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An Analysis of the Seismic History Matching Objective Function

R. Chassagne (Heriot-Watt University), C. Aranha (Tsukuba University) & C. MacBeth* (Heriot-Watt University)

Summary

The goal of this work is to study the effectiveness (robustness, accuracy and speed) of an objective function in the context of seismic history matching; this aspect is the key component for a successful update of the reservoir model. Two main characteristics of the objective function are in focus: which seismic attributes should be matched to, and how to measure the matching. The sensitive factors currently studied are, the attributes at the simulation domain (pressure, water and gas maps, and combinations of these) and the metrics (Kendall Tau, L2 norm, Minimum ration, Pearson correlation) used to compare the two maps, from the seismic and from the model. The optimisation method used to perform the seismic history matching is an auto-adaptive differential evolution algorithm (SHADE). This study has been carried out on a North Sea field. Based on the results and analysis of the seismic history matching experiments, we are able to draw some practical recommendations, on what kind of objective function should be established to update the simulation model with seismic data.

Introduction

Seismic history matching (SHM) has gained popularity as a technique to update a simulation model for field management (Roggero et al., 2013). Two common approaches for SHM is to update the simulation model based either on (1) its static seismic properties (Yin et al. 2015); or (2) its dynamic properties, through incorporation into the history matching loop (Gosselin et al, 2001). This second approach is currently under investigation, and a number of tentative works have been published so far (Obidegwu et al., 2016; Tillier et al., 2013; Jin et al., 2012; Haverl et al, 2005). The main idea behind the use of seismic in the history matching process is that the large quantities of data available in the seismic model could be used to deliver a much more robust prediction. However, no such breakthrough using seismic data has been seen in the literature so far. This leads us to believe that something is still to be understood concerning the crucial step of integrating the seismic data into the history matching workflow. In this paper, we suggest to explore in more detail the main characteristics of SHM in regards to robustness, accuracy and speed, as a first step towards a more comprehensive method. In particular, we study the question of how much data from the seismic model should be integrated into the objective function (OF), and how this data should be evaluated. Does adding more and more data into the OF always improve the quality of history matching? What is the significance of the metric used in the evaluation of the similarity/dissimilarity between the seismic and the model maps?

As production well HM has been exhaustively studied over the years, the present study will focus on the seismic part of the history matching workflow. We assume that the seismic processing has been carried out; by consequence the SHM is performed at the so-called reservoir domain. The different experiments have been carried out on a real field from the North Sea and help us to put forward some recommendations of the design of the OF when seismic data is used in the updating loop.

How Much Data - Different Objective Functions for SHM

In the SHM process, an ensemble of models is generated from the simulator, and compared to the reference seismic data. This comparison is made by evaluating the difference of the saturation maps between the model and the reference. To simulate this process, in this work we generate a “true” seismic map, and a different “initial” model. Then the SHM process uses multiple variations of the “initial” model to match to the designated “true” seismic map.

To perform the matching, we employ a meta-heuristic search algorithm called SHADE (Tanabe and Fukunaga, 2013; Aranha et al., 2015). We select fifty-one parameters of the model to be matched by this algorithm. The OF is composed of one of seven combinations of seismic attributes: “pressure”, “water”, “gas”, “pressure and water”, “pressure and gas”, “water and gas”, and finally “pressure, water and gas”. We compare these different formulations of the OF in order to determine how many attributes should be used in the SHM process.

The results of these experiments are gathered in Figure 1. In order to be able to compare the different OF we report the misfit between the production well data of the individual being tested against the production well data of the true model (vertical axis of Figure 1).

The similarities/dissimilarities of the seismic data in the Objective function is measured using the L2 norm. Out of all the variations described before, the best ensemble of models is obtained when the OF contains all three attributes. A very comparable result is obtained using only two attributes (pressure and gas), so the use of relevant selected attributes for a given model could be an option, instead of just using as much data as is available. Finally, the worst results happen when the three attributes are used in isolation.

We are also interested in investigating the computing time used in the optimisation process. At the early stages of the optimisation process, all the different OF behave in a similar fashion (right side of Figure 1). After this initial stage, we can see that the OF using all three attributes shows a steeper improvement in the misfit value, specially when compared with the single attribute OF. This shows that using more information to constrain the optimisation algorithm does have a beneficial effect without affecting the time convergence of the seismic history matching.

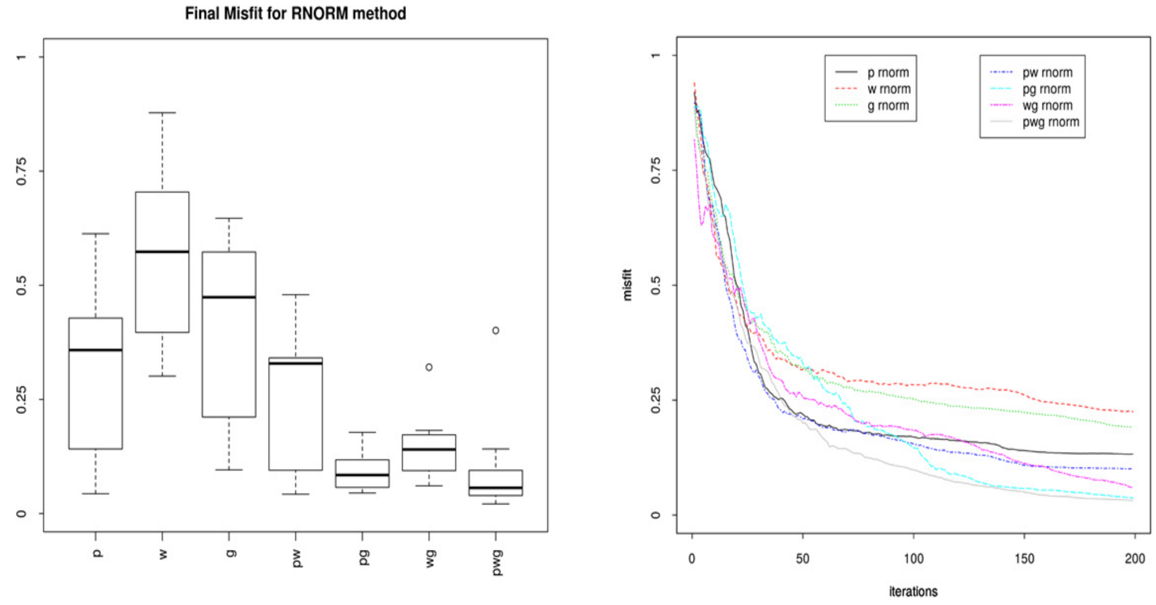

Figure 1 *Left picture is the normalised misfit of the production well data between the final ensemble of models issued by the SHM and the true model. Seven different OF have been tried using seven different attributes combinations (respectively pressure, water, gas, pressure and water, pressure and gas, water and gas, pressure and water and gas). The right picture is the convergence time (in iterations) versus the misfit.*

Testing different seismic similarity metrics

After selecting the attributes to be considered, another important aspect to the Objective Function is how to calculate the similarity or dissimilarity of two models based on these attributes. This mechanism is what will validate a good or bad ensemble of models in the SHM workflow.

Goshtasby (2012) makes a broad review of similarity and dissimilarity metrics. In this work, we select four of the listed techniques and compare their performance in the SHM optimisation process. The metrics chosen were the L2-norm, which is traditionally used for SHM, and three other metrics that showed the best performance in the review above: Minimum ratio (Goshtasby 2012), Pearson correlation (Pearson, 1896), and Kendall's Tau (Kendall, 1938). We can classify these metrics roughly as “pixel by pixel” type (Minimum Ratio and r-norm), in which the values of individual cells in the seismic data are calculated independently, and “global” (Kendall's Tau and Pearson correlation), in which the global pattern of the data is incorporated into the measurement as well.

Following the conclusions of the previous section, we compare the selected metrics by using each of the metrics as an Objective Function incorporating all three attributes. The result of these comparisons is shown in Figure 2. In our experiments, no important differences are observed in the final misfit, regardless of the comparison metric used. In other words, more sophisticated metrics (to the extent explored in this work) do not make a significant difference in the final updated model. Based on these results, we recommend the use of the L2-norm as a sensible choice regarding the measure of similarities within the OF. We have performed the same experiment on other attribute combinations, obtaining similar results.

Also, we measured the computational time spent in each optimisation process, as in the previous section, to test whether any of the metrics would show an advantage to this aspect. However, we could not observe any difference on convergence speed among all four metrics (see the right side of Figure 2). Our experimental results show that there is no observable difference in computing time for the SHM optimisation among the four metrics.

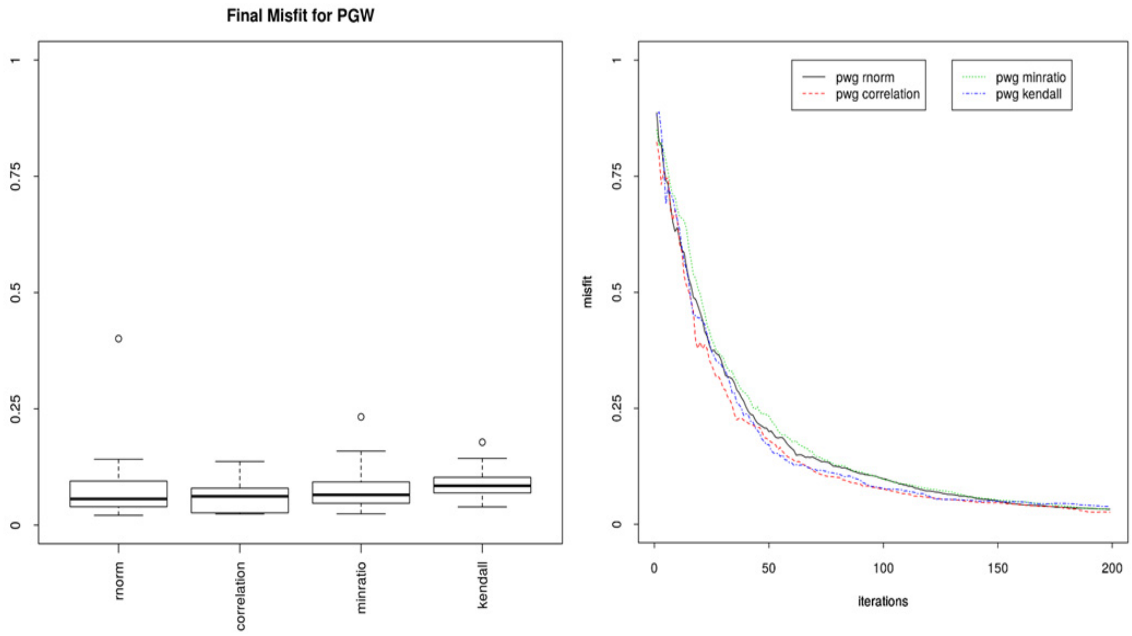

Figure 2 *Left picture is the misfit of the production well data between the final ensemble of models issued by the SHM process and the true model. Four different metrics have been tried on the pressure best performing OF, meaning using pressure and gas and water. Right picture is the convergence time (in number of iterations) for three attributes objective function for all the selected metrics versus the misfit.*

Conclusions

Based on the results of the experiments performed in this study, and considering that they were obtained from a real dataset, it is possible to draw some practical recommendations concerning the use of seismic history matching. The more data (as in number of different seismic attributes) is integrated into the SHM process, the better the ensemble of models is updated. However, even a few relevant selected attributes can serve for a robust update of the model.

Adding more data to the objective function means adding more constraints to the optimisation problem to be solved. Counter intuitively; it does not seem to alter the convergence speed, as compared to the use of fewer data attributes.

The choice of the L2-norm for Seismic History Matching is appropriate and perform as well as more sophisticated metrics. Moreover the computing time is very comparable to other metrics.

Seismic processing, which consist to extract attributes from the seismic domain is a complex work. This study suggests that a right choice of few attributes to be history matched could compensate a brutal approach (maximum of attribute).

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