ГЕОФІЗИКА

UDC 622.24

G. Efendiyev[1], Dr. Sci. (Techn.), Prof., Corr. Member of ANAS
Tel.: +994502809794, e-mail: galib_2000@yahoo.com
P. Mammadov[2], Dr. Sci. (Geol.-Min.), Prof., Academician
Tel.: +994503171415, e-mail: parviz08@list.ru
I. Piriverdiyev[1], PhD Student
Tel.: +994504125240, e-mail: igorbaku@yandex.ru
V. Mammadov[1], PhD Student
Tel.: +994503178800, e-mail: vugar.mammadov@halliburton.com
[1]Institute of Oil and Gas, Azerbaijan National Academy of Sciences
9 F. Amirov Str., Baku, AZ1000, Azerbaijan
[2]Azerbaijan State Oil and Industrial University
20 Azadlig Ave., Baku, AZ1010, Azerbaijan

ESTIMATION OF THE LOST CIRCULATION RATE USING FUZZY CLUSTERING OF GEOLOGICAL OBJECTS BY PETROPHYSICAL PROPERTIES

(Рекомендовано членом редакційної колегії д-ром геол. наук, проф. С.А. Вижвою)

Currently, cluster-analysis or automatic classification problems are widely used in various fields, in particular economics, sociology, medicine, geology, and other sectors, where there are sets of arbitrary kinds of objects to be automatically divided into groups of similar objects based on their "similarities-differences" features. In recent years, these methods have been widely used in data analysis problems. Conventional methods of cluster-analysis suggest a clear partition of the original set into subsets, in which each point is included only in one cluster after the partition. However, it is well known that such a restriction is not always true. It is often necessary to make such kind of partition, which allows determining the degree of membership of each object for each set. In this case it is advisable to use fuzzy cluster-analysis methods. Problems in this formulation arouse interest of specialists dealing with geology, geophysics, oil- and gas-well drilling and oil and gas production. One of the most important results of the study of lost circulation zones is determination of the coefficient of lost circulation intensity.

Purpose. Estimation of drilling mud lost circulation during drilling and emerging risks.

Methodology. The solution of the problems posed in the work was carried out using methods known from mathematical statistics and the theory of fuzzy sets. The technique of processing the results, as well as fuzzy cluster analysis, was used for that purpose. Findings. As a result of the research, 5 classes were obtained, each of which characterizes the rate of mud lost circulation, expressed by linguistic variables. On the basis of this, fuzzy models are constructed, expressing the relationship between the indices of petrophysical properties and the volume of the absorbed solution.

Originality. A method based on fuzzy cluster analysis has been developed, which makes it possible to predict drilling mud lost circulation of different rate at an early stage during drilling.

Practical value. The obtained results allow making decisions on prevention of lost circulation and timely liquidation of their consequences.

Keywords: porosity, permeability, fuzzy cluster, absorption, drilling mud, complications.

With the growth of information processed, stored and received during the work of information processes in large and medium-sized enterprises, as well as scientific activities, its processing, in the form obtained, becomes difficult. There is a need for initial processing of information for its structuring, identification of characteristics, generalization and sorting. For this purpose, classification and clustering processes are used. Classification of documents is the process of ordering or distribution of objects (observations) to classes in order to reflect the relationship between them. A class is a set of documents that have a certain common feature that distinguishes it totally from others. To classify an object means to indicate the number (or name) of the class to which the object belongs. Classifier training is the process of constructing an algorithm in the case when a finite set of objects is specified and it is known to which classes they belong. This set is called sampling. The class affiliation of the remaining objects is not known.

Clustering is the process of splitting a given selection of objects (observations) into disjoint subsets, called clusters, so that each cluster consists of similar objects, and the objects of different clusters differ substantially. Clustering is used when data compression is required. If the original sample is excessively large, it can be reduced by leaving one of the most typical representatives from each cluster. Clustering is also used to detect novelty. Untypical objects are selected that cannot be attached to any of the clusters [2].

It is important to understand the difference between clustering (unsupervised classification) and discriminant analysis (supervised classification). In supervised classification, we are provided with a collection of labeled (pre-classified) patterns; the problem is to label a newly encountered, yet unlabeled, pattern. Typically, the given labeled (training) patterns are used to learn the descriptions of classes which in turn are used to label a new pattern. In the case of clustering, the problem is to group a given collection of unlabeled patterns into meaningful clusters. In a sense, labels are also associated with clusters, but these category labels are data driven; that is, they are obtained solely from the data [11].

Different methods of clustering could be effective for different properties. For example, the Bayes method is used in the presence of a large number of objects in the training sample, to calculate the probability of occurrence of objects most accurately. The support vector method is used in the economy to calculate regression of different values and further prediction. It is used as a classifier in information retrieval systems. The K-means method is used to isolate groups of objects in the economy, in the data analysis, as well as in information retrieval systems. The hierarchical clustering method is used to collect statistical data and is implemented in statistical packages. It is also used for clustering text documents. EM-algorithm is used in information retrieval systems for clustering large amounts of data.

There are two main classifications of clustering methods. One of them is the division into hierarchical and non-hierarchical (or flat) ways of clustering. Hierarchical algorithms (also called taxonomy algorithms) build more than one partition of the sample into disjoint clusters, and a system of nested partitions. Thus, at the output we get a cluster tree, the root of which is the entire sample, and the leaves are the smallest cluster. Downward hierarchical algorithms work on the principle of "top-down": at the beginning, all objects are placed into one cluster, which is then broken down into smaller clusters. "Down-top" algorithms are more common, where at the beginning of the job, each object is placed into a separate cluster, and then we consolidate the clusters into larger clusters until all sampling objects are contained in the same cluster. Thus, a system of nested partitions is constructed. The results of such algorithms are usually presented in the form of a tree – a dendrogram. A classic example of such a tree is the classification of animals and plants. Unlike them, non-hierarchical (flat) algorithms build one partition of objects into clusters.

In general, clustering can be also classified as follows: Soft clustering (overlapping clustering) and Hard clustering (or exclusive clustering) [10]. In the case of hard clustering, each point belongs to only one cluster; while for soft clustering the point belongs to two or more clusters with different degrees of membership. Often, soft clustering is more natural, because points on the boundaries of classes do not have to belong entirely to one of them. Rather, they will belong to several classes with different degrees of membership from 0 to 1. One of the most popular techniques of soft clustering is fuzzy c-means (FCM), and similarly k-means is one of the most common methods of hard clustering.

For each pair of objects, the "distance" between them is measured – it is the degree of similarity. There are many metrics, here are the main ones: Euclidean distance, The Square of the Euclidean distance, Distance between city blocks (Manhattan distance), Chebyshev's distance, and Power distance.

The most common distance function is Euclidean distance. It is a geometric distance in a multidimensional space:

$$p(x,x') = \sqrt{(x_i - x_i')^2}\ . \qquad (1)$$

The square of the Euclidean distance is used to give more weight to more distant objects. This distance is calculated as follows:

$$p(x,x') = (x_i - x_i')^2\ . \qquad (2)$$

Distance between city blocks (Manhattan distance) is the mean of the differences in coordinates. In most cases, this measure of distance leads to the same results as the usual Euclidean distance. However, for this measure, the effect of individual large differences (outliers) decreases (because they are not squared). Chebyshev's distance can be useful when you need to define two objects as "different" if they differ in any one coordinate. Power distance is acceptable where it is necessary to increase or decrease the weight related to the dimension for which the corresponding objects are very different.

The choice of the metric lies entirely with the researcher, since the results of clustering can differ significantly when using different measures.

K-Means Algorithm.

The K-means method is based on dividing the set of observations into clusters that are locally minimized with respect to the distance between the information point and the cluster centroid. The objective function of the algorithm is represented by the formula (3):

$$J = \sum_{j=1}^{k}\sum_{i=1}^{n}\left\|x_i^{(j)} - c_j\right\|^2\ , \qquad (3)$$

where $\left\|x_i^{(j)} - c_j\right\|^2$ is a chosen distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the n data points from their respective cluster centers.

This algorithm is particularly sensitive to randomly selected initial cluster centers. To reduce this effect, the algorithm can be executed many times. This is a simple algorithm that can be used in many areas and is well suited for randomly generated data points.

This method takes the input parameter k, the number of clusters and splits the set of n objects into k clusters, so that the resulting intra-cluster similarity is high, but the similarity between clusters is low. The basic idea is to determine k centroids, one for each cluster. These centroids should be placed in a subtle way due to a different location resulting in different results. Thus, the best choice is to place them as far apart as possible. The next step is to take each point belonging to a given data set and associate it with the nearest center of gravity. When no point is deferred, the first step is completed and the early grouping is performed. At this stage, we need to count k new centroids. After we have these new centroids, a new binding must be done between the same points in the data set and the nearest new center of gravity. A loop has been created. As a result of this cycle, we can see that k centroids change their location step by step, until no changes are made. In others words, centroids no longer move. Finally, this algorithm is aimed at minimizing an objective function, in this case, a squared error function [10].

The Formal algorithm of K-Means is:

1. *Select K points as initial centroids*.
2. *Repeat*.
3. *Form k clusters by assigning all points to the closest centroid*.
4. *Recompute the centroid of each cluster*.
5. *Until the centroids do not change*.

Fuzzy C-Means Algorithm.

As above mentioned, one of the most widely used algorithms in clustering is fuzzy clustering algorithm. Fuzzy set theory was first proposed by Zadeh in 1965 [15] and it gave an idea of uncertainty of belonging which was described by a membership function. For each of the clusters, membership values are assigned to the data points and fuzzy clustering algorithm allows the clusters to grow into their natural shapes. In Fuzzy C-Means (FCM) algorithm each point belongs to the cluster to a certain extent – this is called the membership grade. The technique was suggested by Jim Bezdek in 1981 [4] and it is an improvement on earlier studies. The main advantage of this type of clustering is its flexibility. Points belong to more than one cluster. It allows the gradual membership of points in clusters, located in the range from 0 to 1.

The well-known Bezdek's fuzzy clustering algorithm, known as Fuzzy C-Means, as well as other algorithms based on it, such as PCM, PFCM, FCM-σ, can be useful in many technical fields, for example image analysis, pattern recognition. FCM gives good results in the absence of noise, but it is very sensitive to noise and outliers. In this regard, the centroid is attracted to the outliers, rather than the cluster centers. The use of PCM and PFCM partly solves this problem, because they work better in the presence of noise compared to FCM. But PCM cannot find optimal clusters because of noise, and PFCM does not give good results if clusters vary greatly in size and outliers. The fuzzy clustering algorithms can be divided into two types: one is Classical fuzzy clustering algorithms and the other is Shape based fuzzy clustering algorithms [6].

FCM is based on minimization of the following objective function (4):

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C}U_{ij}^m\left\|x_i - c_j\right\|^2,\ 1 \le m < \infty\ , \qquad (4)$$

where *m* is any real number greater than 1, U_{ij} is the degree of membership of x_i in the cluster *j*, x_i is the i-th of d-dimensional measured data, c_j is the d-dimension center of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the center. Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership U_{ij} and the cluster centers c_j by:

$$U_{ij} = \frac{1}{\sum_{k-1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_j \right\|} \right)^{\frac{2}{m-1}}} \tag{5}$$

$$C_j = \frac{\sum_{i-1}^{N} U_{ij}^m \cdot x_i}{\sum_{i-1}^{N} U_{ij}^m} . \tag{6}$$

This iteration will stop when $\max_{ij} = \{| U_{ij}^{(k+1)} - U_{ij}^{k} |\} < \xi$ where ξ is a termination criterion between 0 and 1, whereas *k* is the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

The formal algorithm of FCM is:

1. *Initialize* $U = [u_{ij}]$ *matrix*, $U^{(0)}$;

2. *At k-step: calculate the centers vectors* $C^{(k)} = [c_j]$ *with* $U^{(k)}$;

3. *Update* $U^{(k)}$, $U^{(k+1)}$;

4. If $\| U^{(k+1)} - U^{(k)} \| < \xi$ *then STOP; otherwise return to step 2.*

In FCM, data are bound to each cluster by means of a Membership Function, which represents the fuzzy behavior of this algorithm. To do that, we simply have to build an appropriate matrix named *U* whose factors are numbers between 0 and 1, and represent the degree of membership between data and centers of clusters.

A comparison between the FCM and K-Means algorithms is performed based on their respective calculation periods taken for the experiments, and based on their respective temporal complexities in [10]. First of all, it can be seen from the observations that despite foregoing advantages, the FCM requires more time for computation than K-Means. So, as we have seen, as soon as the number of cluster increases, the time complexity of FCM increases with a more rapid growth rate than that of K-Means algorithm. This figure shows that K-Means algorithm is less complex than FCM.

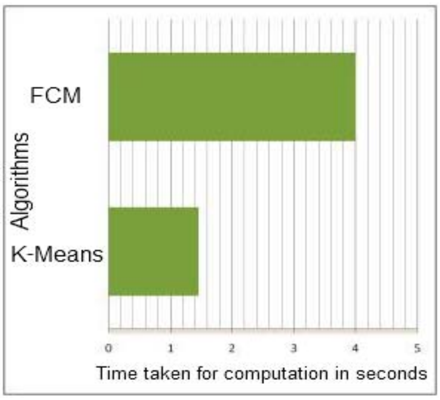

Fig. 1. Comparison between the FCM and K-Means algorithms

Numerous researches of different authors have been devoted to studies of various characteristics of rocks such as porosity, permeability, lithology, etc. [5, 13, 14]. In these works, studies were carried out using the method of statistical modeling through geophysical studies of wells; attempts were made to establish a correlation between various geological and technological characteristics with the aim of further practical application in solving oilfield tasks.

Thus, in [13, 14] the problem of statistical modeling of random fields in three-dimensional space was considered. The model was constructed and an improved numerical simulation algorithm was formulated. The ways of forming and approximating of homogeneous groups with respect to several variables were theoretically justified and shown. In order to analyze the parameters of elastic and acoustic anisotropy, the effect of mineral composition and porosity on these parameters was studied in [5]. The main aspects of the construction of geological and geophysical models are discussed in [9]. This paper gives the classification of geological-geophysical models by stages of prospecting works. The analysis shows that very interesting results have been obtained in recent years, whose application can solve problems of different, including technological, nature.

During solving a number of problems, the authors used methods based on fuzzy sets, which provide successful solving of classification problems, as well as decision-making tasks.

Results of the analysis using c-means method. Usually work on the definition of lost circulation intensity is performed for each well. The intensity of lost circulation is influenced by a number of factors, including lithologic and petrophysical characteristics of the reservoir. The forecast of the expected lost circulation intensity values during the design of wells according to the results of studies of previously drilled wells is a reserve for further reducing of the well wiring cost in the areas, folded by layers which tend to lost circulation. Lost circulation can have varying rate, which can be estimated by using cluster-analysis. Accordingly, the purpose of the present report is the use of fuzzy cluster-analysis for the assessment of rate for this kind of complications in drilling, which include lost circulation of drilling mud. Data about drilling was collected, it also contains measurements, which allowed determining the intensity of lost circulation. Depending on the nature of the original information, two approaches were suggested: statistical and based on fuzzy-cluster analysis [8]. The data was subjected to statistical and fuzzy cluster-analysis using c-means algorithms and an appropriate program. As a result of cluster-analysis, five classes were produced, and each of them is characterized by the relative rate of lost circulation, the relevant characteristics of layers and intensity of lost circulation.

In our work, a cluster analysis was carried out using the c-means method based on two signs [1], influencing the intensity of lost circulation: porosity and permeability. These input signs were set in accordance with the intensity of lost circulation. Each class corresponds to certain degree of rate (catastrophic, serious, intensive, partial, and minor).

However, the desired result of clustering can be also obtained by using hard c-means algorithm, if a set of objects consists of compact clusters and each cluster is noticeably separated from others. At the same time, in practical problems, particularly in geology, oil and gas business, such kind of sets of objects are rare. A set of objects often contains several unprototype objects, which can lead to poor results of clustering due to the shift of cluster centers [1]. To overcome such undesirable property of clear algorithm, FCM-algorithm (fuzzy c-means algorithm) using weighting factors (membership function) to monitor the contribution of the objects into the cluster centers definition, should be applied. FCM-algorithm gives adequate results of clustering if a set of objects contains overlapping clusters. The results of clustering are based on fuzzy membership function, using the relative distances of objects relative to the centers of clusters [3, 12]. For example, an object that is far away from the cluster center, makes a smaller contribution to the clusters centers search process, than objects which are close to the center of the cluster.

As a result of the applying of algorithm, five clusters were obtained [7], and each of them is characterized by petrophysical characteristics matched rate of lost circulation of rocks as following fuzzy rules:

IF the rock is dense and impermeable, THEN lost circulation is minor.

IF the rock is low-porous and moderately permeable, THEN lost circulation is intensive.

IF the rock is moderately porous and low-permeable, THEN lost circulation is partial.

IF the rock is porous and highly-permeable, THEN lost circulation is catastrophic.

IF the rock is highly-porous and permeable, THEN lost circulation is serious.

Term-sets of input and output variables are shown in Figures 2-4.

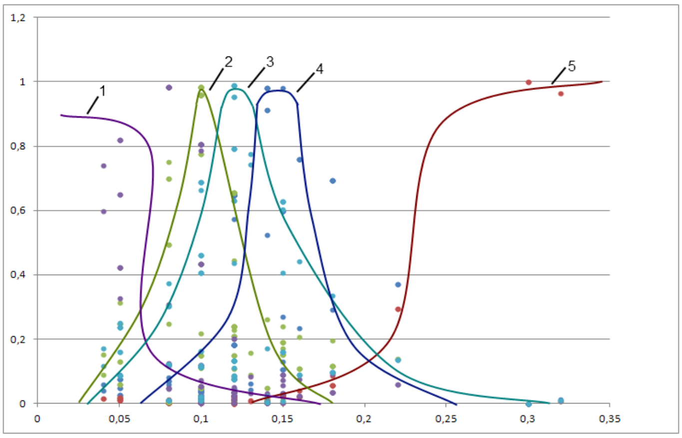

Fig. 2. Term-sets of porosity:
1 – dense; 2 – low-porous; 3 – moderately porous; 4 – porous; 5 – highly-porous

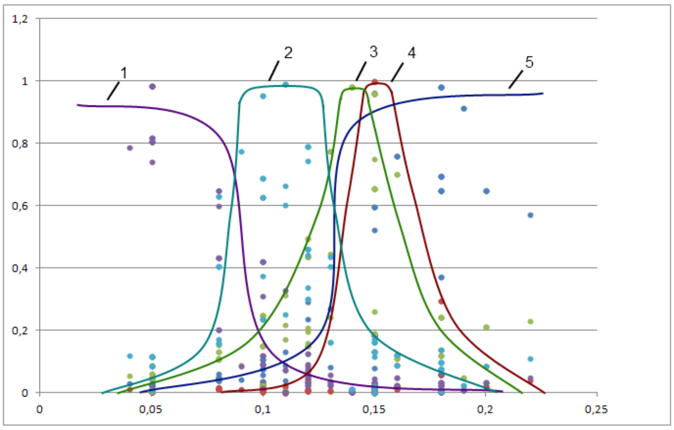

Fig. 3. Term-sets of permeability:
1 – impermeable; 2 – low-permeable; 3 – moderately permeable; 4 – permeable; 5 – highly-permeable

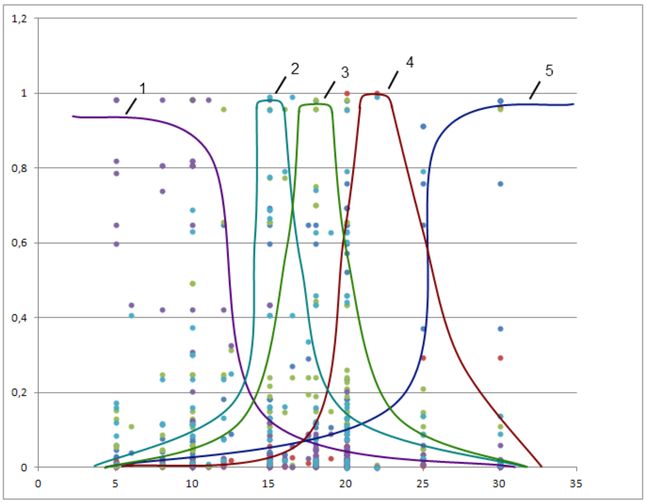

Fig. 4. Term-sets of lost circulation:
1 – minor; 2 – partial; 3 – intensive; 4 – serious; 5 – catastrophic

Thus, to evaluate the effect of geological conditions on the nature of lost circulation in terms of lack of information, mutual correspondence between indicators of petrophysical properties of rocks and rate of lost circulation has been reached on the basis of fuzzy cluster-analysis, that is very important for the early diagnosis of lost circulation and assessment of the risk.

Список використаних джерел

1. Демидова Л. А. Кластеризация объектов с использованием FCM-алгоритма на основе нечетких множеств второго типа и генетического алгоритма / Л. А. Демидова, Е. И. Коняева // Вестник РГРТУ. – Рязань. – 2008. – № 26, 4.
2. Черезов Д. С. Обзор основных методов классификации и кластеризации данных / Д. С. Черезов, Н. А. Тюкачев // Вестник ВСУ. Серия: Системный анализ и информационные технологии. – 2009. – № 2. – С. 25–29.
3. Aliev R. A. Type-2 Fuzzy Neural Networks and Their Applications / R. A. Aliev, B. G. Guirimov. – 2014. – Режим доступу: http://www.springer.com/us/book/9783319090719
4. Bezdek J. C. Pattern Recognition with Fuzzy Objective Function Algorithms / J. C. Bezdek. – New York : Plenum Press. – 1981.
5. Bezrodna I. Mathematical modelling of influence of the mineral composition and porosity on elastic anisotropic parameters of complex sedimentary rocks of Volyn-Podolia area / I. Bezrodna, D. Bezrodnyi, R. Holiaka // Visnyk of Taras Shevchenko National University of Kyiv. Geology. – 2016. – № 73. – С. 27–32.
6. Bora D. J. A Comparative Study Between Fuzzy Clustering Algorithm and Hard Clustering Algorithm / D. J. Bora, A. K. Gupta // International Journal of Computer Trends and Technology (IJCTT). – 2014. – № 10, 2.
7. Clustering of geological objects using FCM-algorithm and evaluation of the rate of lost circulation / G. M. Efendiyev, P. Z. Mammadov, I. A. Piriverdiyev et al. // 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29-30 August 2016, Vienna, Austria: Procedia Computer Science. – 2016. – № 102. – С. 159–162.
8. Forecast of drilling mud loss by statistical technique and on the basis of a fuzzy cluster analysis / G. M. Efendiyev, S. A. Rza-zadeh, A. K. Kadimov et al. // Seventh International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control. Turkey : Izmir. – 2013. – С. 319–322.
9. Kuzmenko T. Theoretical and methodological aspects of creating of geological and geophysical model of hydrocarbon fields / T. Kuzmenko, A. Tyschenko, P. Kuzmenko // Visnyk of Taras Shevchenko National University of Kyiv. Geology. – 2015. – № 71. – С. 61–66.
10. Raulji J. G. A Review on Fuzzy C-Mean Clustering Algorithm / G. Raulji Jitendrasinh // International Journal of Modern Trends in Engineering and Research. – 2015. – № 2, 2. – С. 751–754.
11. Suganya R. Fuzzy C-Means Algorithm – A Review / R. Suganya, R. Shanthi // International Journal of Scientific and Research Publications. – 2012. – № 11, 2.
12. Turksen I. B. Full Type 2 to Type n Fuzzy System Models / I. B. Turksen // Seventh International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control. Turkey : Izmir, 2013. – С. 21.
13. Vyzhva S. Determination of the void space structure of complex rocks using the petroacoustic studies data from the Semyrenkivska area / S. Vyzhva, I. Bezrodna // Visnyk of Taras Shevchenko National University of Kyiv. Geology. – 2016. – № 74. – С. 11–17.
14. Vyzhva Z. About advanced algorithm of statistical simulation of seismic noise in the flat observation area for determination the frequency characteristics of geological environment / Z. Vyzhva, K. Fedorenko, A. Vyzhva // Visnyk of Taras Shevchenko National University of Kyiv. Geology. – 2016. – № 73. – С. 58–64.
15. Zadeh L. A. Fuzzy sets / L. A. Zadeh // Information and Control. – 1965. – № 8, 3. – С. 338–353.

References

1. Demidova, L. A., Konyaeva, E. I. (2008). Clustering of objects using FCM-algorithm on the basis of type-2 fuzzy sets and genetic algorithm. Vestnik of RSREU. Ryazan, 26, 4. [in Russian].
2. Cherezov, D. S., Tyukachev, N. A. (2009). Review of main methods of data classification and clustering. Vestnik VSU, series: system analysis and information technologies, 2, 25–29. [in Russian].
3. Aliev, R. A., Guirimov, B. G. (2014). Type-2 Fuzzy Neural Networks and Their Applications. URL: http://www.springer.com/us/book/9783319090719
4. Bezdek, J. C. (1981). Pattern Recognition with Fuzzy Objective Function Algorithms. New York: Plenum Press.
5. Bezrodna, I., Bezrodnyi, D., Holiaka, R. (2016). Mathematical modelling of influence of the mineral composition and porosity on elastic anisotropic parameters of complex sedimentary rocks of Volyn-Podolia area. Visnyk of Taras Shevchenko National University of Kyiv. Geology, 73, 2, 27–32. [In Ukrainian].
6. Bora, D. J., Gupta, A. K. (2014). A Comparative study Between Fuzzy Clustering Algorithm and Hard Clustering Algorithm. International Journal of Computer Trends and Technology (IJCTT), 10, 2.
7. Efendiyev, G. M., Mammadov, P. Z., Piriverdiyev, I. A., Mammadov, V. N. (2016). Clustering of geological objects using FCM-algorithm and evaluation of the rate of lost circulation. 12th International Conference on Application of Fuzzy Systems and Soft Computing. ICAFS 2016. 29-30 August 2016., Vienna, Austria. Procedia Computer Science, 102, 159–162.
8. Efendiyev, G. M., Rza-zadeh, S. A., Kadimov, A. K., Kouliyev, I. R. (2013). Forecast of drilling mud loss by statistical technique and on the basis of a fuzzy cluster analysis. Seventh International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control. Turkey: Izmir, 319–322.
9. Kuzmenko, T., Tyschenko, A., Kuzmenko, P. (2015). Theoretical and methodological aspects of creating of geological and geophysical model of hydrocarbon fields. Visnyk of Taras Shevchenko National University of Kyiv. Geology, 71, 4, 61–66. [In Ukrainian].
10. Raulji, J. G. (2015). A Review on Fuzzy C-Mean Clustering Algorithm. International Journal of Modern Trends in Engineering and Research, 2, 2, 751–754.
11. Suganya, R., Shanthi, R. (2012). Fuzzy C-Means Algorithm – A Review. International Journal of Scientific and Research Publications, 2, 11.
12. Turksen, I. B. (2013). Full Type 2 to Type n Fuzzy System Models. Seventh International Conference on Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control. Turkey: Izmir, 21.
13. Vyzhva, S., Bezrodna, I. (2016). Determination of the void space structure of complex rocks using the petroacoustic studies data from the Semyrenkivska area. Visnyk of Taras Shevchenko National University of Kyiv. Geology, 74, 3, 11–17. [In Ukrainian].
14. Vyzhva, Z., Fedorenko, K., Vyzhva, A. (2016). About advanced algorithm of statistical simulation of seismic noise in the flat observation area for determination the frequency characteristics of geological environment. Visnyk of Taras Shevchenko National University of Kyiv. Geology, 73, 2, 58–64.
15. Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8, 3, 338–353.

Надійшла до редколегії 12.01.18

Г. Ефендієв[1], д-р техн. наук, проф., чл.-кор. НАНА
Тел.: +994502809794, e-mail: galib_2000@yahoo.com
П. Мамедов[2], д-р геол.-мінералог. наук, проф., академік
Тел.: +994503171415, e-mail: parviz08@list.ru,
І. Півірведієв[1], докторант
Тел.: +994504125240, e-mail: igorbaku@yandex.ru
В. Мамедов[1] Н., дисертант
Тел.: +994503178800, e-mail: vugar.mammadov@halliburton.com
[1]Інститут нафти і газу Національної академії наук Азербайджану
вул. Ф. Амірова, 9, м.Баку, AZ1000, Азербайджан
[2]Азербайджанський державний університет нафти і промисловості
пр-т. Азадлиг, 20, м. Баку, AZ1010, Азербайджан

ОЦІНКА ШВИДКОСТІ ПОГЛИНАННЯ БУРОВОГО РОЗЧИНУ З ВИКОРИСТАННЯМ НЕЧІТКОЇ КЛАСТЕРИЗАЦІЇ ГЕОЛОГІЧНИХ ОБ'ЄКТІВ ЗА ПЕТРОФІЗИЧНИМИ ВЛАСТИВОСТЯМИ

В даний час завдання кластер-аналізу, або автоматичної класифікації, отримали широке застосування в різних областях, зокрема, економіці, соціології, медицині, геології та інших галузях, усюди, де є множини об'єктів довільної природи, які необхідно автоматично розбити на групи однорідних об'єктів за їх ознаками "подібності-відмінності". В останні роки ці методи широко застосовуються в задачах аналізу інформації. Традиційні методи кластер-аналізу припускають чітке розбиття вихідних множин на підмножини, за якого кожна точка після розбиття потрапляє тільки в один кластер. Однак, як відомо, таке обмеження не завжди вірно. Найчастіше необхідно зробити розбиття так, щоб визначити ступінь належності кожного об'єкта до кожної множини. У цьому випадку доцільно використовувати нечіткі методи кластер-аналізу. Завдання в такій постановці привертають інтерес фахівців, що займаються питаннями геології, геофізики, буріння свердловин і розробки родовищ нафти і газу. Одним із найважливіших результатів дослідження зон поглинання є визначення коефіцієнта інтенсивності поглинання.

Мета. Оцінка ступеня тяжкості поглинань при бурінні свердловин і ризиків, які при цьому виникають.

Методика. Рішення поставлених у роботі завдань базувалося на методах, відомих із математичної статистики і теорії нечітких множин. При цьому були використані методика обробки результатів, а також нечіткого кластер-аналізу.

Результати. Під час досліджень отримані 5 класів, кожен з яких характеризує ступінь тяжкості поглинань бурового розчину, виражену лінгвістичними змінними. На основі цього побудовані нечіткі моделі, що виражають зв'язок між показниками петрофізичних властивостей і обсягом поглиненого розчину.

Наукова новизна. Розроблено метод, заснований на нечіткому кластер-аналізі, що дозволяє прогнозувати поглинання різного ступеня тяжкості на ранній стадії в процесі буріння.

Практична значущість. Отримані результати дозволяють приймати рішення із запобігання поглинанням і своєчасної ліквідації їх наслідків.

Ключові слова: пористість, проникність, нечіткий кластер, поглинання, буровий розчин, ускладнення.

Г. Эфендиев[1], д-р техн. наук, проф., чл.-корр. НАНА
Тел.: +994502809794, e-mail: galib_2000@yahoo.com
П. Мамедов[2], д-р геол.-минералог. наук, проф., академик
Тел.: +994503171415, e-mail: parviz08@list.ru
И. Пиривердиев[1], докторант
Тел.: +994504125240, e-mail: igorbaku@yandex.ru
В. Мамедов[1], диссертант
Тел.: +994503178800, e-mail: vugar.mammadov@halliburton.com
[1]Институт нефти и газа Национальной академии наук Азербайджана
ул. Ф. Амирова, 9, г. Баку, AZ1000, Азербайджан
[2]Азербайджанский государственный университет нефти и промышленности
пр-т. Азадлыг, 20, г. Баку, AZ1010, Азербайджан

ОЦЕНКА СКОРОСТИ ПОГЛОЩЕНИЯ БУРОВОГО РАСТВОРА С ИСПОЛЬЗОВАНИЕМ НЕЧЕТКОЙ КЛАСТЕРИЗАЦИИ ГЕОЛОГИЧЕСКИХ ОБЪЕКТОВ ПО ПЕТРОФИЗИЧЕСКИХ СВОЙСТВАМИ

В настоящее время задачи кластер-анализа, или автоматической классификации, получили широкое применение в различных областях, в частности, экономике, социологии, медицине, геологии и других отраслях, всюду, где имеются множества объектов произвольной природы, которые необходимо автоматически разбить на группы однородных объектов по их признакам "сходства-различия". В последние годы эти методы широко применяются в задачах анализа информации. Традиционные методы кластер-анализа предполагают четкое разбиение исходного множества на подмножества, при котором каждая точка после разбиения попадает только в один кластер. Однако, как известно, такое ограничение не всегда верно. Зачастую необходимо произвести разбиение так, чтобы определить степень принадлежности каждого объекта к каждому множеству. В этом случае целесообразно использовать нечеткие методы кластер-анализа. Задачи в такой постановке привлекают интерес специалистов, занимающихся вопросами геологии, геофизики, бурения скважин и разработки месторождений нефти и газа. Одним из наиболее важных результатов исследования зон поглощения является определение коэффициента интенсивности поглощения.

Цель. Оценка степени тяжести поглощений при бурении скважин и возникающих при этом рисков.

Методика. Решение поставленных в работе задач основывалось на методах, известных из математической статистики и теории нечетких множеств. При этом были использованы методика обработки результатов, а также нечеткого кластер-анализа.

Результаты. Во время исследований получены 5 классов, каждый из которых характеризует степень тяжести поглощений бурового раствора, выраженную лингвистическими переменными. На основе этого построены нечеткие модели, выражающие связь между показателями петрофизических свойств и объемом поглощенного раствора.

Научная новизна. Разработан метод, основанный на нечетком кластер-анализе, позволяющий прогнозировать поглощения разной степени тяжести на ранней стадии в процессе бурения.

Практическая значимость. Полученные результаты позволяют принимать решения по предупреждению поглощений и своевременной ликвидации их последствий.

Ключевые слова: пористость, проницаемость, нечеткий кластер, поглощение, буровой раствор, осложнения.