Geosciences and Engineering, Vol. 10, No. 15 (2022), pp. 96–109.
https://doi.org/10.33030/geosciences.2022.15.096

IMPROVEMENT OF SEISMIC SECTIONS AND WELL LOGS FOR JOINT GEOPHYSICAL INTERPRETATION

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Abstract: Seismic and well-logging data are useful for comparison and then integratation for a comprehensive geophysical interpretation. In the course of this work, seismic results were compared with well-logging geophysical data and profiles for more reliable evaluation of groundwater formations in the Tokaj region, north-east Hungary. The seismic results and profiles were obtained by the Common Reflection Surface (CRS) stacking technique. This is an advantageous stacking technique that is expected to greatly improve seismic profiles. In connection with this, we also examined some well-logging geophysical profiles so that we can improve later results. By comparing and examining the two types of sections together, we provide a basis for various method developments that improve the sections. Thus, the aim is to fill in the missing data, so that the well-logging and seismic sections can be examined together as accurately as possible in order to gain a more accurate picture of the subsurface formations. It is important to determine the lithology and petrophysical characteristics using well logs. The section replacement – the improvement of the units – is done using machine learning-based and inversion methods such as factor analysis or cluster analysis. An important outcome in the application of geophysical inversion methods is that the results of different methods can be jointly interpreted and this can significantly increase the reliability of the results. The application of these methods and their development is expected to reduce uncertainty and ambiguity and to increase the accuracy of the sections.

Keywords: *seismic, well-logging, hydrocarbon, inversion, factor analysis*

1. INTRODUCTION

In order to gain knowledge of the information obtained during seismic and well-logging geophysical measurements, data processing must be carried out, and thus sections must be created that are suitable for identifying the underground formations. In general, both seismic and well-logging geophysical sections are very rich in information but there is currently no machine learning-based or inversion procedure to improve the data obtained from the sections. This study aims to give an overview about some modern procedures to enhance the seismic and well-logging data before joint interpretation like machine learning and inversion methods. We focus on examples from the literature; however, we intend to implement the demonstrated procedures on real datasets in the very near future. Although seismic results have been compared with well-logging geophysical data and profiles in terms of more reliable assessment of groundwater formations in North-Eastern Hungary, this paper shows that the common geophysical interpretation is very effective for hydrocarbon reservoirs and we want to highlight that fact.

Methods based on inversion and machine learning can improve sections obtained from structurally ambiguous formations such as complex hydrocarbon storage formations. In the case of these methods, in oilfield applications, it is important to properly interpret the in situ well-logging data, as they provide the basis for the hydrocarbon reserve calculations. In the case of hydrocarbon reservoirs, we usually speak of a complex geological environment [1]. We talk about complex hydrocarbon reservoirs when they consist of several minerals and multiple problems may occur during their exploration. One such problem is that in the case of such reservoirs, the measurements are usually noisier and the noise greatly degrades the quality of the sections. The petrological and petrophysical properties of the formations, such as porosity, may be more complex due to their mineral content, so there are different types of porosity and permeability [2].

There are several phases of research in hydrocarbon basins with diverse structural styles. The final phase is usually the investigation of hydrocarbon deposits accumulated in layer traps independent of structural elements. These are also called hidden traps. In industrial practice, the breakthrough was introduction of the AVO-based (Amplitude Versus Offset) Direct Hydrocarbon Indicators (DHI) and attribute tests for evaluating seismic data. A complex tectonic and hydrocarbon geological situation threatens these traps during re-investigation. The mapping of traps is also a problem in complex geological environments, as detecting them faces significant complications even with the now advanced seismic methods [3].

In hydrocarbon exploration, relatively expensive measurements are made to increase the likelihood of finding an economically valuable oil or gas field [4], so it is advisable to improve the seismic and well-logging sections in such a way that the layer traps or storage can be detected with the greatest possible efficiency and with the least possible risk.

Due to the constant demand for hydrocarbons that still exists today, many technologies and studies are being prepared for the distribution, accumulation, assessment and exploitation of resources. That is why nowadays the petroleum industry is not only trying to research conventional reservoirs. Non-conventional reservoirs are reservoirs that are generally provided by methods that go beyond the known conventional extraction of hydrocarbons; thus, their exploitation is a very difficult task. These non-average formations belong to oil and gas sources where industrial productivity is only possible by changing the permeability or fluidity of the rock [5].

2. SEISMIC SECTIONS AND WELL LOGS

The primary objective of this study is to improve the subsurface image of the layer of geophysical sections using combined seismic and well log data. These stratigraphic parameters are the correlated multi-well datasets, tied well-logging data for seismic data, detailed seismic and well log facies interpretation, sediment identification delimitation of formations, their thickness and lateral changes, derivation of the deposition environments of the formations, and seismic characterization of the subsurface identification of lineaments between different combined applications data types. The main advantage of integrated data analysis is that it provides a more detailed subsurface analysis that intended to increases the reliability of geological inter-pretations [6].

There are several data processing methods available today, but not all of them give a sufficiently accurate picture of subsurface formations and strata boundaries. However, there is a relatively new method that improves profile images with great efficiency. This method is the common reflection surface (CRS) stacking procedure. Seismic sections obtained by CRS processing result in more coherent reflection signals due to increased coherence values. Since the method does not process a single point but an elementary, stacking surface, we can calculate all the reflection points on a given surface, even on curved surfaces. Lateral displacements occur during any processing, but this procedure works without losing lateral resolution [7]. Velocity analysis is very important in all seismic data processing methods, including the CRS method. It affects the quality of the accumulated data and can lead to an unacceptable image that is not very suitable for geological interpretation, so the method requires a more reliable velocity field that can be generated using the CRS method [8]. In contrast with the conventional seismic data processing method [Common Depth Point (CDP) method; *Figure 1*], in the case of the CRS method, the individual sections are very rich in information, so many conclusions can be drawn from them. With the CRS method, the sections and images have been improved in several aspects [8]. Higher signal-to-noise ratio is available, which is based on reflector continuity and noise reduction [9]. The images are clearer because of the better reflection events. This means the reflections are smooth and even, not confusing and fluctuating, the layers are easier to detect and separate. Thus, the seismic sections measured on the surface, the boundaries of the different types of rock bodies, and the traces of the faults and fractures are outlined [8]. The faults play a key role in trapping of hydrocarbons [10]. The CRS seismic method can produce a reliable image of a complex geological structure like complex hydrocarbon reservoirs or marine environments [7, 9]. The aim of hydrocarbon exploration is to identifyand delimit economically exploitable, accumulative structural and stratified traps. These traps can be very fine, complex, and therefore difficult to map accurately [11]. As shown in *Figure 2*, in the case of Miocene or substrate reservoir exploration, seismic mapping of complex structures can be refined by the CRS stacking technique, which facilitates the comparison of logs and seismic data.

Well log and seismic data are widely used in the petroleum industry and exploration to map the subsurface so it is important to improve the quality of these sections [11]. Because the multifocusing method is also suitable for mapping complex structures, it is also used with great efficiency in complex hydrocarbon research. The effectiveness of this method has been proven by Kiss and Takács [12], near to the town of Tokaj, among others.

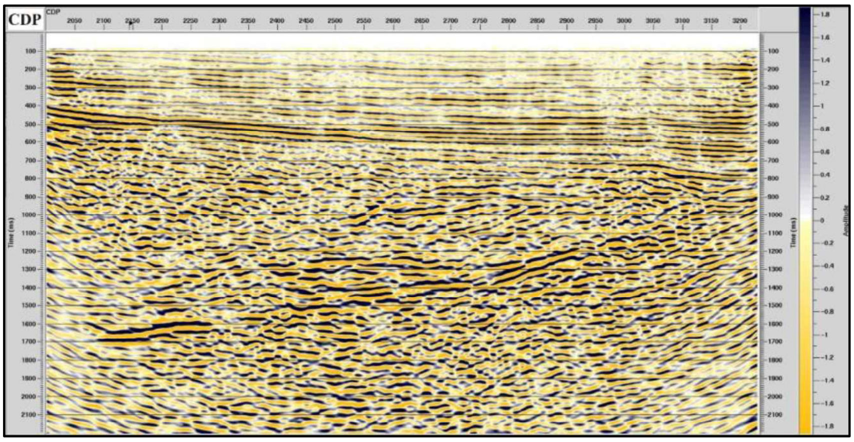

Figure 1

A migrated Common Depth Point stack in the Tokaj area: the x-axis shows the shot points in 50-meter increments, the y-axis shows the time in ms [12]

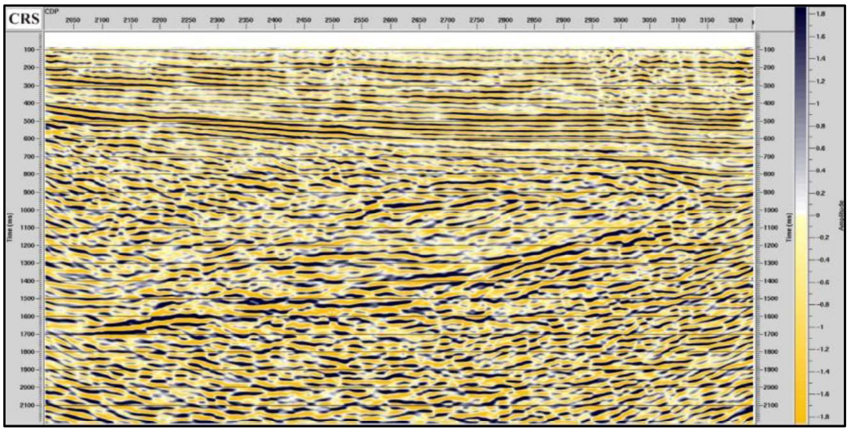

Figure 2

A migrated Common Reflection Surface stack in the Tokaj area: the x-axis shows the shot points in 50-meter increments, the y-axis shows the time in ms [12].

Seismic and well log data sources complemented each other [11]. The combined analysis of seismic and well-logging geophysical data also aids in geological-structural and petrophysical interpretation. To do this, the logs must be inserted into nearby seismic profiles [13]. Seismic profiles provide an almost continuous side view (lateral resolution) below the surface, while the well logs, which are measured with depth, provide a detailed vertical resolution of the geology of the surrounding formations in the vicinity of boreholes [11, 10, 14]. The resolution of well-logging geophysical sections *(Figure 3)* is usually 10-20 cm, much finer than that of seismic data, which is approximately 10-20 m [13].

Seismic profiles are surface seismic data measured in units of time, and can resolve structural and stratigraphic changes that vary beyond the locations of the wells from the arrival time and amplitudes of reflection events with high accuracy [11, 14]. The bandwidth of the seismic data limits the subsurface vertical resolution. High-frequency data are essential to delineate fine hydrocarbon traps. Well logs can be useful in both respects in interpreting seismic profiles. In contrast to seismic sections, they can clearly provide a high-resolution estimate of a number of relevant geological variables during drilling [11]. The number of applicable methods and rock physics parameters is much larger, consequently the mapping of rock layer properties is much more detailed, but well-logging geophysical measurements provide only local information about the studied rocks and raw material reserves, while seismic sections allow lateral extension [13]. The well-to-seismic tie may indicates that the hydrocarbon bearing reservoir is associated with direct hydrocarbon indicators on the seismic sections [11].

The interpretation procedure encompasses the integration of well logs with seismic data, seismic structural analysis, petrophysical analysis, and seismic attributes analysis [10]. For all these reasons, the integration of well logs and seismic data would provide a higher degree of reliability in the mapping of subsurface structural and stratigraphic objects, thus making subsurface understanding much clearer, and these play an important role in the modeling and development of an underground (hydrocarbon) reservoir [11, 14]. Thus, the integration process can also provide insight into the reservoir's hydrocarbon volume, which can be used in exploratory assessments and well planning [11].

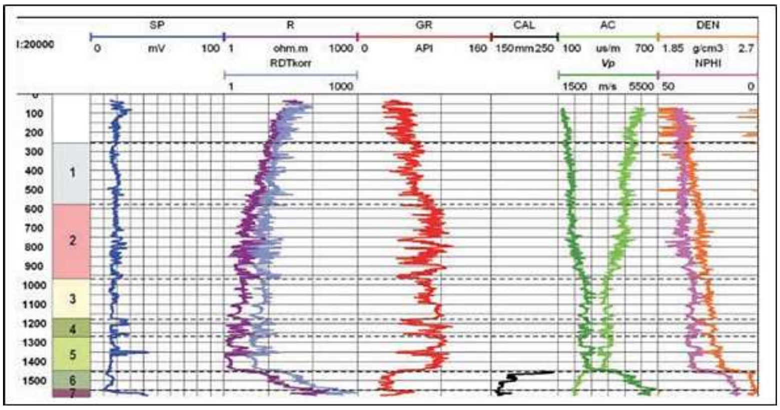

Figure 3

Geophysical well logs of the Magyardombegyház Domb. SW–6 well [15]
Legend: SP: spontaneous potential, R, RDT: electrical resistivity; GR: natural gamma-ray; CAL: caliper log; AC: acoustic profile; Vp: acoustic velocity; DEN: density; NPHI: neutronporosity log. Geological column: 1. Nagyalföld Fm (Upper Pannonian), 2. Zagyva and Újfalu Fm (Upper Pannonian), 3. Algyő Fm (Lower Pannonian), 4. Szolnok Fm (Lower Pannonian), 5. Endrőd Fm (LowerPannonian), 6. Endrőd Fm Tótkomlós Calcareous Marl Member (Lower Pannonian), 7. Variscan basement

3. THE INVERSION PROCEDURE

We need to apply method development to improve geophysical sections. It is generally accepted that the geophysical sections of the well log can be improved by inversion methods. Local inversion is one of the most commonly used techniques for the evaluation of borehole geophysical data [16]. The inverse problem, as its name suggests, is actually the inverse of the direct problem. The flow chart of the inversion procedure is described in *Figure 4*. We have some measured data and *a priori* knowledge and the first step is to define the parameters of the models – this is the direct task. We create the model and we predict the theoretical data from it. Then we compare the measured and calculated data; if the agreement is acceptable we accept the model parameters. If it is not, we have to refine the model until it is acceptable. Inversion methods rely on solving direct problems, so this gives the relationship between the calculated data and the model. It follows that the inverse problem is based on the assumption that there is a correlation between the calculated data and the parameters of the model, so that the model can be created based on this. During the inversion, it can be generally said that the number of measured data points and the number of model parameters do not match, and some norm of the differences between measured and calculated data is minimized [17].

There are both linear and nonlinear inverse problems. If an inverse problem is initially nonlinear, then the result is created by solving linear problems. Errors can be encountered in most geophysical interpretations. These can be either natural or artificial defects. Inversion procedures can be loaded with errors that are either data errors or model errors. Data errors result from measurement conditions, are proportional to the estimated model parameters, and are also errors. Modeling errors can also be encountered. For all these reasons, the precise development of inversion procedures is very important [17]. However, this method has some drawbacks. Measurement data can be noisy and in addition to this noise, the approximate choice of zone parameters also provides additional uncertainty in the result of inversion evaluation. It can also be said that the method is limited by the inversion evaluation per depth point, thus the number of identifiable unknowns is also limited [18]. Layer boundary or thin layer effects can skew the inversion results. At the same time, we can get a finer picture of the changes within the layer [13].

In addition to a number of disadvantages of the method, such as limiting the accuracy and reliability of the estimate, the method also has advantages such as high speed and good vertical resolution. Another disadvantage is that the local inversion method does not support the determination of formation thicknesses. For evaluation, it is advantageous to collect a complete dataset over a longer depth interval. A dataset also contains information on the boundaries of the formation that can be extracted by a particular inversion method, which is the so-called interval inversion method. This method allows the determination of layer boundary coordinates (or layer thicknesses) within the inversion procedure [16].

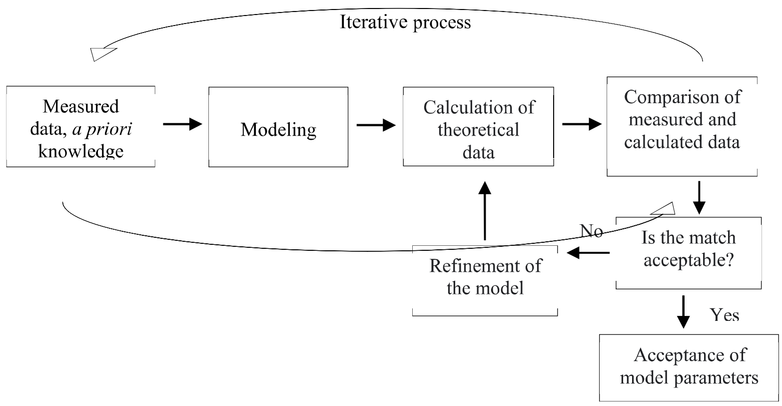

Figure 4
Simple flowchart of the inversion procedure

In well-logging geophysical exploration, we often encounter the problem of inversion. The quantities in the response functions of the probe can be divided into two groups. The first group includes the so-called zone parameters, which are either constant or change slowly over a longer depth. The second group consists of the layer parameters, which are almost constant in each layer. One of the positive features of the inversion technique is that it is also capable of joint inversion. In geophysical inversion, joint inversion means data measured by two or more different geophysical methods or by the same method, but in a substantially different measurement arrangement, by the same inversion method. The more frequently the parameters of the geological structure appear in the definition of the different datasets, the more successful the solution to the inverse problem can be [1].

As a next step, we would like to present a meta-algorithm-based inversion procedure that can simultaneously determine volume-specific petrophysical quantities and zonal parameters [18]. There may be local problems during the procedure. To avoid these, we can use a global optimization method, such as the Genetic Algorithm (GA), which looks for the absolute extreme point of the objective function and whose flowchart is shown in *Figure 5*. GA belongs to the class of evolutionary algorithms that solve optimization problems. Today, the most popular version is Float-Encoded GA, which improves the model population described by the model parameters in an iteration process [4]. In the first step of the method, an initial model is created and then the values of the zone parameters are determined by random search based on a real coded genetic algorithm (FGA). Then, with the fixed values of the newly obtained zone parameters, a series of depth-by-point inversion procedures is performed to calculate the volume-characteristic quantities [18].

The inversion strategy described above has a positive effect on solving the inverse problem. The method can be effectively used to determine the petrophysical properties of near-surface loose sediments. The application of the method ensures the best fit of the measured and calculated profile data [18]. An important indicator of the method is that each individual in the population has a fitness value that indicates its ability to survive. Those with a high fitness value will be the most suitable individuals in the genetic process and will reproduce more successfully in future generations than those who have low fitness values. To achieve the best solution, fitness function is maximized using genetic operations in a random optimum search procedure. For a well-logging inverse problem, a petrophysical model has a large misfit if there is little fit between the observed and calculated data. An appropriate combination of genetic operators, such as selection, crossing, mutation, and reproduction, is used to achieve the absolute maximum of fitness function [4].

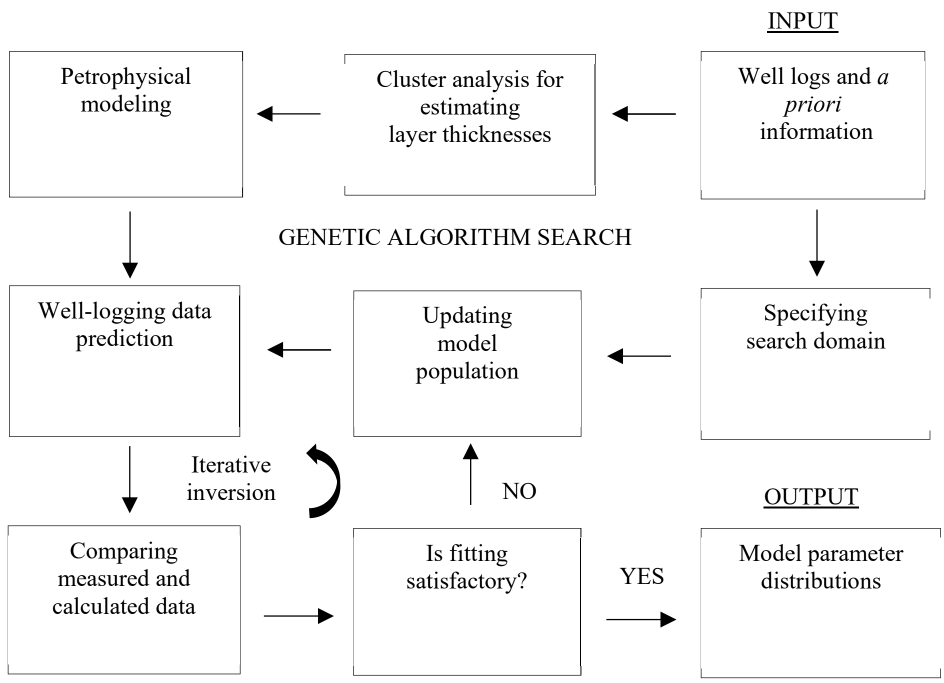

Figure 5
Workflow of the GA-based inversion procedure

As a next step, we present some artificial intelligence-based methods for improving geophysical profiles. The essence of machine learning is to create algorithms that can improve their own efficiency by utilizing the experience that they have gained during the process (for example in artificial intelligence networks). We can divide machine learning methods into three main groups. Without wishing to be exhaustive, the very first group, which is also the most commonly used, is based on supervised learning, including regression analysis and classifications. The second group is non-supervised learning, such as factor analysis and principal component analysis. The last category of machine learning methods is the semi-supervised approach, a combination of the first two groups [19].

In this study, we found the method of factor analysis to be the most expedient to develop. Factor analysis is a multivariate statistical method that involves reducing a large dataset to a relatively smaller number of factors by finding a correlation between the observed variables. By reducing the dimension of variability, we are also able to explore the unobserved properties of the rock that are responsible for the log responses of the observed well [5]. One of the advantages of this method is that it processes all the data in the segmentation interval together and can be used in several dimensions. Petrophysical information from an independent source increases the overdetermination of the inverse problem, which means that it reduces the degree of estimation error and the possible ambiguity of the petrophysical parameters involved in the problem [20].

Factor analysis is also aided by methods of artificial intelligence, such as the differential genetics algorithm-based approach or iteratively re-weighted factor analysis for a more robust estimation of factors and related petrophysical parameters. The well logs extracted by this procedure correlate with the dataset variables. In this case, the extracted factors help to derive the shale volume of the formations [5]. Estimated shale volume values made by the above factor analysis closely fit the values calculated from the commonly used Larionov formula, which confirms the validity of the nonlinear approximation [21], as we seen in *Figure 6*.

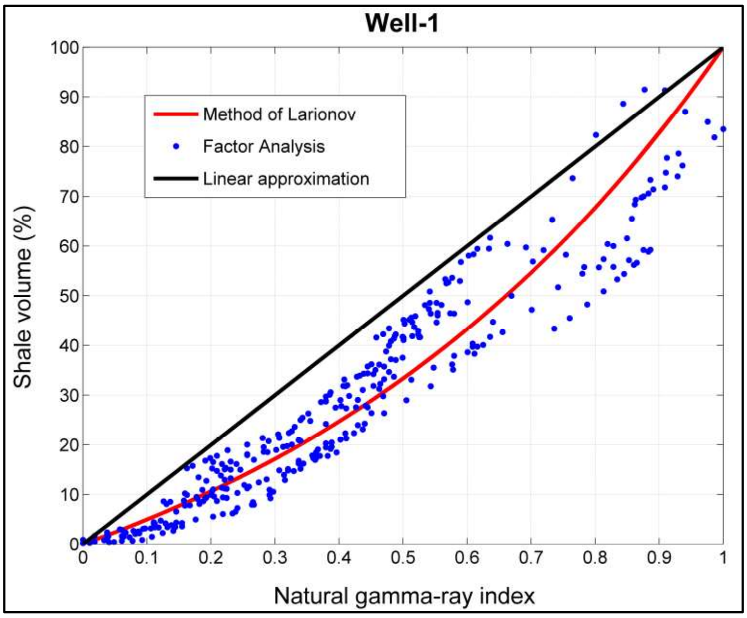

Figure 6

Representation of shale volume as a function of natural gamma-ray index in the Tokaj region [23]

The first factor profile formed from well-logging geophysical sections correlates strongly with the clay content of the reservoirs, so the first factor empirical relationship was established for the estimation of shale volume; from this, lithological units can be well distinguished [5, 20]. The first factor is a good shale indicator. Interpreting these together helps to quantify well logs [5]. The close relationship between the first factor and the clay content can also be well demonstrated in the water storage sections of hydrocarbon exploration wells [18]. Shale volume information given by factor analysis can also be used to reduce the number of unknowns of the well-logging inverse problem. Moreover, it can also be applied to resolve the ambiguity existing between parameters of the geophysical model [22].

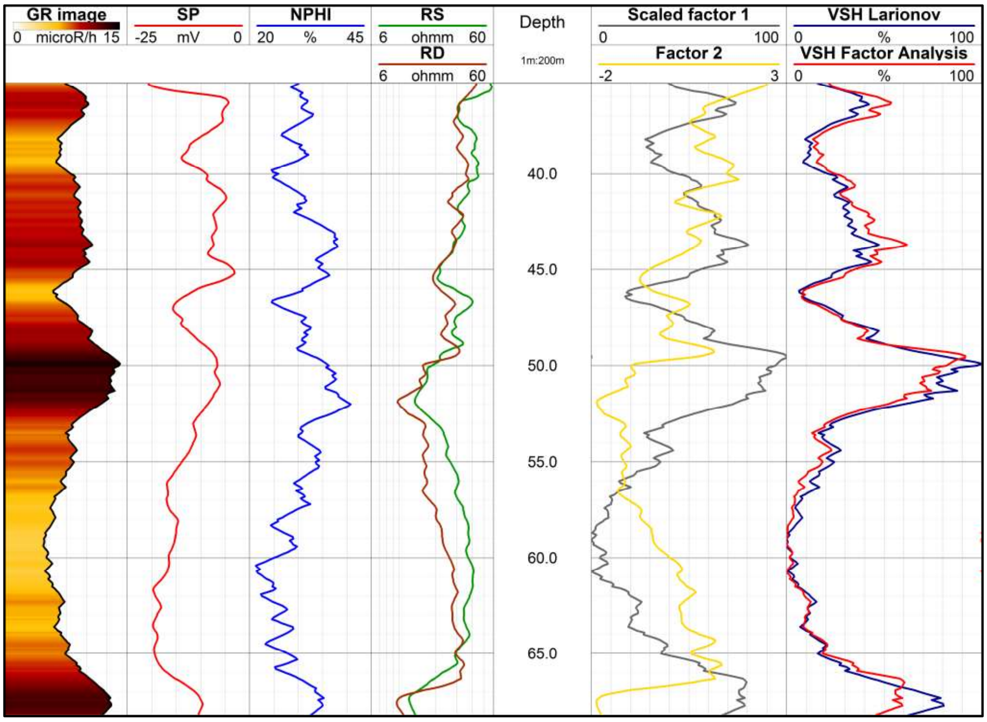

Figure 7

Results of factor analysis plotted on a well-logging section in the Tokaj region: GR – gamma ray, SP – spontaneous potential, NPHI – neutron porosity, RS – shallow resistivity, RD – deep resistivity

Not only seismic but also logging profiles were made in the Tokaj area from the data using factor analysis. An example of factor analysis of well logs can be seen in *Figure 7*. Thus, based on the two seismic sections, it can be said in general that the Tokaj region is a sediment collector. Several sedimentation cycles can be discovered on the sections made in this area. Geologically, the area is 70–80% sand, which is interrupted by intermediate clays. The settlement of mud and silt can be observed in several layers. It can also be said in general that granular layers of quartz material are located below the cover layer. Rhyolite tuff can also be observed in the area, such as signs of andesite volcanism. Over time, a system of fractures has developed here, which has divided the mountain into blocks, thus creating a stepped structure of the bedrock. There was once a subsidence along these fractures. Then the wind-blowing of the sediments accumulated here, creating the loess cover typical of the area. Typically, a higher-resistance granular layer of quartz material is placed under the clay, with a low geoelectric resistance, followed again by a low-resistance bed or intermediate layer. The decrease in resistance in some places on the log sections corresponds to the clay layer that appears [23].

Fragmentation led to the formation of faults, which the seismic profiles (*Figure 1* and *2*) illustrate nicely. The seismic profile also indicates the pre-Cenozoic basement. The layers in the deepest position have a small amplitude, so sandy layers are unlikely to appear there. Both seismic and well-logging geophysical research has shown that the geological structure of the area begins with the Miocene and that the onset of volcanism can be traced back to this period. According to the interpretation of the seismic profile, the volcanism in the area was cyclical, just like in the case of sediment formation. Based on the two seismic profiles, the Upper Pannonian sedimentary assemblage settles on the Miocene sequence. Layer thicknesses can be determined on well-logging geophysical sections, and layer boundaries can be specified in combination with seismic sections. In well-log sections, the layer content can be determined with the help of core data, such as a clayey or sand layer, and in seismic sections, not only the vertical but also the lateral extent can be defined.

In the case of seismic exploration, the seismic waves return from different media at different times, so if we know the different layer contents from the well-logging data, it is easier to interpret them. Thus, from the point of view of geophysical models, it is very advantageous to investigate them together.

4. CONCLUSIONS

The aim of the study is to summarize the interpretation of seismic and well-logging geophysical sections. This can be achieved by developing different geophysical methods. The combined interpretation of well-logging data and seismic measurement results can effectively reduce the (short-term) geological risk of the exploration phase, so the geological model developed with their help can significantly contribute to the success of raw material production. The greatest uncertainty is the delimitation of the individual geological formations and the determination of their petrophysical state. Seismic measurements have a positive effect on reducing geological uncertainty [24]. Methods based on machine learning and inversion methods greatly improve the accuracy of the sum profiles and the combined interpretation of well-logged and seismic profiles. The growing demand of the oil industry for highly reliable petrophysical information requires advanced data processing techniques [4].

To achieve a good and unique solution, prior geological and geophysical information must be built-in by the user properly. Moreover, in case of the global optimization phase (GA), some experience is needed to set the combination and control parameters of genetic operators and to decide when it is possible to switch over to linear optimization. The optimal set of basis functions depends on the variation of lithology and pore fluids along a borehole. To increase the overdetermination of the inverse problem, it is important to search for parameters that can be fixed during the inversion procedure. This can reduce the uncertainty and ambiguity of inversion estimates [4]. With these procedures, seismic and well-logging sections can be improved in a number of ways.

Because of the joint interpretation of the seismic and well-logging profiles, geological formations can be better interpreted. In the examples shown, the coherency of the Pannonian sediments made possible a more precise mapping between the Mesozoic sedimentary and volcanic formations. The possible boundary and internal structure of the volcano can also be observed. The top of the pre-Cenozoic basement became more coherent due to the joint interpretation.

FURTHER OBJECTIVES

In addition to the development of machine learning methods on well logs, later plans include jointly interpreting borehole geophysical and seismic data using AVO analysis, which will allow for the spatial extension of information on possible strata content along the seismic profile.

ACKNOWLEDGMENTS

We would like to thank the Department of Geophysics of the University of Miskolc for the creation of the infrastructural background, the Mining and Geological Survey of Hungary for its support, and Háromkő Geological and Geophysical Research Bt. for the data.

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