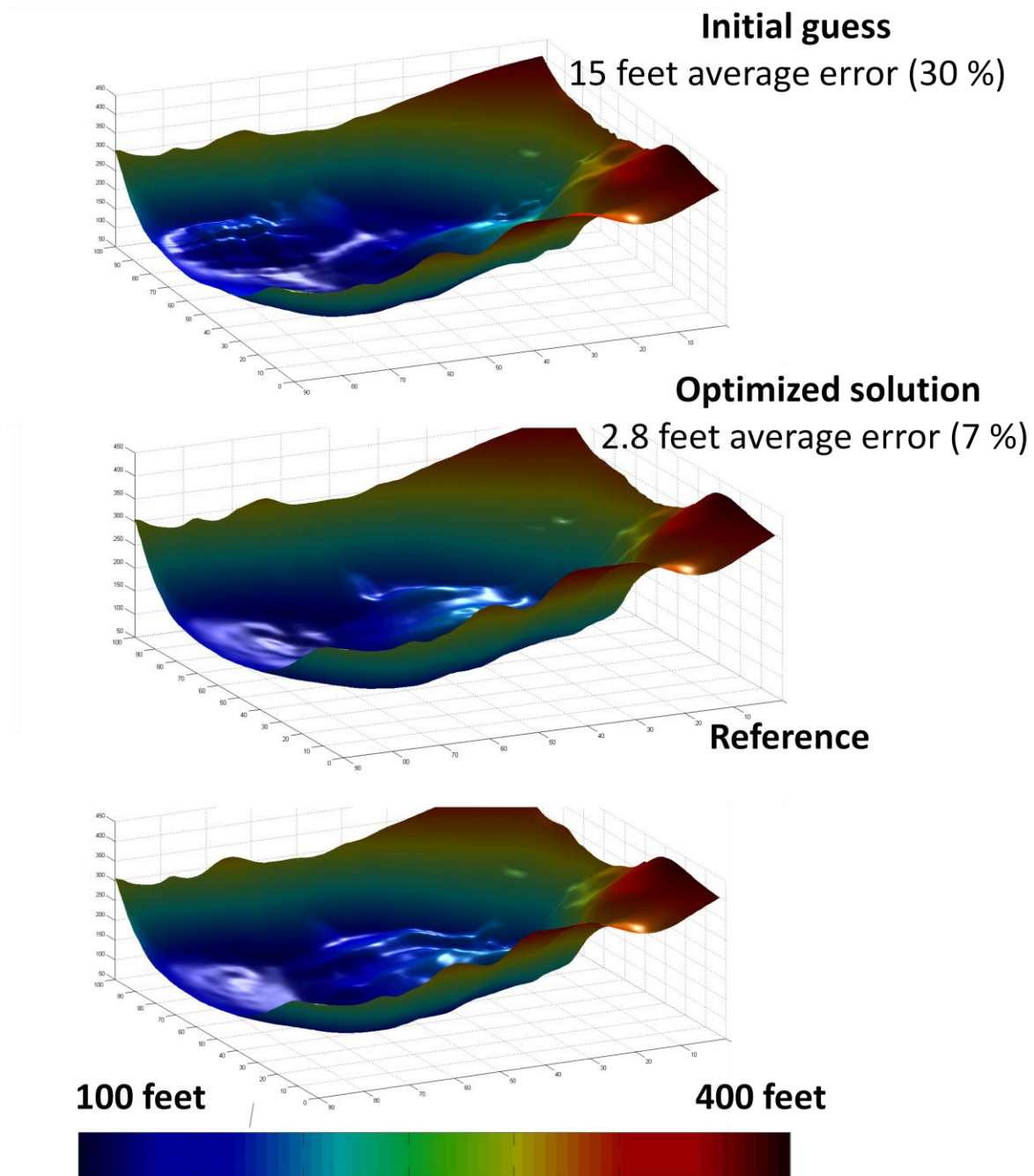2.8 feet average error (7 %)

Reference

100 feet   400 feet

Figure 16 Comparing initial matched and reference top surface. The result is obtained after 700 iterations. The channel structure is also reproduced in the optimal solution.
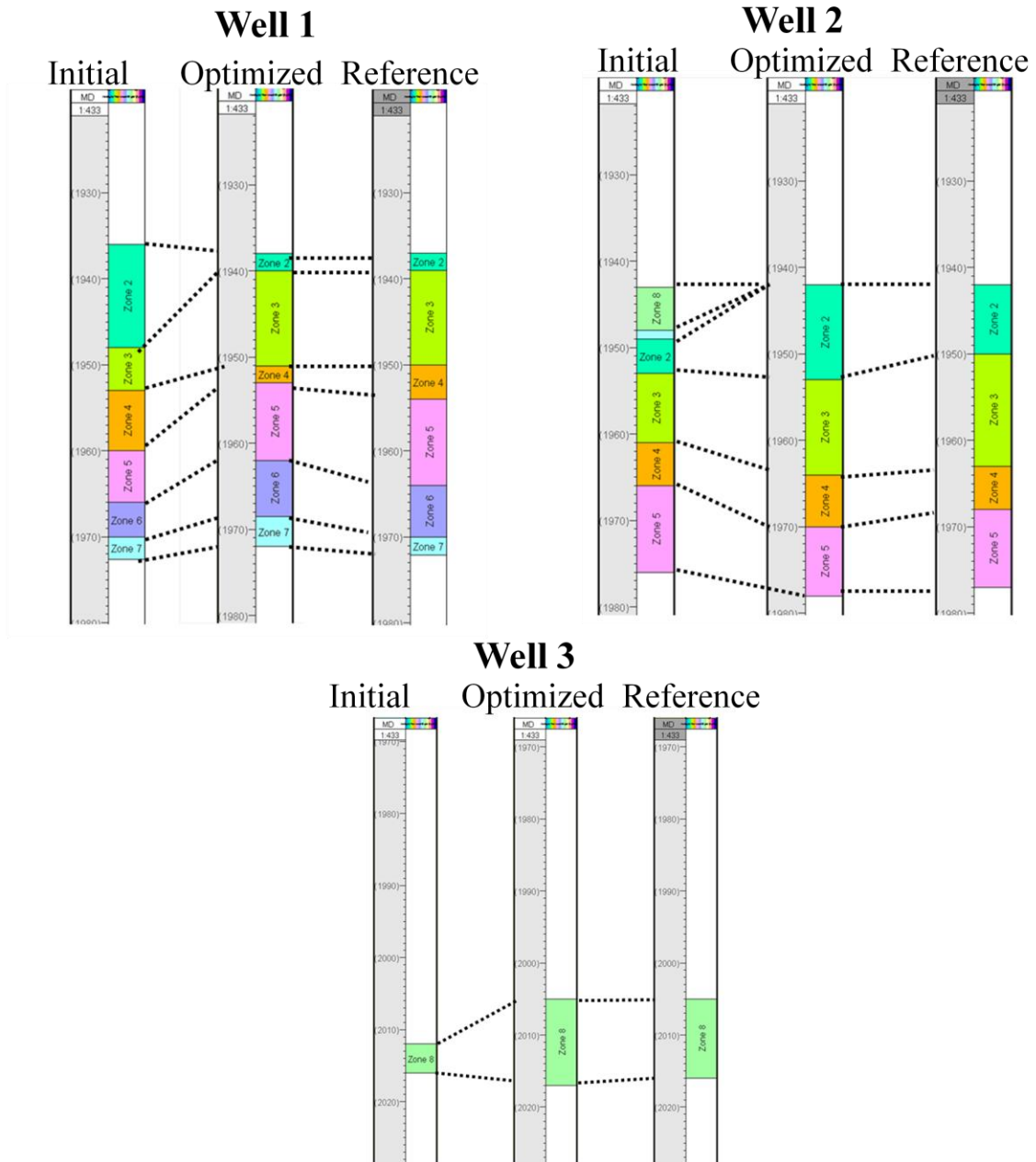
Figure 17 Comparing initial matched and reference wells. The channel structure is reproduced in the optimal solution. The result is obtained after 700 iterations. The average mismatched is 1.1 feet per lobe. In general, the mismatch is due to larger simulated thickness than the reference. The model may not be able to reproduce the correct variably in lobe thickness.

5.Computational performance

The results of the case study outlined above show that it is possible to condition hybrid geostatistical models to realistic data. The accuracy of the match is defined by the quality of the model itself(kind of superfluous). However, the efficiency in matching data is controlled by the optimization approach. This feature is very important because it determines the applicability of such methods. The computational cost caused by the iterations of expensive forward models has always been a major limiting factor in their use for reservoir modeling. To evaluate the efficiency of our approach, we first compare it with a random sampling approach. Six thousands realizations are generated and the minimal mismatch is set as a reference. This value gives a good indication of how close the model can be to the data set. The second comparison is with a traditional optimization approach, consisting in optimizing all parameters at once. In this example case, fourteen lobes involve solving an optimization problem with 43 parameters. For the study, each of the optimization sequences starts with initial guess. Two series of optimization are performed, the first considering the seismic and the second accounting for both wells and seismic)
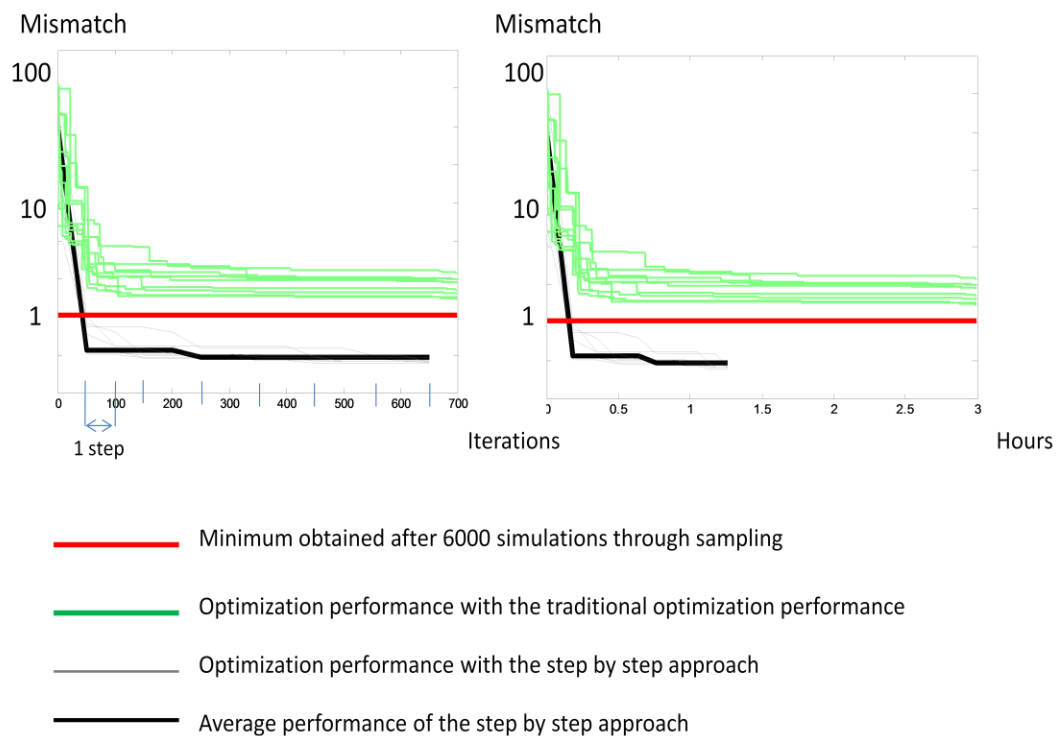
Thickness data

When considering the number of i=iterations, our method is more effective than the traditional optimization approach (fig. 18). When comparing it with random sampling, our approach obtains better fits than the best sampled model. The traditional optimization approach does not work very well because of the complexity of the problem. It is equivalent in term of performance than the rejection algorithm. With our method, a good match is obtained after only one step (50 iterations). Indeed, adding a similar noise all the lobes during the first steps allows producing and controlling big change in the algorithm behavior, and finding a local optimum is then easier.

When considering computational time, the efficiency of the algorithm is also better, since the simulation time of a single realization decrease during the optimization processes. For the same number of iterations, the final result is obtained after only 1.5 hours, versus 3 hours for the traditional approach or sampling.

Thickness and well data

The same behavior is observed for this example than the previous one (fig 19). It seems however that the algorithm needs more iterations to converge to a good solution. The optimization problem is more complex since the model also needs to fit the internal geometry present at the wells locations. Large improvements are still visible after 300 iterations.

Figure 17 Optimization performance of the method for the thickness information. Comparison with the traditional optimization approach and a sampling approach.
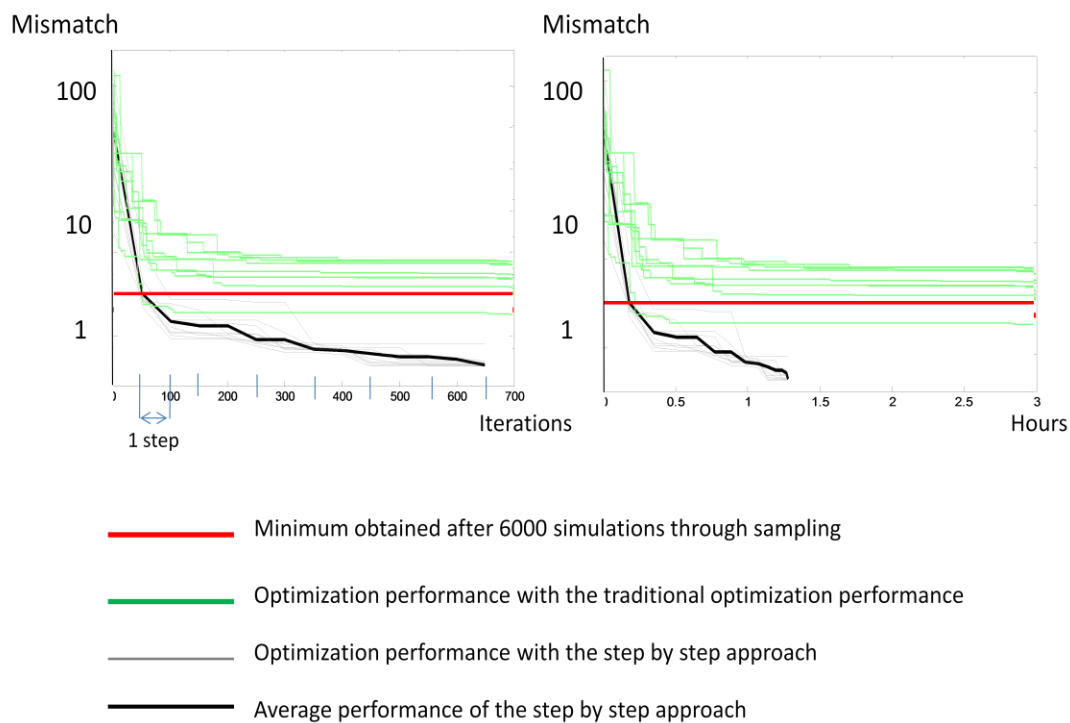
Figure 18 Optimization performance of the method for the thickness information and well data. Comparison with the traditional optimization approach and a sampling approach

6.Conclusion

This paper presents an optimization workflow to fit hybrid geostatistical models to well and thickness data. The results show that it is possible to efficiently condition hybrid geostastical models to thickness information and few wells data. The matching framework preserves the geological consistency of the model and does not need log data interpretation. This approach requires having in the model a Gaussian noise perturbing the structures of the geobodies. Such noises influence directly and at each time step of the depositional sequence, the topography and the placement of the lobes. Applying perturbations on these noises allows adjusting the entire deposition model. After the deposition of a lobe, its noise can be perturbed to optimize the placement of the following lobes.

Conditioning is optimization problem, which is efficiently solved by a subdivision the problem. At each step, one same noise is added to all lobes and then optimized. It allows decreasing the number of parameters and simplifying the optimization problem. After each step, the first lobe being deposited is integrated in the paleotopography. Therefore, the number of lobes being simulated decreases after each step, increasing the efficiency of method. This methodology, applied to a realistic data set, shows good results as the model fit thickness information and log data faster than when using traditional optimization methods.

The extension of the work is to apply the optimization scheme for history matching problems. A realistic property modeling algorithm requires then to be implemented inside the hybrid geostatistical models. In addition, an accurate horizontal and vertical discretization is required to capture the geological details (Zhang 2009). A very fine grid is then needed, and it may lead to expensive flow simulation.

7.Acknowledgments

8.Bibliography

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