Reducing Uncertainty in Modelling Fluvial Reservoirs by using Intelligent Geological Priors

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Abstract Automatic history matching reservoir models using geological features is made challenging by the inability of the modeller to avoid selecting unrealistic reservoir models. In the current practice, of modelling fluvial reservoirs, the geometry of sandbodies is based on uninformative, deterministic or two-dimensional geological priors. These priors can lead to a broad field of unrealistic models, which may not be appropriate for a specific case. We propose a new approach to resolve these problems by developing robust models of the non-uniform geological parameters space that should be sampled from to find realistic geological models, which could be then incorporated into a framework for automated history matching and uncertainty quantification.

In this work we show how reservoir models based on realistic geological priors can reduce the uncertainty in oil production. We built multi-dimensional geological priors using intelligent techniques, namely Artificial Neural Networks (ANN), Support Vector Regression (SVR) and One-Class SVM (OC-SVM). These techniques allow the priors to capture hidden relations from multiple data sources (modern depositional environments and outcrops). We sample from the realistic priors within the history-matching framework to achieve the flow responses that match the production data.

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Introduction

History matching is the process of using production history to improve the estimates of geological and reservoir parameters in a specific hydrocarbon field. These parameters should be modified to induce the reservoir simulator to reproduce production history. In the case of automatic history matching these parameters are changed automatically until finding a good match with the production history.

Automatic history matching reservoir models using geological features is made challenging by the inability of the modeller to avoid selecting unrealistic reservoir models. There are two main causes for this (1) the selection of unrealistic combinations of geological parameters (e.g. a river channel that is 1 ft wide and 1000 ft deep) and (2) the inability of the modelling method to guarantee the generation of realistic models. In the current practice, of modelling fluvial reservoirs, the geometry of channel sandbodies is based on deterministic or two-dimensional geological priors. These priors can only find relationships between two parameters and lead to a broad field of unrealistic models, which may not be appropriate for a specific case.

We propose a new approach to resolve these problems by: (1) developing robust models of the non-uniform geological parameters space that should be sampled from to find realistic geological models, which could be then incorporated into a framework for automated history matching and uncertainty quantification. (2) Developing a technique that allows us to parameterise a multi-point statistics model of the reservoir based on geological parameters rather than abstract features, like the *affinity* parameter used in SNESIM.

In this work we show how reservoir models based on realistic geological priors reduce the uncertainty in oil production. We built multi-dimensional geological priors using intelligent techniques, namely Artificial Neural Networks (ANN), Support Vector Regression (SVR) and One-Class SVM (OC-SVM). These techniques allow the priors to capture hidden relations from multiple data sources (modern depositional environments and outcrops). Furthermore, we can predict realistic parameter combinations, not observed in the available data; but still plausible in nature. We sample from the realistic priors within the history-matching framework to achieve the flow responses that match the production data. History-matched models produced under geological realistic conditions reduced the uncertainty in predicting production responses.

Geological Priors in Modelling Meandering Channels Facies

Figure 1 is a representation of the geomorphic parameters of meandering channels (channel width, thickness, meander wavelength and amplitude) commonly used to generate geo-cellular facies models. The geological prior information commonly used for modelling channel facies geometries are ranges of these geomorphic parameters (uniform priors). This methodology could mislead the generation of facies models, ending with unrealistic models.

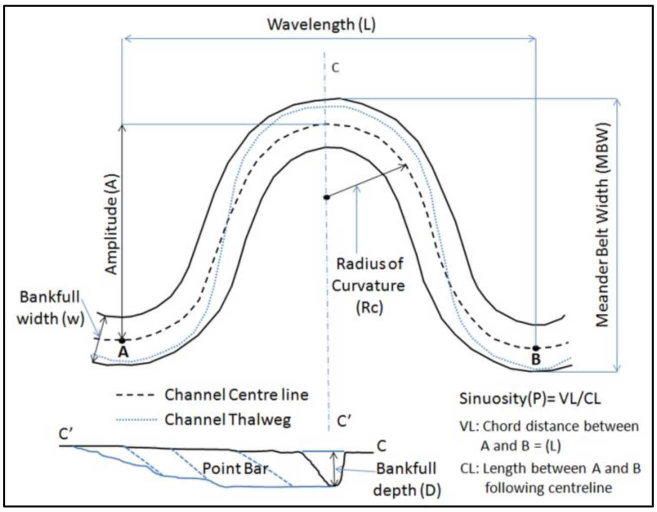

Figure 1 Representation of the geomorphic parameters of meandering channels (channel width, depth, meander wavelength and amplitude).

In Figure 2 we can observe that empirical equations do not represent the actual behaviour of the relations between channel geomorphic parameters.

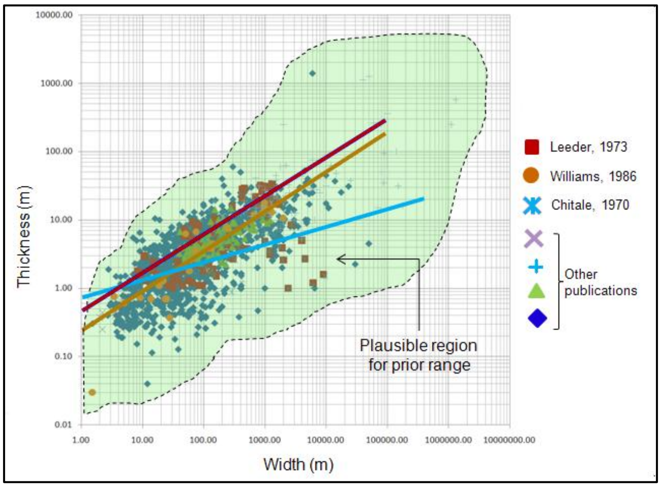

Figure 2 2D Plot Channel Width vs Channel Thickness, with data from different authors. We can observe that empirical equations do not represent the distribution of the data. In light blue is the linear regression obtained from [3] data, in red the one proposed by [4] and in orange the one obtained from [8] data.

Intelligent Prior Information

We highlight that generating prior information for modelling meandering channels is a multidimensional problem. It is necessary a technique that can build a more realistic representation of priors than linear empirical equation or uniform ranges.

We used Machine Learning Techniques (MLT) to built intelligent prior models, MLT manage multidimensional problems since it is a very powerful approach for analysing multivariate data with complex hidden relationships.

To generate these prior representations we used 714 data points taken from the literature, with information related to fluvial channel geometry: channel thickness, channel width, meander amplitude and wavelength These data were compiled using Artificial Neural Networks and Support Vector Regressions.

Artificial Neural Networks(ANN) and Support Vector Regression (SVR)

In order to visualize the dependencies between the geomorphic parameters of meandering channels we use two techniques Artificial Neural Networks (ANN) and Support Vector Regression (SVR).

The results obtained using ANN present some unrealistic artefacts that could mislead interpretations, e.g., see [7]. There were obtained four 3D surfaces, built with SVR that represents the relationships between the channels geomorphic parameters used here. These surfaces can be used as realistic prior information models for generating fluvial facies models [7].

One Class Support Vector Machine (OC-SVM)

SVR and ANN models demonstrated that all the geomorphic channel parameters are directly related. To generate a realistic facies model we need to select a combination of parameters that can reproduce realistic channel geometry. These two statements take us to another machine learning technique: One-Class Support Vector Machine (OC-SVM), see [2]. This technique considers all the data points as they belong to one “positive” class, everything outside this class do not belong to it and is considered as “negative”. The application of this technique to our case suggests that every combination of geomorphic parameters observed in nature belongs to a positive class and any combination of parameters outside this class is going to be considered as unrealistic. OC-SVM needs to be tuned by modifying their hyperparameters and analysing training and testing errors.

We evaluated the probability of a combination of geomorphic parameters to be realistic using OC-SVM, by transforming the OC-SVM results into probability. We applied a sigmoid function to the OC-SVM output:

$$p(x)=\frac{1}{(1+\exp(ax+b))} \quad \text{with} \quad a<0 \tag{1}$$

where: $p(x)$ is the probability

x is the decision value obtained from OC-SVM (which indicates how close is this value to be outside from the "positive" class).

a and b were tuned via maximum likelihood using a validation (independent) data subset.

Figure 3(a) shows how the new probability output can be used to designate a combination of channel geomorphic parameters as realistic. I our case we used a probability of 0.1 as a cut-off to select realistic combinations of parameters.

Figure 3(b) is a representation of the 4-dimensional OC-SVM model considering the 4 geomorphic channel variables used in this work, this multidimensional cloud is considered as the realistic domain of combination of channel parameters.

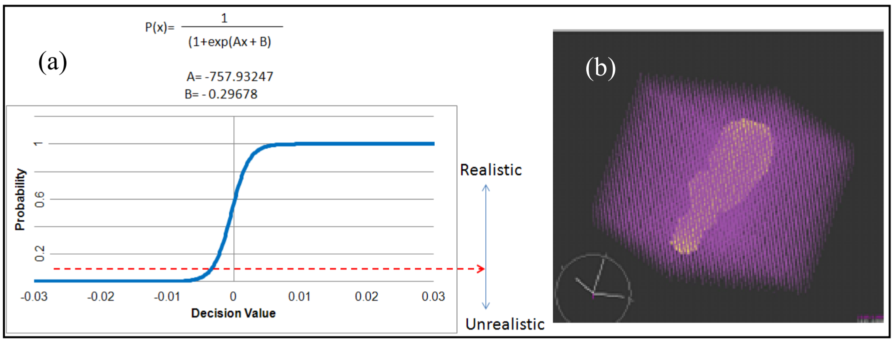

Figure 3 (a) Sigmoid function to evaluate the probability of a combination of geomorphic channel parameters to be considered as realistic. (b) Representation of the 4-D prior information, using OC-SVM, every combination of parameters inside the yellow "cloud" is considered as a realistic combination of channel geomorphic parameters. In purple we can see the points outside the realistic "cloud" which are considered as unrealistic combinations of parameters.

Facies Modelling

Meandering channel facies

Meandering channels developed in unconfined plains move laterally within the valley leaving coarse deposits (sand and gravel) while the channel migrates, these deposits are called point bars. When the channel avulses, typically left deposits of fine sand, silt and clay. Bordering the channels there are formed the levees, features that are composed by silt and fine sand and are formed during high level flows. Channels are surrounded by fine grained material (silts and clays) that form the floodplain deposits [5].

For this work we only considered a model with three facies: Point bars, Channel deposits and flood plains, being point-bar facies the ones with best reservoir quality (porosity and permeability).

Geostatistical Facies Modelling (Multiple-Point Statistics)

In this work we use Multiple Point Statistics as the geostatistical technique to generate meandering facies models, due to their advantages over object based models and sequential indicator simulation. Using MPS will allow us attaching meandering sandbodies to the well and seismic data which is very difficult to do using object based models. MPS has the advantage of generating realistic geological facies models compared to Sequential Indicator Simulation (SIS).

It has previously been observed that there is not a good control on the geomorphic channel parameters of the output channels when using MPS. In [7] we can see that they solved this problem by creating a series of neural networks, which transform the geomorphic parameters into the *affinity* parameters used by the MPS algorithm SNESIM. The use of these neural networks allows the control in the geometry variations of the output channels.

Field Application

To test this methodology we used the second stratigraphic unit of the synthetic reservoir Stanford VI, see [1]. As Figure 4 shows, this stratigraphic unit was formed by meandering channel deposits composed by three facies: channel, flood-plain and point-bars. As the problem to be highlighted here is the impact of facies geometry on the history-match process, petrophysical properties were set constant for each facies.

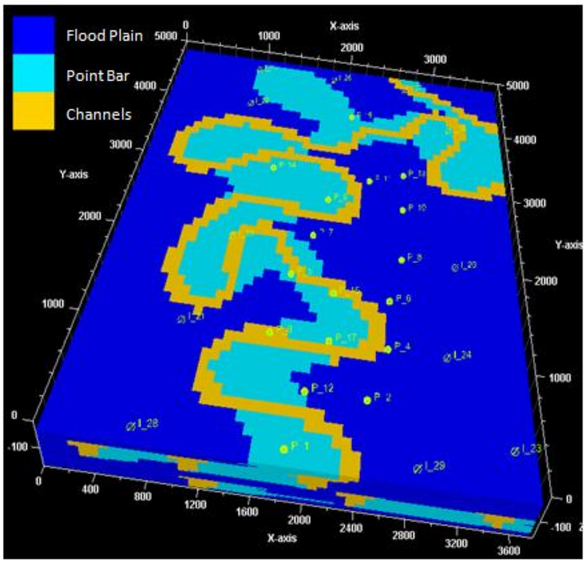

Figure 4 Visualization of the Facies distribution in Stanford VI Reservoir (Stratigraphic Unit B). This unit is composed by meandering channel, point bars and floodplain deposits.

Table 1 shows the porosity and permeability associated to each facies and basic information of this reservoir is shown in Table 2.

Table 1 Petrophysical properties (Porosity and Permeability) associated to each facies.

Facies	*Porosity*	*Permeability (k_h)*	*Permeability (k_h)*
Channel	5 %	5 mD	1.5 mD
Point-Bar	17 %	500 mD	150 mD
Floodplain	0.0001 %	0.0001 mD	0.00001mD

Table 2 Stanford VI Synthetic Reservoir Properties

Property		*Property*	
STOOIP	363 MM STB	**Grid**	50x50x40
Pressure Datum	5000 psi	**Cell dims**	75x100x1 (m)
Wells (inj)	11	**Prod. Start**	01 Jan 1976
Wells (pr)	18	**Days of Prod.**	2000

Automated History Matching and Uncertainty Quantification

Figure 5 illustrates the workflow of the automated history-matching process where we included the realistic geological prior information models. In this case we incorporated the prior information compiled using One-Class SVM.

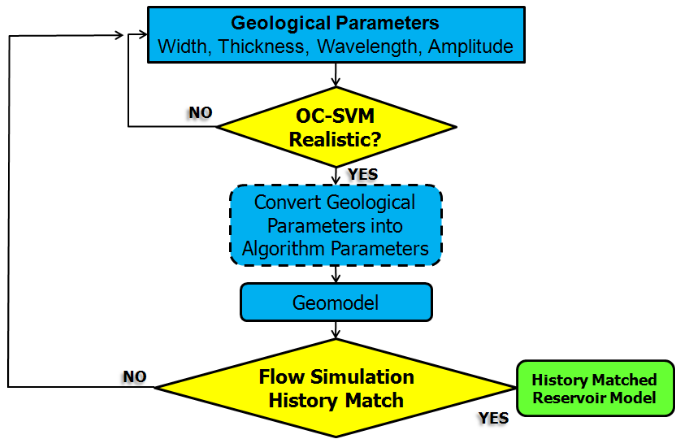

Figure 5 Automated history-matching workflow including the realistic geological prior information models related to the geometry of the channels.

Our proposed workflow starts by selecting a realistic combination of channel geomorphic parameters from the prior information built using OC-SVM, the next step is to build a facies model. We used Multiple Point Statistics in this case, and we introduce to this process a series of training images which the workflow will choose probabilistically. After generating the facies model and populated this geological grid with petrophysical properties, the flow simulation is performed and the history match process begins, if the history match is not good the workflow starts again until we obtain a number of history-matched models.

In recent years, research has been quantifying uncertainty by generation of multiple history-matched reservoir models rather than seeking the best history match model, see [6].

Most uncertainty quantification studies use a Bayesian approach, which starts with a prior information of a reservoir commonly expressed as probabilities, these prior probabilities are then updated using Baye's rule, see [6]. The data that is used to update the prior probability are the observations about the reservoir (e.g., production data). By generating multiple models that match history data and consistent with prior data, we are able to estimate uncertainties in prediction reservoir performance.

For the history-match process the sampling algorithm we used was Particle Swarm Optimization [6]. Particle Swarm Optimization (PSO) is a population-based stochastic optimization algorithm, which was extended by [6] to be applicable on uncertainty quantification in reservoir modelling. PSO was extended using the concepts of Neighbourhood Algorithm (NA) by running NAB code; see [6], which computes the posterior probability under the assumption that the misfit surface is constant in each Voronoi cell surrounding a particle.

The sampling algorithm uses the negative log of the likelihood or misfit *M*. Assuming that the measurement errors are Gaussian, independent and identically distributed, the misfit is calculated using the conventional least-square formula.

$$M = \sum_{t=1}^{T} \frac{(q^{obs} - q^{sim})_t^2}{2\sigma^2} \qquad (2)$$

Where *T* is the number of observations, *q* is the rate, superscripts *obs* and *sim* refer to observed and simulated, and σ^2 is the variance of the observed data, see [6].

Results

Figure 6 illustrates the evolution of the misfit during the process of history-matching and we can observe how the models try to converge during the process.
It is clear that the number of models generated to obtain low misfit reduces when using intelligent priors.

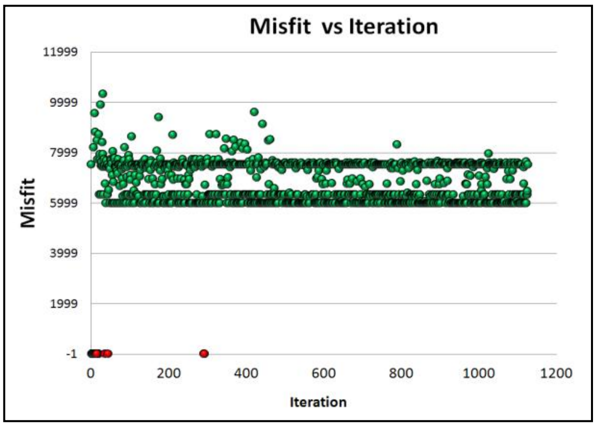

Figure 6 Misfit vs Iteration plot, we can observe how the models are converging. Red dots are models with unrealistic set of geomorphic parameters and a misfit of -1.

Figure 7 is a comparison of the Truth Case with the best history matched model and the worst history matched model, we can observe similarities between the model with the best mist and the Truth Case. It is important to highlight that all the models generated have been built with realistic combinations of geomorphic parameters.

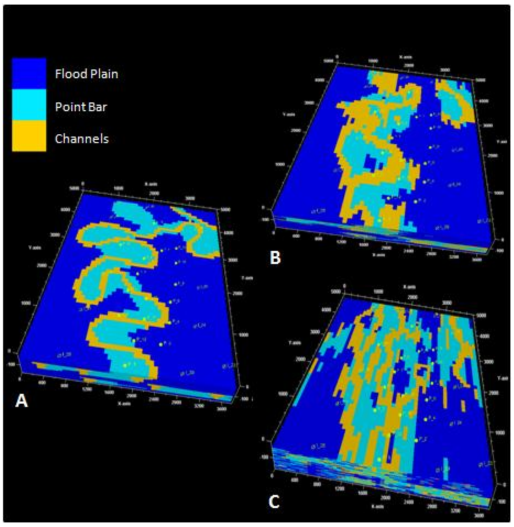

Figure 7 is a comparison of (A) the Truth Case; (B) the model with the best misfit and (C) the model with the worst misfit.

Figure 8 is a comparison of the production history and the best history matched model. We can observe a relative good match although it is clear that the matching is not perfect.

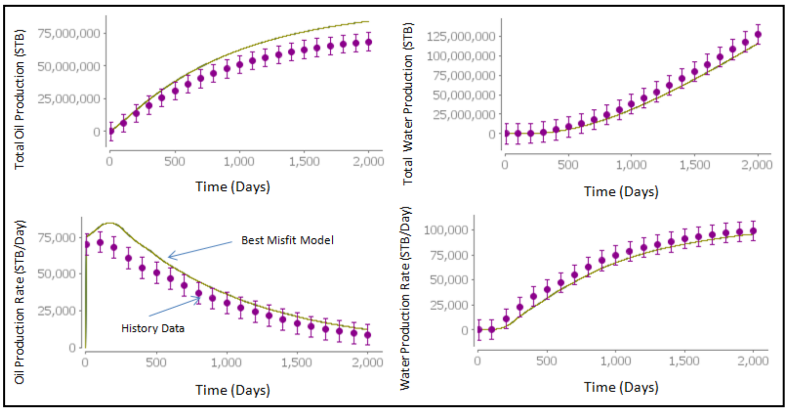

Figure 8 Comparison of the best history-matched model and production data.

We can identify in Figure 9 the sampling history for each geomorphic parameter, and it is clear that the concentration of points is increasing close to the truth case.

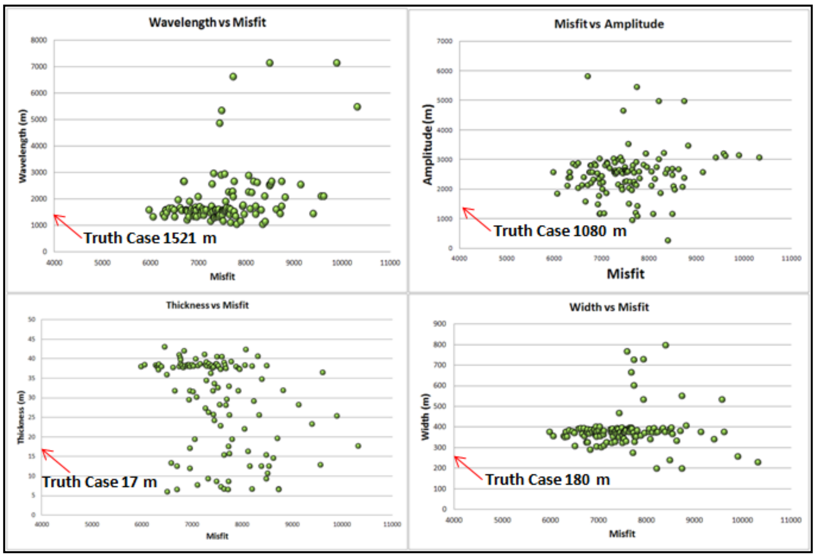

Figure 9 Sampling history for each of the four geomorphic parameters, we can observe that the population of samples was getting crowded close to the truth case.

Conclusions

- Building intelligent prior models reduces the uncertainty of predicting reservoir behaviour, since using only realistic combination of geomorphic parameters reduces the spread of the generated solutions.
- Using intelligent geological prior information reduces the number of flow simulations by avoiding unrealistic models in history-match which consequently reduces the computational time.
- Realism in the geometry of the geobodies in the reservoir models is achieved by using intelligent geological prior information.
- There is a problem in reducing the misfit in some models, and we associate this problem with not enough control over the connectivity of the reservoir facies model. The next step in this work is to generate multiple realizations and their connectivity screening.

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