

Application of deterministic and stochastic geostatistical methods in petrophysical modelling – a case study of Upper Pannonian reservoir in Sava Depression

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Abstract

Deterministic methods are still widely used for reservoir characterization and modelling. The result of such methods is only one solution. It is clear that our knowledge about the subsurface is uncertain. Since stochastic methods include uncertainty in their calculations and offer more than one solution sometimes they are the best method to use. This paper shows testing of the deterministic (Ordinary Kriging) and stochastic (Sequential Gaussian Simulations) methods of reservoir properties distribution in the Lower Pontian hydrocarbon reservoirs of the Sava Depression. Reservoirs are gas- and oil-prone sandstones. Ten realizations were obtained by Sequential Gaussian Simulation, which are sufficient for defining locations with the highest uncertainties of distributed geological variables. The results obtained were acceptable and areas with the highest uncertainties were clearly observed on the maps. However, high differences of reservoir property values in neighbouring cells caused the numerical simulation duration to be too long. For this reason, Ordinary Kriging as a deterministic method was used for modelling the same reservoirs. Smooth transitions between neighbouring cells eliminated the simulation duration problems and Ordinary Kriging maps showed channel sandstone with transitional lithofacies in some reservoirs.

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1. INTRODUCTION

Application of mathematics in geology is relatively new approach in the interpretation of subsurface geology. Geostatistics, as a part of geomathematics began its development in the second half of the last century. Two great scientists are the founders of the Kriging method: Prof. Dr. Daniel Krige and Prof. Dr. George Matheron. The Kriging method is a mathematically advanced interpolation method, which estimates the value of the variable in the grid. This method is very well described in KRIGE (1951) and MATHERON (1965). Common application, as well as the intensive development geostatistical methods paralleled the software development and the appropriate IT infrastructure altogether. Geostatistical methods can be divided into deterministic and stochastic methods. In deterministic methods, all the conditions which can influence the estimation have to be completely known. Deterministic results can be unambiguously described by the completely known finite conditions, so deterministic analysis can only offer one solution. It is clear that the true geological model in the subsurface is singular, but since the description of the subsurface is based on well data (point data), it is not possible to be certain that the solution obtained with geostatistical methods is the correct one. This is why all geostatistical methods contain some uncertainty; they are a way of estimating the subsurface conditions and they can provide only the most probable solution, in other words the model which is the closest to the real conditions.

In reservoir characterization, petrophysical modelling, especially the porosity modelling is important for getting insight into the spatial variability of different properties. In the case that porosity is mostly connected with the depositional environment of the reservoir rocks in the study area, this may pave the way for

interpretation of sedimentary environments and depositional mechanisms. Within the present study, new porosity modelling has been performed with the aim of introducing and analysing the uncertainty of reservoir properties. Different deterministic and stochastic distribution methods were tested and analysed to choose the most acceptable one.

2. GEOLOGICAL DESCRIPTION OF THE STUDY AREA WITHIN THE SAVA DEPRESSION

Generally, during the Late Pannonian and Early Pontian, many subsided structural units in the entire Pannonian Basin System were reactivated due to the thermal subsidence (MALVIĆ & VELIĆ, 2011). Accommodation space for a huge volume of sediments was created. During these periods, the main regional sandstone hydrocarbon reservoirs were deposited in the SW part of PBS (VELIĆ, 2007). Turbidites were the dominant clastic transport mechanism in the Croatian part of the Pannonian Basin System during the Late Pannonian and Early Pontian (e.g. RÖGL, 1996, 1998; VRBANAC, 1996). Although there are some theories about the local material source, it was proven that most of material originates from the Eastern Alps. Due to lengthy transport distances, only the medium and fine grained sands and silts reached the Sava Depression. In the calm period, when turbiditic currents were not active, typical calm hemi-pelagic marls were deposited.

The study area is located in the north-western part of the Sava depression. The location itself is a hydrocarbon field with a structure of an asymmetrical brachianticline, with a somewhat longer axis of northwest-southeast strike, and with a slightly pronounced peak in the southern part. A fault system of NW-SE strike extends along the western part of the field.

The lithological composition of the reservoirs is fairly simple – medium and fine-grained sandstones (lithoarenites) in continuous alternation with marls. Marls are compact, dense brown-grey rocks. Both sandstone and marl layers are not always continuous; there are frequent pinch-outs and sections where different sandstone layers are in direct contact. The whole series was divided into 11 sandstone intervals, referred to here as S1 to S11. S1 to S4 are saturated with gas (in the gas cap) and oil rim, and they represent one hydrodynamic unit. S5 to S10 are saturated with oil, representing a second hydrodynamic unit, while S11 is water-saturated. All of the reservoirs in the series (S1-S11) were classified as representing the Upper Pannonian. Some of the reservoirs (S2, S3, S5, S7 and S10) are elongated in the NW-SE direction and they have the geometry of channel sediments. According to porosity and net pay distribution in the model it could be assumed that those reservoirs have the coarsest material deposited in the channel centre, which laterally, toward channel borders changes into basinal marls through transitional lithofacies (sandy marls and marly sandstones). Other reservoirs (S1, S4, S6, S8, S9 and S11) have greater areal extents and minor thickness variability representing rather sand lobes or similar type of deposits.

3. APPLIED GEOSTATISTICAL METHODS

Some methods give only one solution, i.e. for the same input data and by applying the same method, the result is always going to be the same, i.e. the same map is constructed. These are the deterministic methods, although it is correct to call them deterministic interpolation methods. Such methods are still commonly used for reservoir characterization and modelling, despite the fact that our knowledge about geological processes is far from complete. Still, we are aware that such deterministic interpretation cannot be unambiguous and certain, but it is often described as the most probable. Since a completely deterministic system is almost impossible by nature, it might be better to use stochastics wherever possible. Stochastic methods are a standard part of mathematical geology and are increasingly being used as an integral part of the tools for hydrocarbon reservoir characterizations worldwide.

Alternatively, stochastic realizations provide a different number of solutions for the same input data set. Those solutions can be very similar but never identical which is why all obtained solutions or results are equally probable. In stochastic processes the number of realizations can be any number we desire. The more realizations there are, the lower the uncertainty, i.e. there is a higher certainty that a number of realizations are close to the real geological situation. 100 realizations is the most common

number in practice because it gives a level of certainty that is high enough for reservoir characterizations. There are conditional and unconditional simulations. In conditional simulations, the well data are considered as hard data, unlike in unconditional simulations where these data are not constant. The explanation for this approach is that well data is just point data extrapolated to the whole cell in the 3D reservoir model. Cell dimensions in the model generally are 50 x 50 or 100 x 100 m and the point data again give some uncertainty. If the well had been positioned slightly differently, the cell in the 3D model would probably have different property values. This is why the point data in unconditional simulations is „surrounded” with measured data variance and the cell value will be chosen within this interval. Generally, conditional simulations are more often used.

3.1. Basics about Ordinary Kriging method

The Kriging method is one of the mathematically advanced deterministic interpolation methods. It is used for variable value estimation at the grid points. The result is a continuous surface created from a set of input points (Figure 1). This method was named by a mining engineer and professor at the Johannesburg University, D.G. Krige, who developed this to estimate the gold concentration of a mine (KRIGE, 1951). Other scientists including de WIJS, (1951), MATHERON, (1965), HOHN, (1988), ISAACS & SRIVASTAVA, (1989), and DUBRUBLE, (1998) continued to develop the method. The goal of the method is to determine spatial relationships between real, measured data and the location where the value should be estimated. As a first step of Kriging mapping, variogram analysis must be performed. Therefore, except for the distance between a measured and estimated location, the local or Kriging variance was taken into account. This means that the difference between the expected and estimated values is minimal. During Kriging estimation each data item is weighted by the weighting coefficient (λ).

Kriging estimation is given by the simple equation (1):

$$Z_K = \sum_{i=1}^n \lambda_i \cdot z_i \quad (1)$$

Where:

- z_K – estimated value
- λ_i – weighting coefficient at the „i” location
- z_i – real, measured data at the „i” location

The most often used Kriging technique is Ordinary Kriging, where the sum of all weighting coefficients must be 1. An expression for the Ordinary kriging estimation technique is given by the matrix equation (2):

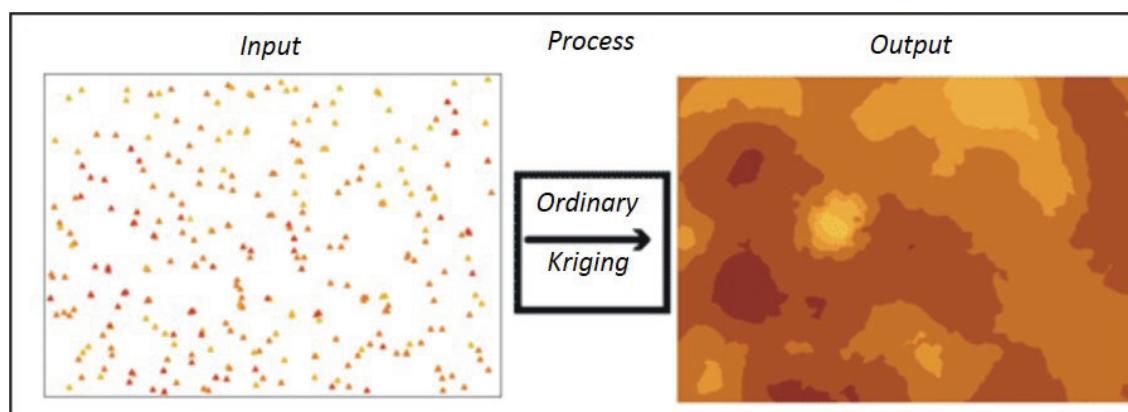


Figure 1. The process of Ordinary Kriging (<http://www.bisolutions.us/A-Brief-Introduction-to-Spatial-Interpolation.php>)

$$\begin{bmatrix} \gamma(z_1 - z_1) & \gamma(z_1 - z_2) & \dots & \gamma(z_1 - z_n) & 1 \\ \gamma(z_2 - z_1) & \gamma(z_2 - z_2) & \dots & \gamma(z_2 - z_n) & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(z_n - z_1) & \gamma(z_n - z_2) & \dots & \gamma(z_n - z_n) & 1 \\ 1 & 1 & \dots & 1 & 0 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma(x_1 - x) \\ \gamma(x_2 - x) \\ \vdots \\ \gamma(x_n - x) \\ 1 \end{bmatrix} \quad (2)$$

Where:

- γ – variogram value;
- z_1, \dots, z_n – real, measured value at the locations 1 to n;
- x – location where new value should be estimated;
- μ – Lagrange multiplier.

3.2. Basics about Sequential Gaussian Simulations

Sequential Gaussian Simulations are very well described in GEIGER (2006) and MALVIĆ (2008). Basically, they are not an interpolation method, but after normal transformation, the data are most often defined by the properties of a normal distribution and estimation is performed in cells without well data to produce simulations. A random choice of location is used to estimate one cell (the first introduction of randomness, i.e., stochastic). The value of the selected cell is estimated mostly by Kriging from other points in a spatial model. It is important to note that these points can be hard data or previously simulated points. After a cell is estimated deterministically, a new value is „surrounded” by the interval $\pm 3s$ (using the variance of the „zero” solution). Using a random choice (the second introduction of randomness), any value from this interval can be accepted as simulated for the cell. The procedure is repeated until estimates of all cells have been made (Figure 2). It is important to emphasize that all realizations are equally probable. It is quite clear that the more realizations there are the lower the uncertainty is. 10 realizations, which are performed in the first phase of this study could just provide a rough insight into the area of the highest uncertainty in the analysed reservoirs, which later was actually the area with few or even without any well data. Although all realizations are equally probable, it is impossible and meaningless to show them all. Realizations P5, P25, P50, P75 and P95 or just P5, P50 and P95 are most often presented. Realization P5 shows a solution where 5% of all solutions have lower values and realization P95 shows solution where 5% of all solutions have higher values. Such inter-

pretation is valid for all other P realizations. Following this pattern, realization P50 should represent a mean value because 50% of all realizations have higher, and 50% have lower values than the selected one.

The main advantage of SGS is the possibility for estimating values in all cells of a model through a set of realizations. There is however a disadvantage, e.g., simulated values can be significantly different in neighbouring cells, which can cause many problems in numerical simulation as proven by sensitivity performed on required simulation time. Although this may not be a problem in cases with large cells which may better describe the subsurface than interpolation.

4. INPUT DATA AND MODELLING PROCESS

Input data set used for geological model construction comprised well log data (from 86 wells), quantitative log analysis, core data (from 28 wells) and previously constructed 3D structural models. All these data have been integrated and analysed. A new geological model was built in Petrel™, with cell dimensions of 50 x 50 m. The vertical resolution of the cells is 2.5 m.

4.1. Structural modelling

A reliable structural model is a precondition for performing petrophysical modelling. The tops and bottoms of the 11 sandstone reservoirs (22 horizons) together with interlayered marls determined 21 zones. Two types of reservoirs were recognised: reservoirs with relatively uniform gross reservoir thickness in the field area and those with great lateral thickness variability. The latter have been identified as channel bodies. According to these observations, a layering method within the individual zones in the model was adopted. It was concluded that a better layering method in the case of channel bodies with great lateral variability of thickness was layering with constant layer thickness and following the top of reservoir, while in the other cases proportional layering was chosen. So, layering with constant layer thickness (2 m) was performed by „Follow top” method for the S2, S3, S5, S7 and S10 „channel” reservoirs, and „Proportional” type of layering was performed for S1, S4, S6, S8, S9 and S11 sandstones. Differences between „Follow top” and „Proportional” types of layering are shown in Figure 3.

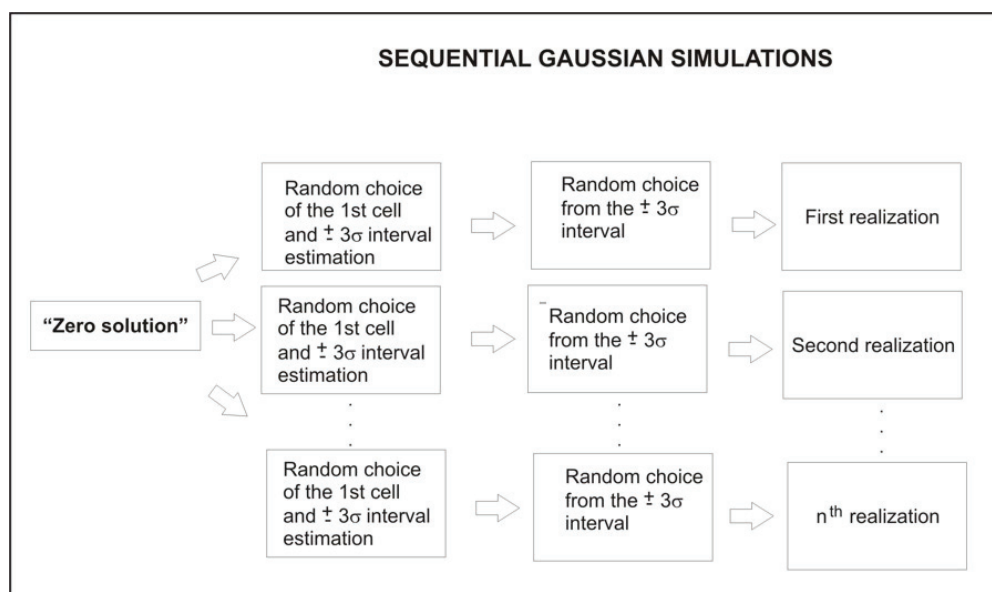


Figure 2. The process of Sequential Gaussian Simulations.

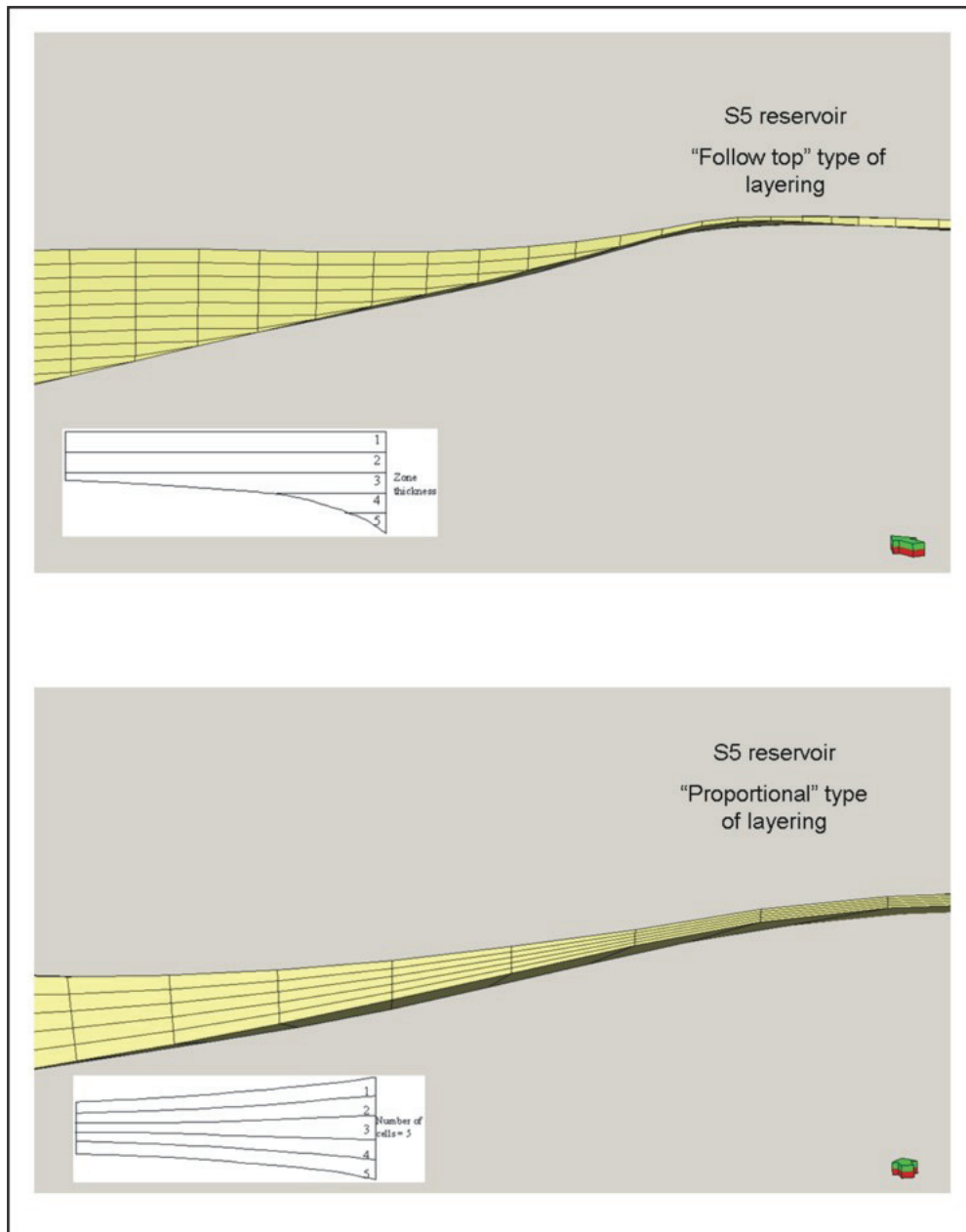


Figure 3. Two types of layering method; „Follow top” used for channel bodies, and „Proportional”, used for reservoirs with relatively uniform gross reservoir thickness (NOVAK ZELENKA et al., 2016).

4.2 Petrophysical modelling (porosity distribution)

Analysis of petrophysical parameters was performed using: (1) the old deterministic petrophysical log analyses of effective porosity and; (2) porosity measured on core samples. Cored wells and intervals, as well as wells with petrophysical log analysis are evenly distributed all over the field and are representative of the lithological and petrophysical parameters of the analysed Lower Pontian sandstone series.

After correction of core porosity for overburden pressure, depth correlation of log analyses and coring data was performed. In most cases smaller corrections were necessary (up to 5 m) during correlation of depth intervals (Figure 4).

Input data for porosity modelling included porosity measured on core samples as well as porosity resulting from deterministic petrophysical log analyses. A significant porosity mismatch has been observed (especially for porosity values from 0 to 15%)

when comparing core porosity data (corrected for overburden pressure and adjusted by depth) and the data obtained by petrophysical log analyses. The relationship between well log and core data is given by equation 3 and Figure 5:

$$y = 0.545x + 12.71 \quad (3)$$

Where:

- y = Overburden corrected core porosity
- x = Porosity from petrophysical log analysis

Generally, porosity obtained by the petrophysical log analysis was significantly underestimated (especially for the interval from 0 to 15%) compared to porosity measured on core samples under reservoir conditions. Quality control of acquired well log data and performed analysis showed that the available data set consisted mainly of old, low resolution Spontaneous Potential, Gamma ray and Resistivity data but lacked in measured porosity

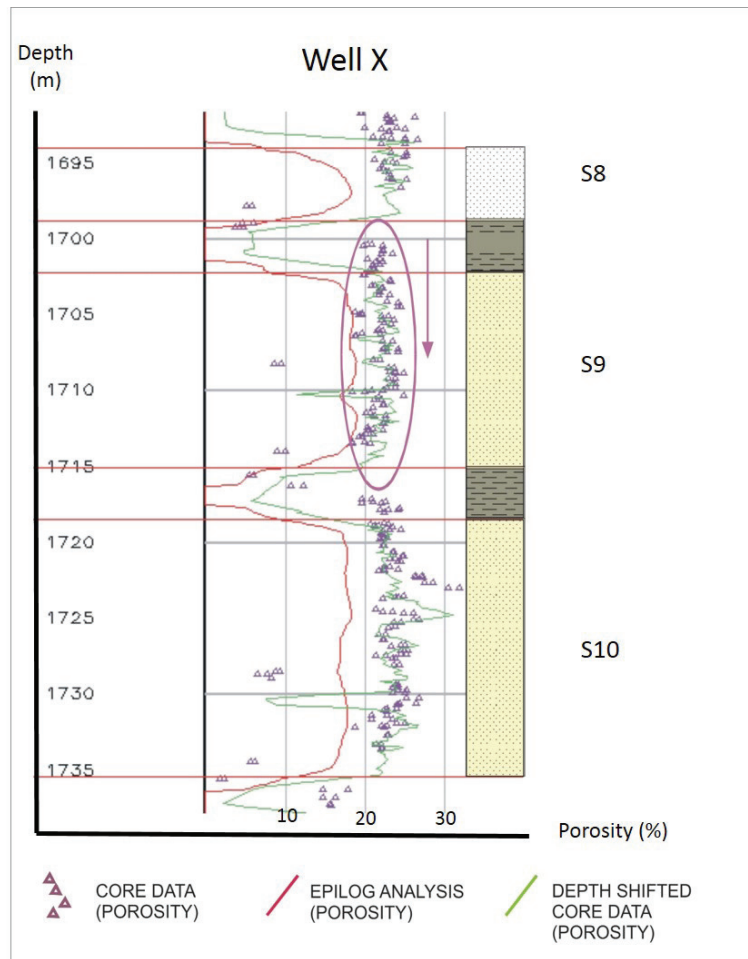


Figure 4. Depth shifting between the core and log effective porosities (NOVAK ZELENKA et al., 2016).

logs. The measured Spontaneous Potential represented the main input for deterministic calculation of effective porosity. Porosity measured on core samples obviously was not taken into account in the process of petrophysical log analysis. However, since the main scope of the case study presented here was the analysis of

different methods of petrophysical modelling and their influence on reservoir simulation results, no new petrophysical analyses were performed. Therefore, the mathematical relationship (eq.3) has been applied on porosity coming from petrophysical log analysis in order to obtain more reliable porosity data. The results are

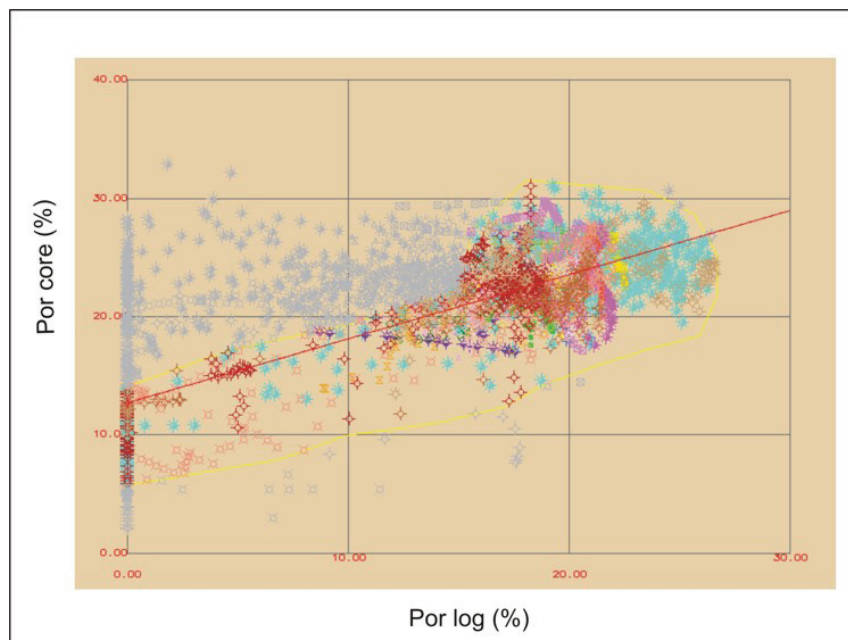


Figure 5. Cross plot diagram of porosity (core) vs. porosity (petrophysical analysis of well logs). Linear correlation was established.

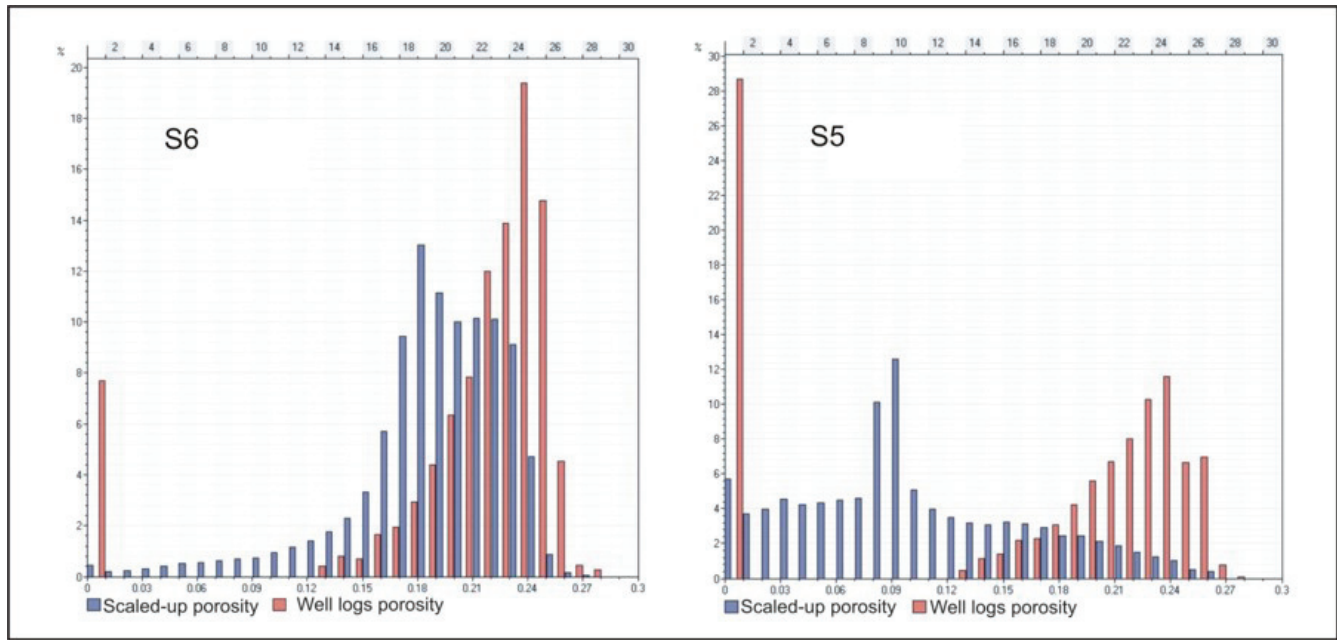


Figure 6. Original and upscaled porosity histograms, observe that the whole range of data between 0 and 12% porosity is missing in the input data as a consequence of the applied single linear mathematical relationship.

corrected porosity logs for all wells having porosity logs from quantitative log analysis.

Corrected porosity logs were then upscaled in the model representing the input for porosity modelling. Upscaling is a process of averaging input data in the model cells containing well data. In this way just one value is assigned to a cell. There are different upscaling methods, i.e. logs can be upscaled as minimum, maximum or arithmetic mean, and other properties can be also used to bias the estimated value. In the upscaling process of the study, the scale-up method was the arithmetic average. Original and upscaled corrected porosity were analysed using histogram plots for each reservoir separately as illustrated on Figure 6. for reservoirs S6 and S5. Quality control of corrected log porosity

values showed that the whole range of data between 0 and 12% porosity is missing as a consequence of the unique mathematical relationship applied. Moreover, there is an evident mismatch between the input data and upscaled data as a result of averaging in upscaling. For that reason, a new relationship between the log and core data using simple linear regression was established by two equations; one for the lower (eq. 4) and another one (eq. 3) for the higher porosity values (Figure 7.):

$$y = 1.6x \tag{4}$$

After applying the two different equations for the high and low porosity values, a quality check using histograms (Figure 8) showed that porosity values in the range from 0 to 12% were re-

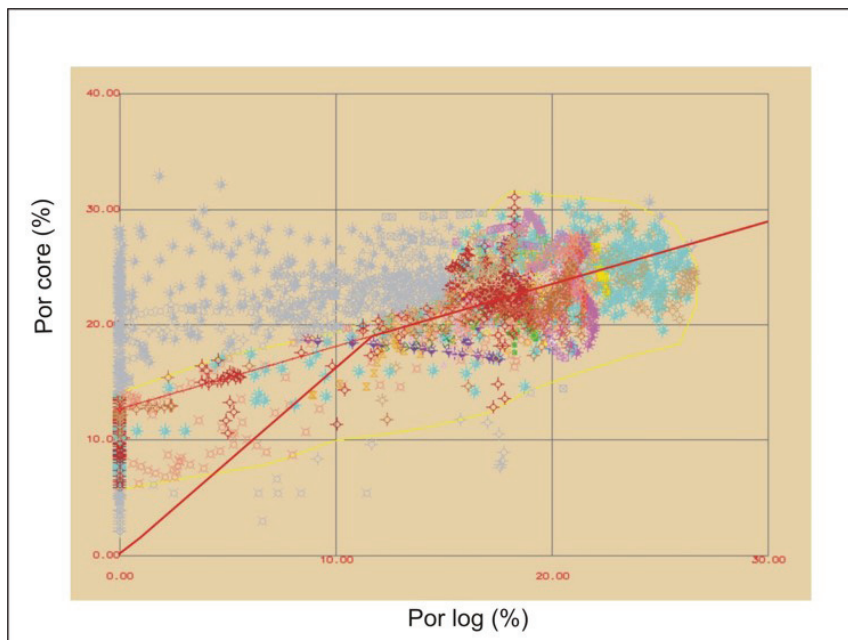


Figure 7. Cross plot diagram porosity (core) vs. porosity (petrophysical analysis) with linear relationships established separately for low and high porosity value intervals (NOVAK ZELENKA et al., 2016).

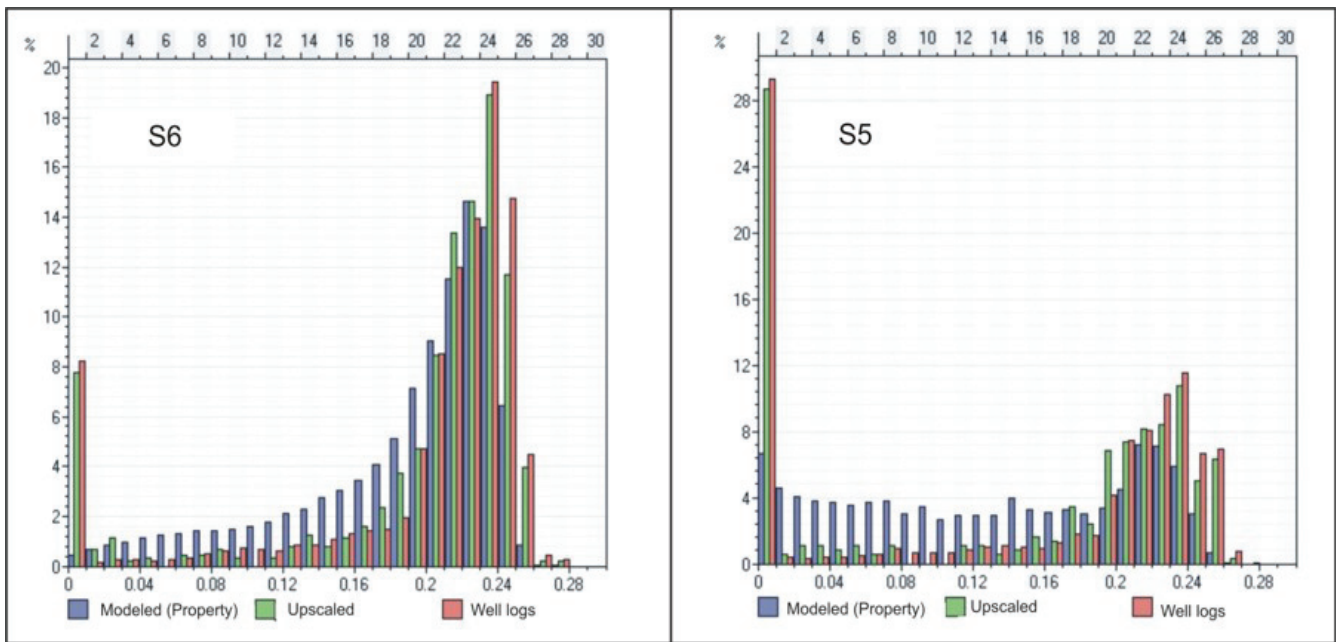


Figure 8. Histograms of porosity after applying the two equations.

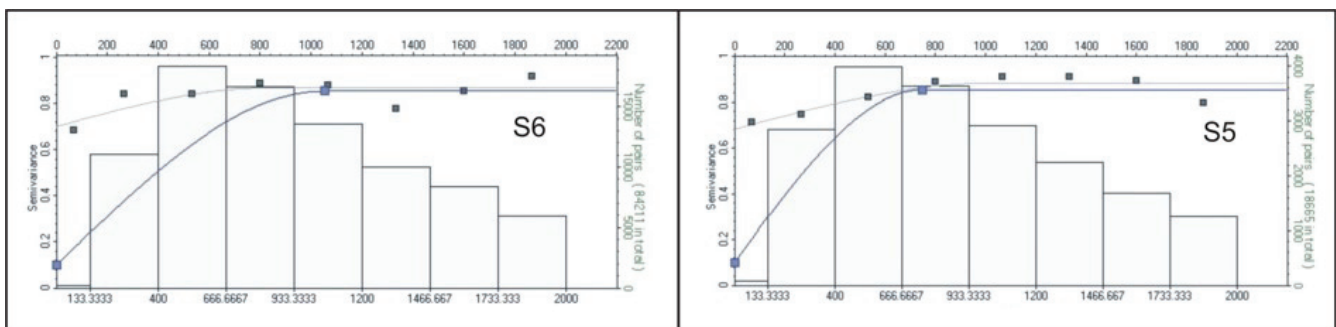


Figure 9. Variograms of porosity for the S6 and S5 reservoirs.

covered. Also, the match between the input corrected log porosity and upscaled values was considered satisfactory. Modelled, Ordinary Kriging distributed values showed lower values than the original data (Figure 8) because the mean and the variance of the Kriging estimates are considerably less than the true values. The mean values are lower because Kriging performs declustering of the original data and the variance is lower because of the smoothing effect of Kriging. The general trends are reproduced quite well (DEUTSCH & JOURNAL, 1997).

Before porosity distribution, data analysis was performed and variograms for each reservoir were calculated (Figure 9).

Different stochastic and deterministic methods of porosity distribution were examined.

In the first phase, 10 realizations of Sequential Gaussian Simulations (SGS) of porosity distribution were performed. Figure 10 shows two different realizations for the S6 and S5 reservoirs. Maps clearly show some areas with huge differences between estimated cell values in different realizations, for example the northern and north-western parts of the S6 reservoir and the eastern part of the S5 reservoir. These parts are areas with the highest uncertainty caused by a lack of well data. Large differences between the neighbouring cell values can be also very clearly observed in all realizations (Figure 10).

Due to the simulated values which were significantly different in neighbouring cells, problems occurred in fluid flow simu-

lation during dynamic modelling as proved by the sensitivity performed on required simulation time (Figure 11). Implementation of SGS modelled porosity resulted in unacceptable simulation durations of 12–16 hours for approximately 20 years of production history.

Finally, to avoid problems in numerical modelling, porosity has been distributed using the Ordinary Kriging method (Figure 12). A synthetic lithofacies log had been created based on porosity (if the porosity was higher than 11% the lithofacies log represents sandstones, otherwise it represents marls), and it had been used as a bias for porosity upscaling. The value of 11% of porosity was chosen based on correlation between porosity and permeability. 11% porosity matches a permeability of $1 \cdot 10^{-3} \mu\text{m}^2$, which was proved as the lowest permeability for oil production in the studied reservoirs. In this way input porosity data are weighted according to prevailing lithofacies. Porosity logs had been up-scaled using arithmetic average methods for each reservoir. A channel sandstone body (S5 reservoir) is clearly observed in the central part of the Ordinary Kriging map (Figure 12 right). It is clearly seen that the higher porosities are in the channel centre, while toward its borders porosity decreases. This could point to the existence of transitional lithofacies including sandy silts and silty sandstones. A smooth transition between neighbouring cells makes an Ordinary Kriging solution more acceptable in numerical modelling (Figure 13).

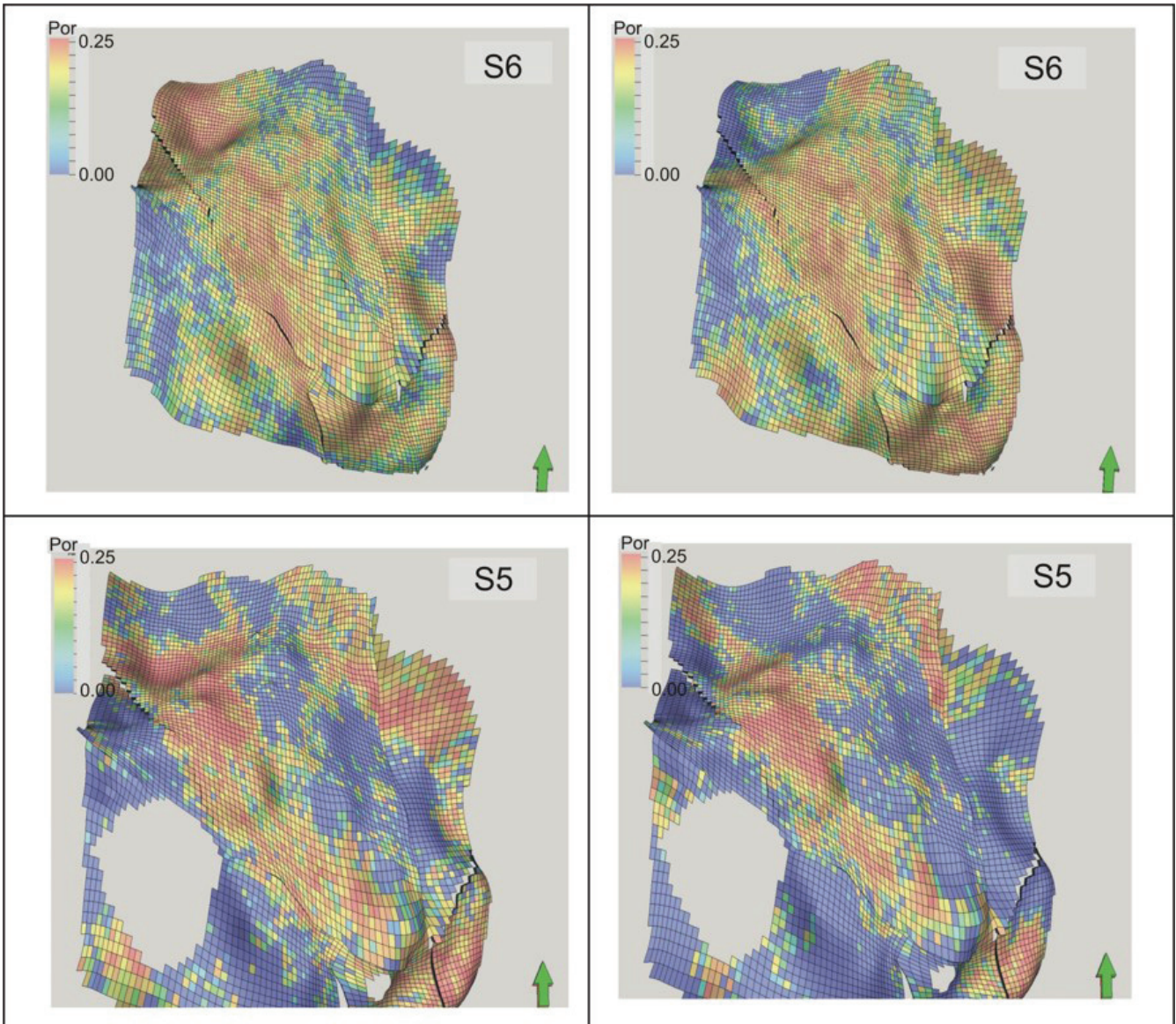


Figure 11. Illustration of simulation duration for different property model realizations (SGS realizations 1-5).

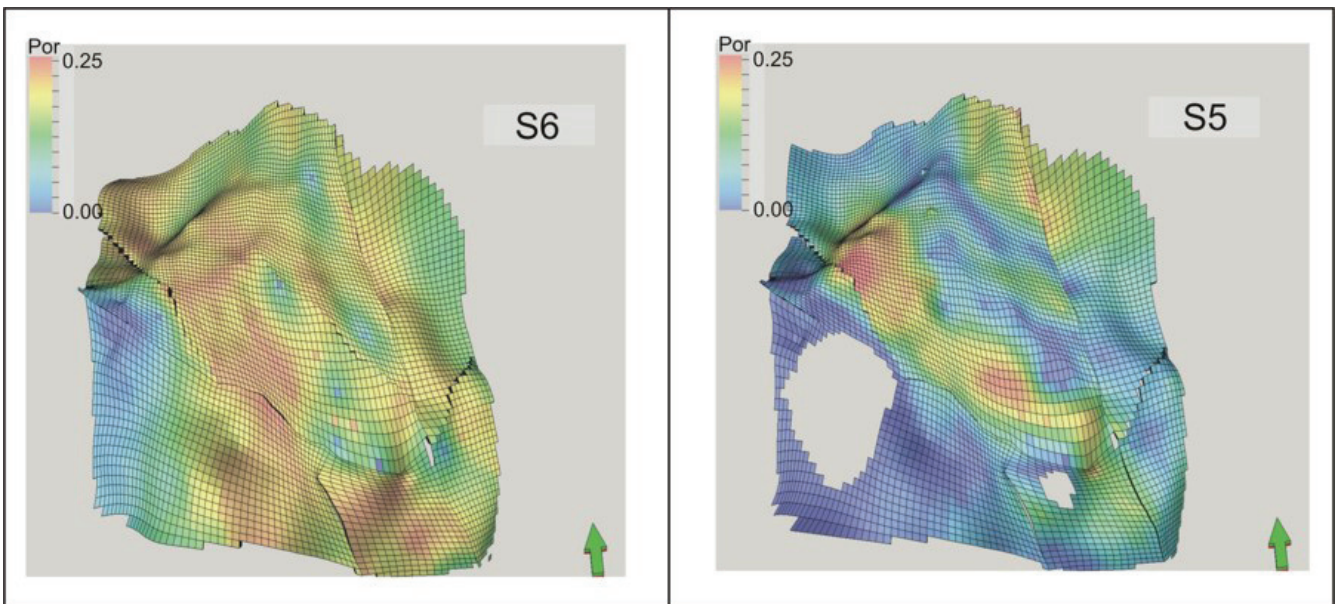


Figure 12. Porosity distribution obtained by Ordinary Kriging in S6 (widely distributed over the area) and S5 (channels) reservoirs.

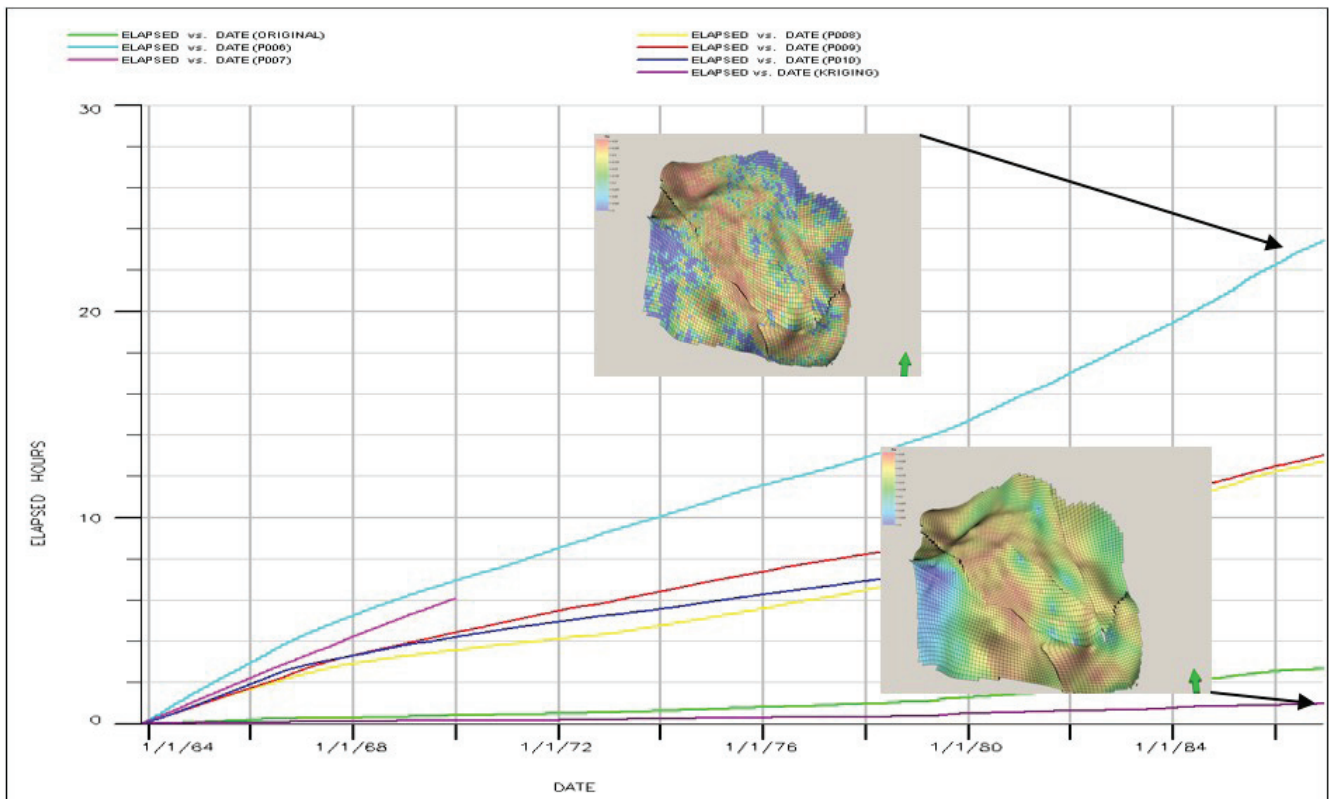


Figure 13. Simulation time (SGS realizations 1-5 and Kriging) (NOVAK ZELENIKA et al., 2016).

5. CONCLUSION

The analysed reservoirs, recently defined as Lower Pontian, consist of medium and fine-grained lithoarenites in continuous alternation with marls. Marl layers are not always continuous and in some parts of the reservoirs sandstone layers are in direct contact with each other.

The input data set used for geological model construction comprised well log data, quantitative log analysis (vintage data), core data and previous geological model. All these data have been integrated and analysed. A structural model was defined with 21 zones (11 sandstone reservoirs and 10 intercalated marl layers). Two different layering methods were applied; „Follow top“ for the reservoirs recognized as channel bodies with great lateral variability of thickness and „Proportional“ for all others that did not show the geometry of channel sandstones but rather laterally extensive layers over the study area. Corrections for overburden pressure and depth correlation of log analyses and coring data were performed. Relationships between log and core data were established by two equations; one for the low and the other for the high porosity values. After variogram analysis for each reservoir was undertaken, different stochastic and deterministic methods of porosity distribution were examined. 10 realizations of Sequential Gaussian Simulations were performed which enabled a clear insight into the reservoirs uncertainty. Areas with the highest uncertainty were caused by a lack of data. Realizations obtained by Sequential Gaussian Simulations had significant differences between neighbouring cell values. Consequences of such differences were many problems that occurred in numerical simulation, e.g. simulation time drastically increased. It can be concluded that well data alone are insufficient as an input for Sequential Gaussian Simulations as a reservoir property distribution method. Implementation of continuous data derived from 3D

seismic volume as an additional input would certainly improve the results. Porosity distribution obtained by Ordinary Kriging was more acceptable in numerical modelling, since the transition between neighbouring cells was very smooth and most probably better reflects the real geological picture. In the reservoirs recognized as channel bodies, higher porosities are located in the channel centre, while toward the channel margins porosities decrease. Higher porosity values could represent pure sandstones. Porosity decreasing towards the channel margins indicates sandstones with a more silty and marly component, i.e. to silty sandstones and sandy silts.

Dynamic simulation must match former production history as well as future production prediction. Taking into account that the geological model represents the main input for numerical simulation of fluid flow, it is important that it fulfils the requirements of dynamic modelling process. One of these requirements is a reasonable simulation time. The study showed that selection of the reservoir property distribution methods have a significant influence on the applicability of the geological model in dynamic modelling.

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