

SPE 30591

## Use of Well Test Data in Stochastic Reservoir Modelling

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This paper was prepared for presentation at the SPE annual Technical Conference & Exhibition held in Dallas, U.S.A., 22–25 October 1995.

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### Abstract

The aim of the study is to condition stochastic generated realizations on well test data in order to improve simulation of facies and petrophysics in fluvial reservoirs. First we have used the pressure data to estimate the shortest distance from the well to a possible channel boundary and thereby simulate the channel structures. The well test also provides the permeability average in the part of the channel intersected by the well. Together with core/log data and general knowledge of the reservoir this have been used to simulate permeability. These permeability realizations is input to a numerical flow simulator and compared with experimental results of the well test.

### Introduction

Lack of relevant data is often a hindrance to proper reservoir management, particularly for offshore reservoirs at an early stage. Therefore, it is important to use all the available data to their full extent. There is still a considerable uncertainty that should be quantified.

By using a stochastic approach it is possible to include various types of data and to quantify the uncertainty. It is important to have an efficient algorithm for generating different stochastic realizations. The algorithm should be compatible with other software programs, which are used in reservoir evaluation. In this paper it is demonstrated how information from transient

pressure well test may be used in an existing commercial software package, and how this improves the reservoir description and history matching and thereby reduces uncertainty in the results.

Stochastic modelling principles have become increasingly popular and many companies base their reservoir management on results from stochastic models. Several techniques are currently available<sup>1–5</sup>. The focus is still on heterogeneity modelling, i.e. generating one or a few realizations which satisfies a geological interpretation and a set of specified data. There is, however, a growing use of stochastic models also in history matching<sup>6</sup> and quantification of uncertainty both of volumes<sup>7</sup> and production<sup>8,9</sup>. Quantification of uncertainty requires a quantification of the geological and geophysical interpretation, specification of the distributions of the most important parameters in the stochastic model, and many realizations of the stochastic model.

Typically, the following data are used: well observations, spatial distributions of facies and petrophysics, and seismic horizons. There has been an increased use of seismic data for both facies and petrophysical modelling<sup>10,11</sup>. Most stochastic models may easily include seismic data. The crucial point is the correlation between the seismic and petrophysical variables. The correlation is probably significant in many reservoirs,<sup>10,11</sup> but is difficult to estimate. In addition there are some technical challenges related to the difference in scale between the seismic and petrophysical data.

This paper reports our experience in including the use of well test data in a stochastic reservoir model. Our aim is to use all available data in the reservoir modelling. Within the Norwegian petroleum research community there are similar projects focusing on seismic data, production data, well logs etc. The same software tools are used in the different projects such that it is possible to use all the information in the same project.

### Well test data

There has been an intensive development in the use of well test data<sup>12–16</sup>. One approach is to use analytical tools to estimate pressure support and from that infer properties like distance to faults, permeability height product, channel geometry etc. This approach has the advantage that it usually gives a good interpretation of the well test. Since analytical tools are used, numerical problems due to large pressure gradients close to wells are avoided.

An even more challenging task is to estimate the permeability in a large number of grid blocks surrounding the well. There are some promising results. This approach is, however, believed to be more sensitive to noise in data, and a unique interpretation is unlikely.

A third approach is used in this paper after an evaluation of both the characteristics of the different techniques together with some practical considerations. The information from the well tests should be combined with other available information like well logs, seismic, and geological interpretation. It is important to combine with other software tools used in the project like stochastic simulation software, mapping package and reservoir simulator. This procedure depends on the available software and experience in the actual project. In this approach analytical and numerical well test tools are used in order to interpret the well test and estimate e.g. distance to flow borders and effective permeabilities close to the well. The stochastic generated realizations are then conditioned on these interpretations. Reservoir simulations are used to confirm that the realizations satisfies the well test. In some cases it is, however, necessary with some adjustments in the parameters.

The most intuitive method to combine well test data with stochastic generation of reservoirs is to generate a sufficient number of stochastic realizations. Then the realization which best fits the data is chosen. This requires an enormous amount of computing power. Alternatively, some key parameters may be estimated from the tests, and kept fixed in the simulations. This reduces the need for computing power considerably. Experimental design techniques may be used when combinations of several parameters values are necessary in order to obtain match of the well test<sup>17</sup>.

In this paper we propose techniques using well test data in a large stochastic model without increasing the computing requirements significantly. This requires that the well test is interpreted and some model parameters are estimated.

Information from well tests may be the distance to faults, connection between two wells by a high permeable zone, distance to the nearest border of a channel penetrated by a well, and average permeability or possibly a permeability-thickness product ( $kh$ ) in a zone. The interpretation may include uncertainties, e.g. the distance to the border of the channel is between 200 and 300 m, or there is a 30 percent probability for a fault and 70 percent probability for a border of the channel. This interpreted well test information with uncertainty in the parameters, should be included in the stochastic model. In this paper the stochastic

model for channel geometry is a marked point process<sup>18</sup>, and is a Gaussian model<sup>19,20</sup> for the permeability. This is a typical two stage model<sup>21</sup>. The well test analysis may give distance to the boundaries of a fluvial channel and permeability-thickness product in the channel close to the well. For a fluvial model it has previously been reported how to use the information that the same channel is observed in different wells<sup>18</sup>. The same technique which is presented here may be applied to the modelling of faults presented by Munthe *et al.*<sup>22</sup> where the interpretation of the well test may be the distance from the well to a subseismic fault.

### Stochastic model

In this section we will give a short description of the facies and petrophysical model.

**Facies model.** The facies model is based on a marked point process modelling permeable channels in a low permeable matrix. The model has been presented earlier in separate papers<sup>18,23</sup>. It is focused on the geometry of the channels, because the geometry of the channels are better understood than the geometry of the background facies. In the model a channel belt is a separate object which consists of several separate channels (**Fig. 1**)

Each channel consists of a main channel, crevasse splays connected to the channel, and barriers inside the main channel (**Fig. 2**)

Each channel and its associated crevasses are described by several 1D correlated Gaussian fields relative to a main axis. The barriers are assumed to be ellipsoids. There is a large number of parameters in the model including net-to-gross ratio, direction of channels, number of channels in each channel belt, number of crevasses per channel, dimensions of each channel, and intensity of barriers. All the different parameters are specified as distributions. In the model it is possible to condition on a large number of wells. It is possible to specify the probability that the same channel is observed in different wells or the probability can be calculated based on the other parameters in the model. One can also combine geometric information interpreted by the model and additional information from e.g. well test, detailed well logs etc. The type of model has been used in several large field studies<sup>9,25</sup>.

The model has been extended to allow each well observation in a channel to include the information of the distance from the well to the nearest border of the channel (**Fig. 3**)

If the channel width is 1000 m, and no additional information is available, the distance from the well to the border of the channel is uniformly distributed between 0 and 500 m. The program is extended such that it is possible to condition on the distance being e.g. between 100 m and 200 m, or a fixed distance.

The direction of the channel is found by the stochastic model as a trade off between the different parameters, mainly the distribution for the direction of channel belts (specified by the user) and the well observations.

This model has also been extended in order to use seismic data<sup>24</sup>. The seismic input is a 3D grid of impedance or amplitude values and a conditional probability function for channel sandstone given the seismic variable. A Bayesian technique is used in order to condition on the position and size of the channel and channel belt.

**Petrophysical model.** The permeability is modeled as a log-Gaussian field<sup>19</sup>. The permeability has different distributions in the four facies: channel, barrier, crevasse, and matrix. The permeability is typically high in the channels, medium to poor in the crevasses and poor to very poor in the matrix and barriers. It is well known<sup>26</sup> how to condition on (log-)Gaussian fields in points, or how to generate correlated fields for e.g. permeability, water saturation, and porosity. We usually simulate Gaussian fields using a sequential simulation algorithm described in Ref. 20, but there are also other fast simulation algorithms, see Ref. 27.

From a well test the effective permeability  $k_e$  for flow into a well may be estimated. This is not a point value but a complicated average found by solving the Laplacian equation locally around the well. In Ref. 15 a method is demonstrated, for conditioning effective permeability from a well test using a simple flow model. Since it is difficult to condition directly on this simple flow model, a relative time consuming iterative scheme was proposed. A Gaussian model, however, may be conditioned by using a weighted arithmetic average

$$k_a^a = \int k(y)w(x-y)dy \dots\dots\dots (1)$$

and a log-Gaussian field by using a weighted geometric average

$$k_a^g = \left( \int k^{-1}(y)w(x-y)dy \right)^{-1} \dots\dots\dots (2)$$

Thus simple techniques would not increase the computing time considerably. The function  $w$  satisfies  $\int w(x)dx = 1$ , and determines the volume where the average is taken. We will use the notation  $k_a$  instead of  $k_a^a$  if a Gaussian field is used and  $k_a^g$  if a log-Gaussian field is used. Conditioning on  $k_a$  is a well known technique from the mining industry<sup>26</sup>. In a well test, the permeability closest to the well bore will dominate the effective permeability around from the well. In a circle symmetric reservoir,  $k_e = k_a$  if  $w(x) = \frac{c}{\|x\|}$ , i.e. the weight is inversely proportional to the distance to the well. Therefore, there is a strong correlation between  $k_e$  and  $k_a$  for this choice of  $w(x)$ . The actual correlation value will, however, depend on the variogram used. The exact correlation must be found for each variogram separately.

It is possible from the well test to estimate  $k_e$  with some uncertainty. Then  $k_a$  is estimated from the given estimate of  $k_e$  using the correlation between  $k_e$  and  $k_a$ . If in addition the log or core permeability in the well  $k_w$  is known, this should also be used to give an improved estimate for  $k_a$ . Then the (log-)Gaussian field is conditioned on  $k_a$  directly without increasing the computer time significantly. Our experience is that the

uncertainty in the well test dominates the uncertainty in the estimate of  $k_a$ .

The strong model correlation between  $k_a$ ,  $k_e$  and  $k_w$  is demonstrated in **Fig. 4**. The figure shows the distribution for  $k_e$  given different information. In the field example the expected permeability value is  $E[Z] = 1.0$ , and a spherical variogram is used with a range such that there is a positive correlation in the volume where  $w(x) > 0$ . Without knowing  $k_a$  and  $k_w$  there is a large variation in  $k_e$ . This variation decreases significantly by knowing only  $k_w = Z(0)$  and even more by knowing both  $k_w$  and  $k_a = \langle Z(0) \rangle$ . The figure also shows two different curves for distribution of  $k_e$  given different values of  $k_a$ .

## Field applications

In the actual field studies we have used reservoir data from the Norwegian sector of the North Sea. These include well log data and permeability results from a well test. The procedure is illustrated in **Fig. 5**.

The input to the model is, in addition to petrophysical and seismic data, results from a well test interpretation. From the well test we estimate the distance from the well to the border of the channel, and the effective permeability for flow into the well.

The stochastic modelling consists of two stages; facies modelling and petrophysical modelling. First the channels satisfying the well observations are simulated. These are again used together with permeability data to simulate the permeability field in the defined reservoir. The permeability is input to the reservoir simulator. Upscaling is not necessary because the simulation grid blocks are very small close to the well. Ideally, we will obtain the same results from the reservoir simulation as from the well test. However, some difference may occur due to channel geometry, permeability variations, approximations in the reservoir simulator, etc. Hence, it may be necessary with 1-2 iterations in order to obtain a satisfactory match.

The technique has been tested on several case studies. One of these is reported in this paper.

In this case study a synthetic field data based on a North Sea reservoir is used. The data available were a structural map of the reservoir given as a flow simulator grid, top and bottom depth maps, different well measurements, and results of well tests. **Fig. 6** shows the facies interpretation in the well and **Fig. 7** shows a histogram over the permeabilities in the channels in the well.

One realization is picked out and a well test for this realization is performed. This realization is denoted the reference case. From the well test we estimated the distance from the well to the nearest channel boundary in the reference case to be between 50 and 200 meters. The average channel width is 1000 m. A set of channels satisfying these observations and the direct channel observations in the well were applied in the simulator. A fine grid of  $40 \times 100 \times 20$  blocks was defined where each cell was given a label stating whether it was in a channel or not (**Fig. 8**).

Using the well test information and well log, the permeability both in the channel and in the background was simulated on this grid. The permeability was simulated as a log-Gaussian field with a spherical variogram function with correlation length of 200 meters horizontally and 1 meter vertically. In this test study the permeability tensor was assumed to be isotropic.

From this fine permeability grid we made a upscaling into the original Eclipse grid of size 39x13x9 blocks for the actual reservoir and gave the porosity in the channels a constant value like 0.29.

Then the well test was simulated under two conditions: (1) Reservoir simulated conditioned on well test data and (2) the same without this conditioning. The rate versus time in these two cases are shown in **Fig. 9** and **Fig. 10**. It is observed that under the same conditions except for the well test conditioning, the spread of data is smaller when based on the well test than without. The distribution is also closer to the reference case. The variability which is left is believed to be due to variability in the distance to channel border (50-200 m), heterogeneities in permeability and numerical effects.

### Concluding remarks

It is demonstrated how transient pressure well test data may be used in a stochastic reservoir model.

The well test data improves the stochastic modelling, and reduces the variability.

The aim is that the additional work using well test data in the stochastic modelling is acceptable such that it will be used in ordinary field studies. This requires a further developing and testing period and an implementation in a commercial software package.

### Acknowledgments

We would thank our colleagues at the different companies, in particular Øivind Skare, Norwegian Computing Center who have implemented the extension of the fluvial model in the computer program. We also thank our companies for permission to publish this paper.

### Nomenclature

$k(x)$  = Permeability tensor field. Here assumed being scalar

$w(d)$  = Weight function when doing arithmetic or

geometric averages of permeability

$k_a^a(x)$  = Arithmetic permeability average

$k_a^g(x)$  = Geometric permeability average

$k_e$  = Effective permeability

$k_w$  = Well permeability

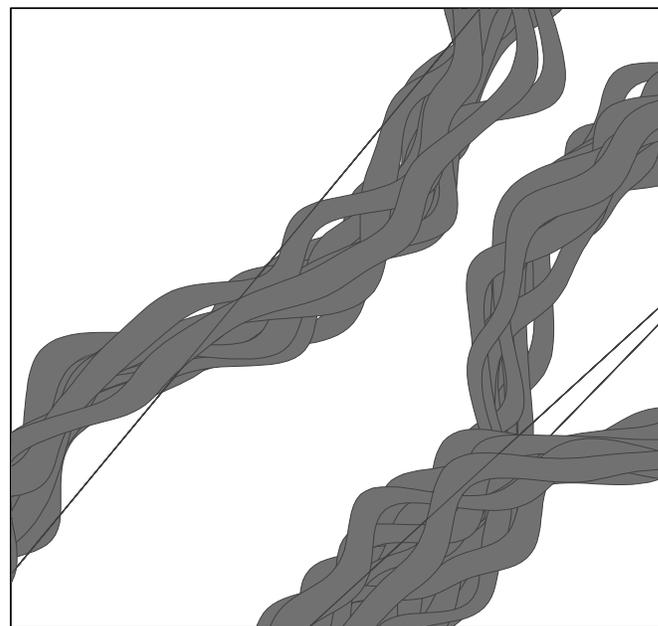
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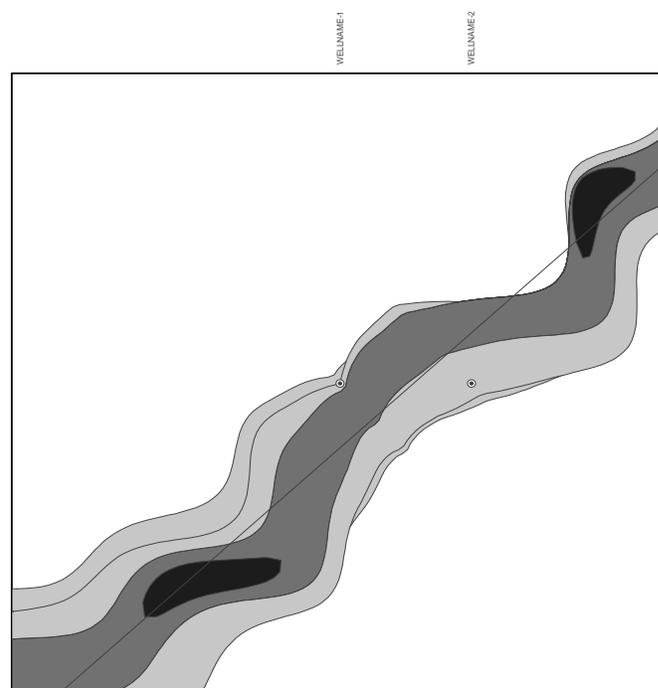
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## Figures



**Fig. 1. Three channel belts with their main axis projected into a horizontal plane. Each channel belt consists of several channels.**



**Fig. 2. One channel with two barriers and two crevasses on each side. Two wells penetrate the two crevasses.**

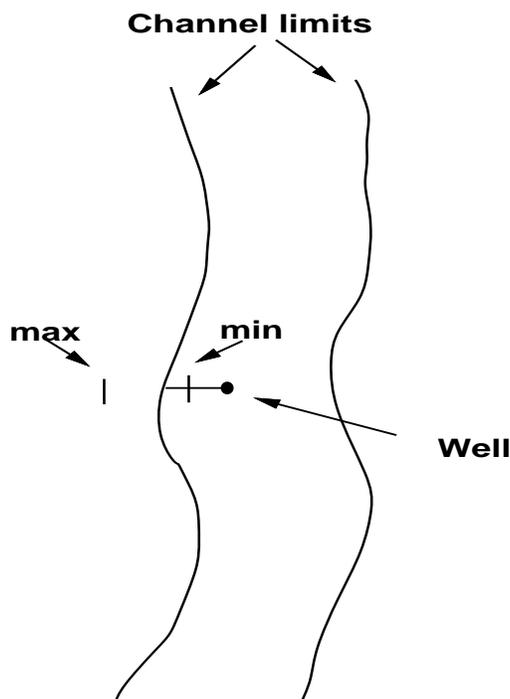


Fig. 3. Schematic illustration of a channel and relevant well test information. It is possible for the user to specify a minimum and a maximum distance from the well to the channel border.

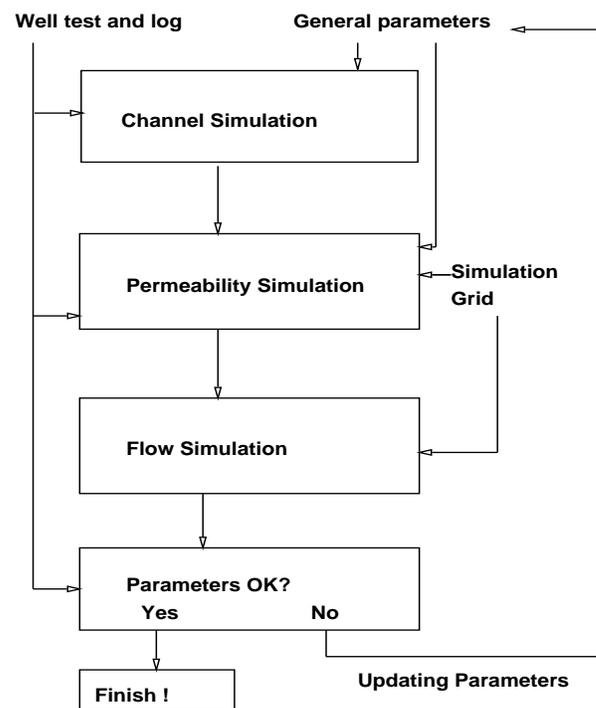


Fig. 5. Flow diagram to match transient pressure well test.

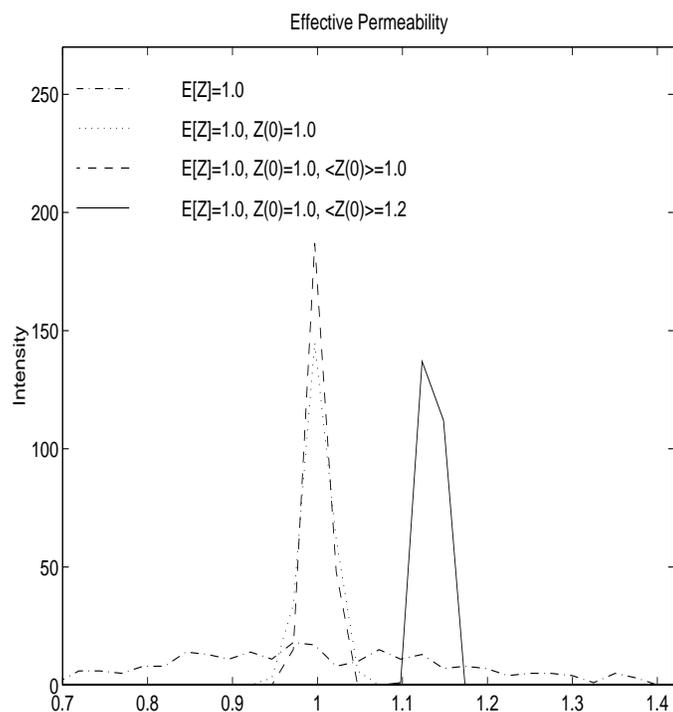


Fig. 4. The distribution of the effective permeability  $k_e$  when only the expected value is fixed and for different values of  $k_a$  and  $k_w$ . Notice that there is a large variation in effective permeability if only the expected value is known which reduces considerably if either the point value  $k_w = Z(0)$  or the average  $k_a = \langle Z(0) \rangle$  is known.

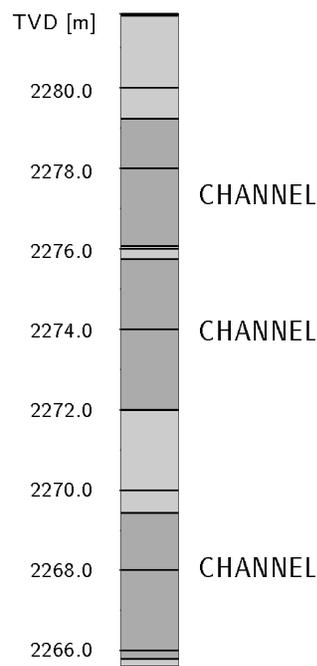


Fig. 6. Facies interpretation in the well.

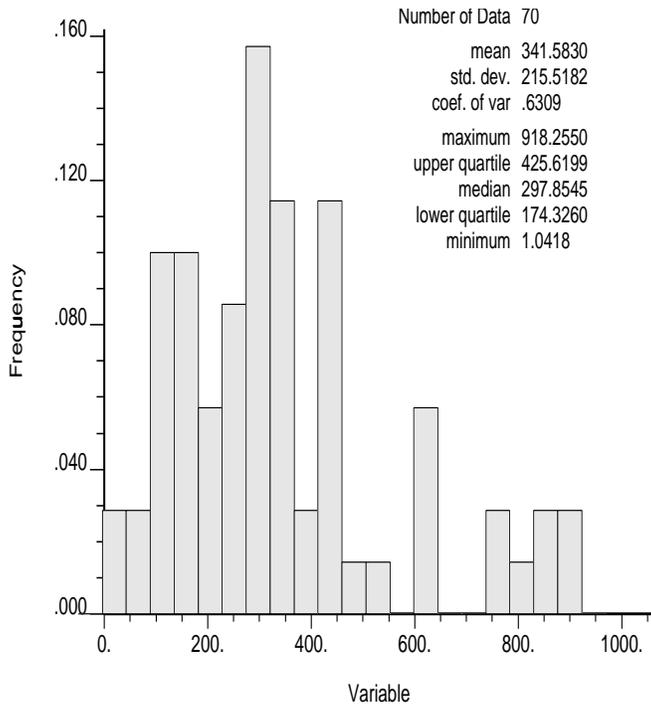


Fig. 7. Histogram over the permeabilities in the channels in the well.

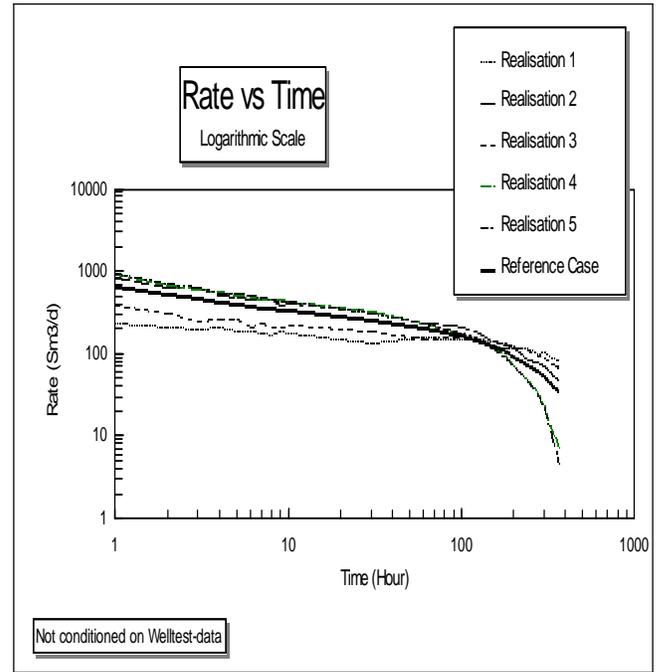


Fig. 9. Rate versus time for realizations not conditioned on well test.

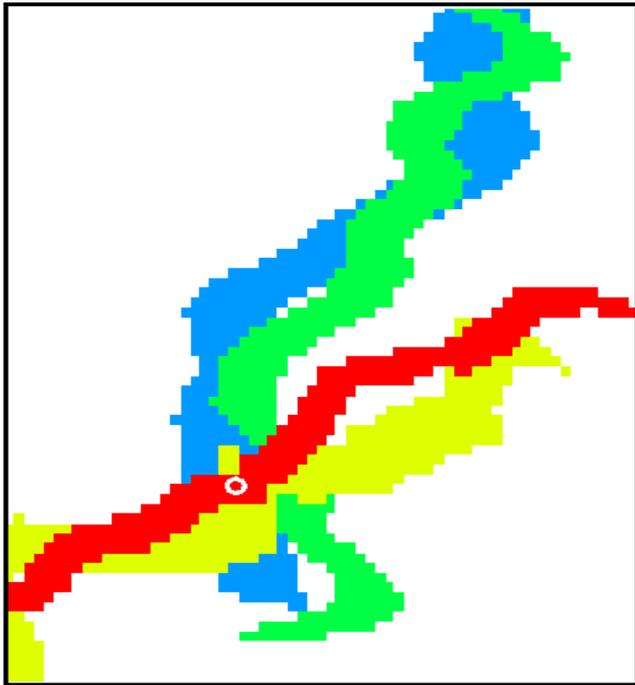


Fig. 8. One realization of channels. The well is indicated by the white circle.

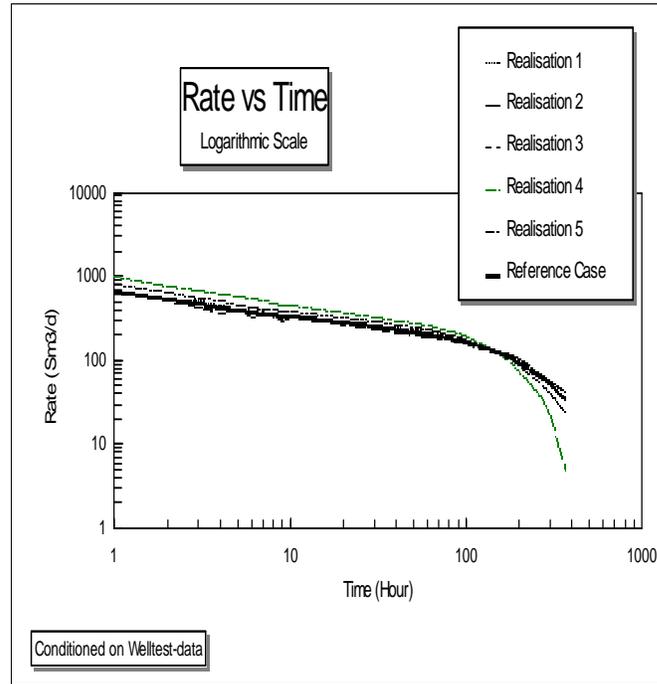


Fig. 10. Rate versus time for realizations conditioned on well test.