METHOD OF COMPLEX INTERPRETATION OF SPECTRAL DECOMPOSITION FOR SEISMIC FACIES ANALYSIS AND PARAMETRIZATION OF LITHOLOGICAL TRAPS

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ABSTRACT

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The study aims at creating a method for complex interpretation of spectral decomposition for seismic facies analysis, parametrization of potential lithological traps, prediction of effective reservoir thicknesses in the inter-well space and risk reduction in the assessment of reserves and resources. The method of spectral decomposition using the Wavelet transform was applied during the research. This method of seismic route decomposition was used as part of the proposed methodology. Many clustering methods from the Sklern Python library were used. The study placed a premium on the KMeans methods. Correlation analysis and qualitative interpretation of the obtained seismic images were used to link geological and seismic information. The developed method of sorting the centres of spectral curves clusters allowed a joint analysis of wells data and clustering results. The developed approach was applied to comprehensively study the paleochannel systems of the West Siberian, Timan-Pechora and Volga-Ural oil and gas provinces. The advantages of the proposed technology over attribute analysis, spectral characteristics analysis and RGB blending were proved by comparing the deposits of the above-mentioned provinces. Various geological objects in the wavefield were identified using qualitative interpretation and then linked with wells data. This technology proved to be the best when using quantitative interpretation. High correlation coefficients between the effective thicknesses in wells and the results of spectral curves clustering were obtained.

KEY WORDS: 3D seismic measurements, dynamic interpretation, RGB Blending, spectral decomposition, clustering of amplitude-frequency spectra, terrigenous deposits.

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INTRODUCTION

The current state of the hydrocarbon deposits resource base poses new challenges to the oil industry. The deposits with thinner reservoirs and high lateral and vertical heterogeneity require a higher technological level of each stage of exploration and production of hydrocarbons (HC). Seismic measurements are an integral part of the geological survey. However, there are new challenges when forecasting properties in the interwell space. The existing dynamic analysis methods have some engineering constraints and do not fully solve the set geological tasks. Advanced methods of attribute seismic analysis, spectral decomposition, dynamic analysis algorithms open up new opportunities for qualitative and quantitative interpretation of seismic data, thus, allowing the discovery and development of more complex deposits. A new method of complex analysis of the spectral decomposition results has been developed when seeking a new approach for predicting effective thicknesses based on seismic data. The new method is based on the clustering of the target interval by the amplitude-frequency spectrum form followed by cluster sorting.

Literature review

According to numerous studies, various spectral decomposition techniques have been successfully applied at most deposits worldwide (Al-Maghlouth et al., 2017; Hamerli et al., 2019; Xiang et al., 2021; Yuan et al., 2019; Zhang et al., 2017). Many studies and publications devoted to this topic confirm the increasing popularity of spectral decomposition. Castagna and Sun (2006), Chakraborty and Okaya (1995), Chopra and Marfurt (2015), Dewett et al. (2021), Partyka et al. (1999), and many other scientists have recently changed their research direction from attribute analysis to the study of algorithms and spectral decomposition application. Spectral decomposition allows the interpreter to identify the well-known from the theory effects of the seismic signal peak frequency dependence on the time power of a thin layer. Thus, the interpreter can control the behaviour of thin reservoir layers with a power of less than 1/4 of the seismic wavelength. In Western literature, this phenomenon is called the tuning effect by Cooke et al. (2014), Meza et al. (2018), Partyka et al. (1999), and the reservoir time thickness where this effect is observed is called tuning thickness.

The spectral decomposition results depend on the method chosen to decompose the initial data into individual frequencies. Many decomposition methods have appeared since the beginning of spectral decomposition development. One of the first decomposition methods was the Short Term Fourier Transform (*STFT*). This method involves the calculation of the time-frequency spectrum using the Fourier transform in the selected time window. According to this method, the time-frequency solution is determined by the length of the selected window. As a result, the resolution will strongly depend on the length of the window selected by the interpreter (Butorin, 2016). Fig. 1 shows the problem of window selection when using the Fourier transform. The figure analysis allows concluding that it is impossible to estimate the low frequency in a short window correctly - moreover, the wider the window, the lower the detail level.

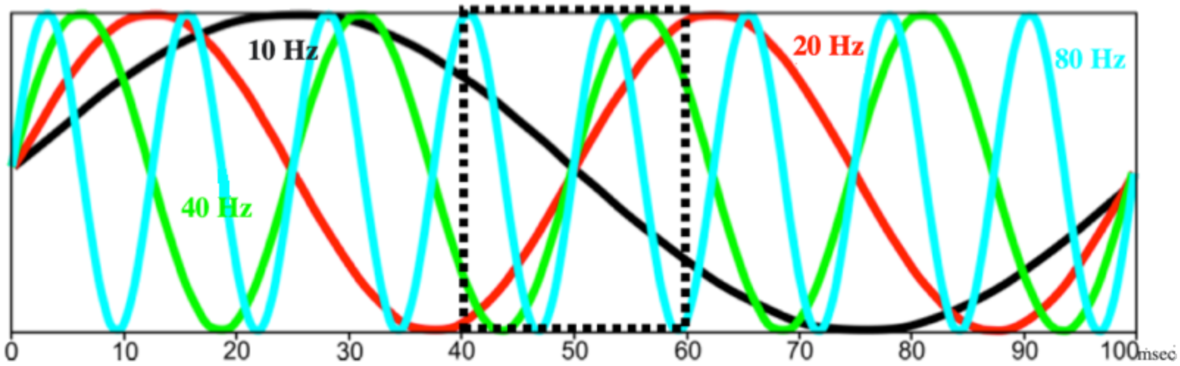

Fig. 1. Various frequency harmonics in a short evaluation window according to the Fourier transform.

The wavelet transform has recently been used for seismic measurements and various engineering tasks. Continuous Wavelet Transform (CWT) allows using various wavelets in signal analysis. Instead of calculating the time-frequency spectrum, time-scaled maps are constructed. They are called scale charts (Rioul and Vetterli, 1991). A constant analysis window is not the main difference between the CWT and the Fourier transform but an increased time-frequency resolution.

Later, a new approach to transform time-scaled maps into time-frequency maps appeared. The time-frequency continuous wavelet transform allows obtaining a large frequency resolution at low-frequency time-section intervals. When analyzing high frequencies allows obtaining a high time resolution (Castagna and Sun, 2006; Chopra and Marfurt, 2015) . The optimal frequency-time resolution parameters of the TFCWT method make it indispensable in the analysis of seismic data.

Another method, or a group of methods, is related to wavelet analysis but differs in the formulation of the problem. Some authors call this direction spectral inversion (Butorin and Krasnov, 2016; McArdle and Paton, 2014). According to many studies, spectral inversion methods allow reconstructing the signal spectrum in minute detail, making it possible to study the features of energy distribution over frequencies more accurately. This method is characterized by a very high resolution of the results obtained. However, there are few software complexes in which this algorithm is implemented. Thus, this method is not widely used in seismic data interpreting.

The CWT algorithm is the most used for many reasons. It is the basis for most existing spectral decomposition methods used for predicting effective thicknesses in the inter-well space. Various methods of interpreting spectral decomposition results can be used at a quantitative and qualitative level. Greg Pertika proposed one of the methods of quantitative prediction (Partyka et al., 1999). It is based on the analysis of low-frequency components. Low-frequency components have a low temporal resolution, and the tuning effect is observed only at high capacities (>40m). However, their use is possible even for the quantitative interpretation of thin layers. The following assumption has been taken as a basis for this method. According to a linear or close to a linear law, the energy of a single low-frequency component increases until the tuning effect is achieved. In other words, if the power of the target interval varies from 5 to 50 meters, then at the interval speed of 4000 m /s, the tuning effect for a maximum thickness of 50 m will be achieved at a frequency of 20 Hz. Therefore, as the thickness of the target interval decreases, the energy at a frequency of 20 Hz will gradually decrease. The papers of foreign by Partyka et al. (1999) and Russian scientists Butorin (2016), and Murtazin (2016) contain modelling results and practical examples.

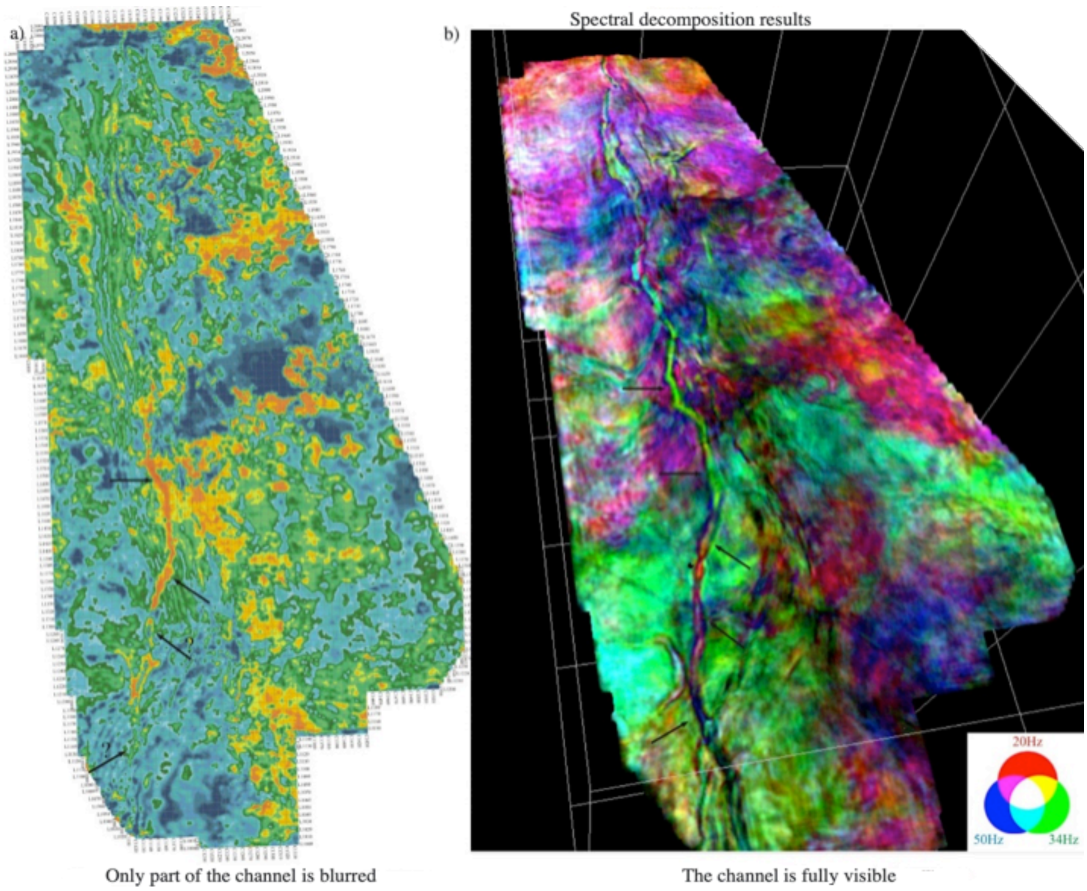

Fig. 2. Comparison of the results of seismic facies analysis (a) is partial or blurred. Only a part of the channel and RGB blending along the P2-VI formation are identified.

Qualitative interpretation of the spectral decomposition results has a broader range of techniques compared to a quantitative interpretation. A map qualitative analysis can be made in the formation segment at various frequencies (Murtazin, 2016; Murtazin and Sirazhiev, 2017). It allows for various reasons to see parts of the formation, which full-frequency data don't show since they are hidden or dusky (Olneva et al., 2018; Olneva and Zhukovskaya, 2016, 2017). However, the results obtained represent only a narrow spectral band of the amplitude-frequency, and some reservoir parts are not displayed at these frequencies. Thus, a comprehensive analysis of several frequencies is necessary. RGB-blending is a kind of such analysis (Murtazin, 2016). This algorithm allows simultaneous visualization and analysis of three frequencies. The amplitudes at each point are analyzed based on the predominance of one or another component. The pixel colour value in the red-green-blue spectrum is calculated (Murtazin, 2016) (see Fig. 2).

Goal setting

The tasks within the framework of the study are as follows:

1. Analysis of currently used spectral decomposition algorithms for seismic measurements.
2. Development of a method for complex analysis of the wavefield spectral decomposition results.
3. Justification of the choice of clustering algorithm.
4. Development of a method for sorting spectral curves to link with geological information
5. Testing of the developed approach on the example of paleochannel systems of the West Siberian, Timan-Pechora and Volga-Ural oil and gas provinces for predicting effective thicknesses in the inter-well space.

The most common analysis method is to study the relation of the amplitude frequencies characteristics with the formation parameters (Hamerli et al., 2019; Partyka et al., 1999; Xiang et al., 2021). The analysis of individual frequency components shows that frequencies that worsen the amplitude characteristic correlation and effective thicknesses are eliminated from the general recording spectrum. The display of individual geological bodies also improves. However, even with the improved dependence of the individual frequency and the effective thickness, the features manifesting at other frequencies are lost.

RGB blending eliminates the gap described earlier. At the same time, three frequencies reflecting most of the formation features in some cases are described (Fan et al., 2017; Zeng, 2017). However, the amplitude-frequency response is more than three frequencies. Moreover, the RGB results are not interpretable. The analysis of the above shortcomings helps understand which parameters the new method should possess.

Thus, the method should possess the following properties:

- it should take into account all frequencies that are in the informative range of the amplitude-frequency characteristic of the area of interest;

- eliminate the RGB blending disadvantages to make the results of the new method quantitatively interpreted;
- have a physical meaning from the point of view of the forecast validity of effective reservoir thicknesses.

METHODS AND MATERIALS

The spectral curves clustering consists of the following main steps:

- decomposition of the original seismic cube into frequency components. The wavelet transform (CWT) method is chosen from all the methods of wavefield decomposition into frequency components. In comparison to the Fourier transform, this method doesn't have such gaps as a constant analysis window, and it has an increased frequency-time resolution;

- selection of the initial pulse. In this case, it is the Morlet pulse. According to research, this pulse provides improved resolution and display of small and hard-to-distinguish objects in the seismic field compared to other synthetic and extracted pulses;

- calculation of energy for frequencies with a given step. The step of 2-5 Hz between the frequencies is optimal. In this case, a detailed display of all the spectrum features is achieved, and the number of values on the resulting amplitude spectrum will not be too large. A large number of values complicates the interpretation of clustering results. Too small frequency step increases the algorithm time and reduces the practical significance of the method;

- formation of a cube of spectral curves. The amplitude characteristics of various frequencies calculated in the previous step form a cube. Frequencies are plotted along the Z-axis of the cube. Each trace of the cube represents a spectral curve at a point or interval of the reflecting horizon;

- interpretation of the materials obtained in the previous steps. The method of clustering traces by their shape using neural network technology is chosen.

Each trace of the cube represents a spectral curve at a point or interval of the reflecting horizon (Fig. 3).

The method is called spectral curves clustering (Patent No. 2718135, Russian Federation).

The resulting cube of spectral curves is difficult to interpret in its pure form due to the high data dimensionality and the received data volume. Thus, the clustering algorithm of the spectral curves cube is an essential part of the method.

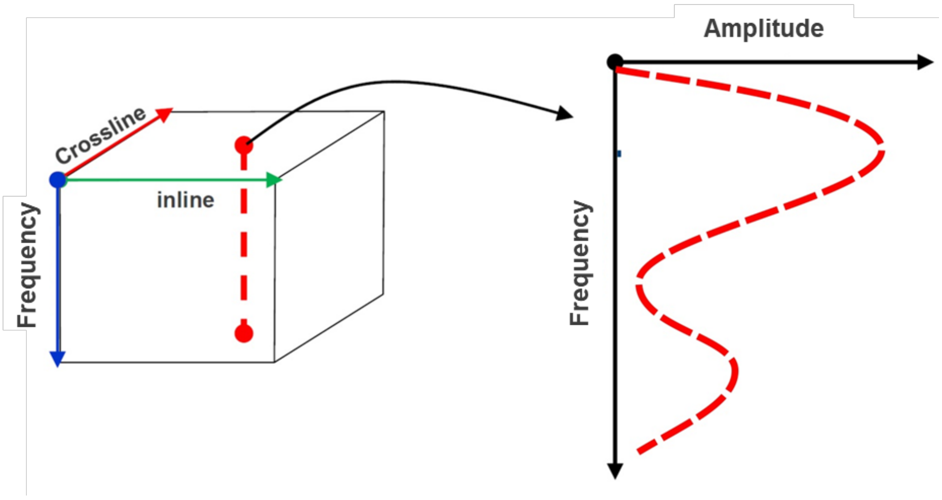

Fig. 3. Schematic representation of the spectral curve.

RESULTS

The solution to the problem of finding the most productive algorithm for large datasets like seismic data needs testing all algorithms from the Sklearn machine learning library. Table 1 shows the number of points clustered using the algorithm for a specific time interval. According to the analysis of the results, the first four clustering algorithms are not suitable for seismic data processing due to their low performance. Fast cluster and DBSCAN algorithms are suitable for seismic data clustering. However, in this case, the cube clustering time is about 12 hours.

Table 1. Comparison of different clustering types performance.

	Interactive <10sec	<5min	<60 min	<12 hours
AffinityPropagation	2,000	10,000	25,000	100,000
Spectral Claster	2,000	5,000	25,000	75,000
Agglomerative	2,000	10,000	25,000	100,000
DeBaCl	5,000	25,000	75,000	250,000
Fastcluster	50,000	100,000	500,000	1,000,000
DBSCAN	75,000	250,000	1,000,000	2,500,000
KMeans	1,000,000	3E+7	4E+8	5E+9
MiniBatchKmeans	5,000,000	1.5E+8	2.1E+9	2.5E+10

Thus, only the last two algorithms are suitable for interactive seismic data processing. Although the DBSCAN algorithm clusters data better, the Kmeans and MiniBatchKMeans algorithms allow quick selection of parameters, the correct research window and the number of clusters, finally giving the best result.

The Mini Batch KMeans clustering algorithm is a variant of the KMeans algorithm built into the Sklearn library. This algorithm uses dataset mini-samples to reduce the calculation time and optimizes the same target function. Mini-samples are subsets of input data randomly selected at each learning iteration. Mini-samples significantly reduce the number of calculations required for a local solution convergence. Unlike other algorithms that reduce the k-means convergence time, Mini Batch KMeans clustering algorithms give results that are usually only slightly worse than those of the standard algorithm.

The algorithm repeats between two main steps, similar to k-means clustering. In the first stage, data are taken randomly from a dataset to form a mini-sample. They are then assigned to the nearest centroid. In the second stage, the centroids are updated at random, unlike k-means clustering. Unlike k-means, this is done on a selective basis. For each sample in the mini-package, the assigned centroid is updated using the average stream value of the sample and all previous samples assigned to this centroid. As a result, the rate of the centroid change decreases over time. These steps are performed until convergence or a given iteration number is reached.

Fig. 4 shows the results of the two algorithms and the difference between the clustering results. As can be seen from the last cross plot, the difference in clustering points is minimal. Thus, performance is the main criterion for the final choice of the clustering algorithm. The derived time metrics show that clustering time decreases five times when using the Mini Batch Kmean algorithm compared to Kmeans. Thus, the Mini Batch Kmean algorithm was chosen for the software module.

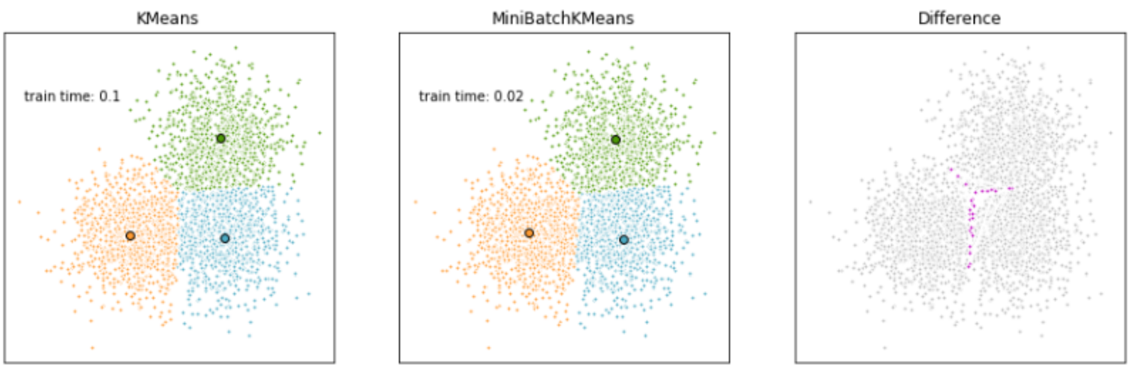

Fig. 4. Results of comparative testing of KMeans and Mini Batch KMeans algorithms.

All the algorithms discussed above have a disadvantage when used to analyze seismic data. These algorithms are aimed at data clustering and assigning a random number to each cluster. The number of the cluster centre is not essential for most tasks and areas of application of these algorithms. It is much more essential to mesh the point clouds into clusters.

Therefore, clustering is not the only task to be solved using the algorithms for seismic measurements. Since a change in entry format or the amplitude curve shape is regular, the correct value assignment to the cluster centres becomes as essential as the clustering algorithm. The matter is that the 'best' cluster centres are characterized by an energy shift to a more low-frequency region and have higher energy values. Therefore, sorting should be carried out so that clusters characterizing increased thicknesses are at the beginning. And further, in the order of the energy pick shift in the cluster towards high frequencies. For sorting at the software level, a coefficient that would limit the area of energy comparison in the frequency domain is necessary. Call this coefficient the sorting coefficient. The coefficient cuts off the cluster centres by frequency so that only low- and mid-frequencies are taken into account when sorting from higher to lower energy. According to numerous tests, the recommended values for this coefficient are from 3 to 4. Therefore, the larger the coefficient is, the more significant the role of low frequencies. The smaller the coefficient, the more the influence of medium frequencies.

The Vasyugan suit Iu1-1 formation of the South-Shinginsk deposit has become one of the cases for testing the efficiency of the methodology proposed by the author. The analysis of dynamic and kinematic parameters of seismic recording revealed the impossibility of predicting effective thicknesses based on seismic measurements using standard techniques. The analysis of seismic attributes convergence, seismic facies analysis and the inversion results showed low correlation coefficients from 0 to 0.5. The study of elastic parameters using GIS data also confirms the complexity of geological section forecasts applying standard techniques. The analysis of acoustic impedance in some wells of the deposit showed an almost complete overlap of collector or non-collector lithotypes and the impossibility of their separation in the acoustic field. The clustering of spectral curves was applied to predict effective thicknesses in the interwell space.

Fig. 5 shows the results of correlation analysis of the spectral curves cluster map and the values of effective thicknesses in wells. As shown on the cross plot, the correlation coefficient was 0.79. Ten wells drilled after the study confirmed the forecast power of the described technique.

Economic indicators of newly drilled wells have been calculated to assess the economic effect of the proposed technique. The increase in the accumulated economic effect (NPV) when using spectral curve clustering amounted to 99,565,217 rubles, which is proven by the results of drilling ten wells. Cumulative oil production is 300.7 thousand tons.

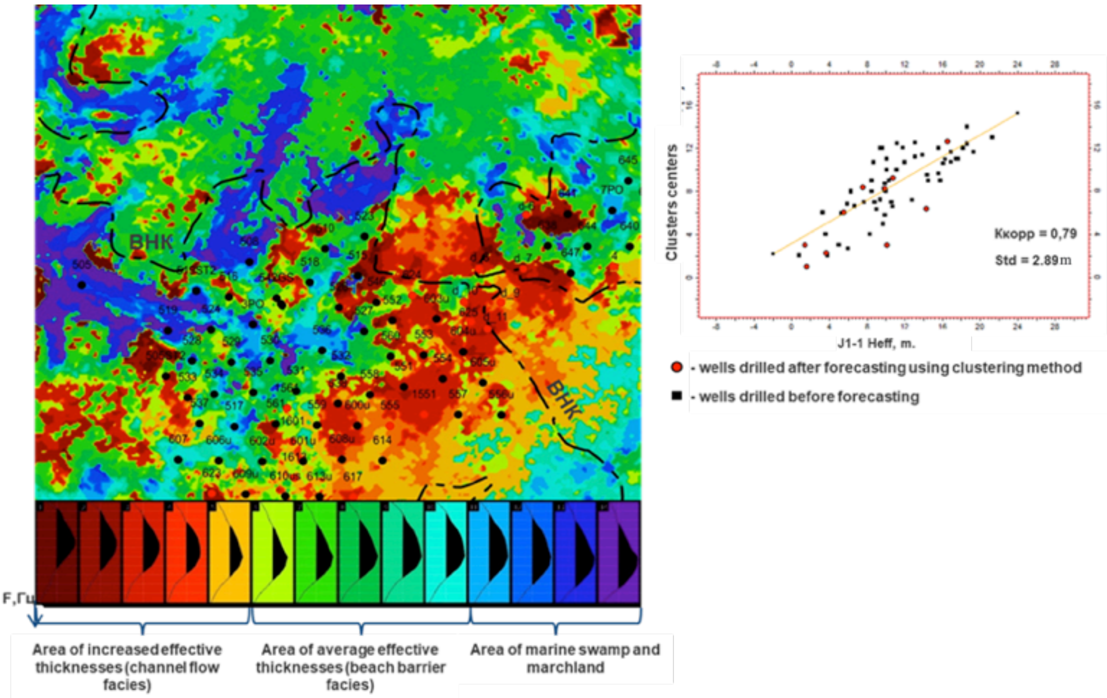

Fig. 5. Results of regression analysis of the South-Shinginsk deposit wells.

DISCUSSION

The application of spectral curves clustering proved to be effective for predicting the effective thicknesses of some deposits of the Tomsk region, Khanty-Mansiisk autonomous district and Perm Territory. This technique can certainly be applied in other regions. It allows forecasting effective thicknesses with sufficient physical conditions such as the collector and individual layers thicknesses, the collector acoustic contrast and the seismic data frequency composition.

The obtained results can be compared to the study of Greg Partika, which played the most significant role in introducing spectral analysis into seismic interpretation (Partyka et al., 1999). In his paper, he presents a 'tuning cube'. It is similar to a spectral curves cube. However, the Fourier transform is used to create a tuning cube. Another difference is the use of cubes of spectral characteristics. Greg Partika suggests using this cube for more convenient analysis of individual frequency components. Though, he doesn't consider the possibility of interpreting the cube traces. Other researchers who used tuning cube analyzed only individual frequency components, too (Bataller et al., 2019; Miao et al., 2007; Xiang et al., 2021). Thus, the proposed method has a scientific novelty as it involves techniques that were not used in other studies. One of these techniques is the clustering of the spectral curves cube. It allows avoiding high dimensions and joint analysis using wells data. Another one is sorting applied to link with geology. In modern complex studies of hydrocarbon deposits, spectral decomposition is mainly used together with other methods of dynamic analysis (Cooke et al., 2014; Dewett et al., 2021; Khonde and Rastogi, 2013; Miao et al., 2007). Neural networks or multi regression help combine the results of the spectral curves clustering with other methods.

The results of the spectral curve clustering prove its more significant effect in comparison with other methods of dynamic analysis of seismic data, which is achieved for terrigenous reservoirs composed of sediments of meandering systems. The following facts prove this:

1. The shape and the spread of the meanders are directly related to the dispersal of sand-shingle material, which has an acoustic stiffness different from the host rocks. Thin sandstone alternations in accretion complexes of channels achieve a tuning effect at a specific frequency. The information about this frequency can be obtained just by decomposing the wavefield into separate frequencies (Feng et al., 2020; Zhang et al., 2017).

2. As mentioned above, the channel parts have different effective thicknesses. Therefore, the channel parts will achieve the tuning effect at different frequencies. Thus, the complex riverbed structure cannot be described thoroughly using full-frequency attributes or transformations based on full-frequency data such as inversion. Besides, several frequency components where the channel parts achieve tuning effect are necessary for a complete description of the channel system. The accounting of several components is possible using RGB blending and the spectral curves clustering proposed in this paper.

3. Since channel objects can lie on top of each other at a distance of about twenty meters, their separation in a full-frequency field will be difficult. Such objects will interfere in the wave field, making the singled-value localization difficult (Gao et al., 2020; Ni et al., 2019). This can lead to an incorrect conceptual model of the reservoir and high risks when drilling an object, especially in the case of horizontal wellbore placement.

Thus, the proposed method of spectral curves clustering can completely solve all of the above problems. This technique has vast potential for replication since the importance of deposits with a high degree of lateral variability (lithologically limited deposits) is increasing.

CONCLUSION

The method presented in this paper proved to be effective at the deposits mentioned above. The Gazpromneft company applied it to solve problems at the stage of geological exploration and field development. The study's theoretical significance lies in the scientific substantiation of the spectral curves clustering and a new way of sorting clusters to integrate seismic and wells data.

The developed method improves the forecast of effective reservoir thicknesses in the inter-well space, which is of great practical importance for seismological monitoring of field development. Implementing the method as a software module allows its interactive use in the current production process.

The results of the spectral decomposition analysis obtained using the spectral curve clustering were used to characterize in more detail the geological section in the interval of productive deposits at some of the fields of the Perm Territory and the Komi Republic and to refine the conceptual geological model at several fields in the Western Siberia region.

Competing interests.

The authors declare that they have no competing interests.

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