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Intelligent Identification and Prediction of Volcanic Rock Based on Artificial Neural Network

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Abstract: Volcanic rock is complex and has various types. Lithology identification is the key to truly solve the gas bearing characteristics of complex lithology. In order to solve the existing volcanic lithology intelligent identification and prediction research of artificial neural network in this paper, the algorithm implementation steps and from calcium alkaline, basic and three basic properties of the volcanic lithology classification is discussed, on the basis of in view of the volcanic rock lithology intelligent identification and prediction application general situation of the region and volcanic rocks in the data analysis were described simply. And volcanic rock lithology under the integration of artificial neural network intelligent identification and prediction model to carry on the design, and through this algorithm under different number of iterations for core data of typical samples for identification and prediction of the experimental data show that this algorithm is of mudstone, siltstone, argillaceous siltstone three lithology recognition accuracy up to 93.51% on average. Therefore, it is verified that the intelligent identification and prediction of volcanic rock under the fusion of artificial neural network has high accuracy.

1. Introduction

Lithology identification of igneous rocks is the key basis for the division of lithofacies and eruption periods. Due to the frequent volcanic eruptions and many complex factors in diagenetic processes, the distribution law of rocks in different rock layers will not only change, so it is difficult to identify and predict igneous rocks.

Nowadays, more and more scholars have conducted a lot of research in the intelligent identification and prediction of volcanic rock lithology through various technologies and system tools, and some research results have been achieved through practical research. Osimobi J C studies the characteristics of volcanic rocks in the study area on the basis of core, rock slice, logging and seismic data, and establishes a set of volcanic rock identification methods. The volcanic eruption cycle and lithofacies distribution are also predicted. The results show that weakly alkaline basalts are the main types of volcanic rocks in the study area, ranging from basic volcanic rocks to acidic volcanic rocks and from lava rocks to pyroclastic rocks. The Cenozoic volcanic rocks are the products of three stages of volcanic eruption. The distribution of volcanic facies such as volcanic exhalation facies, exhalation facies, explosive facies and volcanic deposition is identified and predicted. It has certain significance for the further exploration and development of oil and gas in this area [1]. Cramer R used the method of "composition + structure" to identify the lithology, and on this basis studied the connection and difference between lithology and lithofacies, established a recognition model for geological lithology, established the corresponding relationship between logging information and geological lithology to determine the characteristic model of the eruptive and effusion facies. By analyzing the relationship between effective reservoirs and lithology and lithofacies, the distribution law of effective reservoirs is clarified, which is of great significance to the characteristics of volcanic spatio-temporal expansion, reservoir prediction and well drainage [2]. Caggiano A classified and identified the lithology and lithofacies of volcanic rocks based on core observation and seismic characteristics collected and analyzed well data, and proposed the corresponding lithology identification method. The main geological features are andesite and dacite, followed by volcanic breccia and tuff. There are also some localized formations in basalt and rhyolite. The identification of lithofacies mainly depends on the internal characteristics of well logging curves and the combination of the external shape of seismic reflection and structural features [3]. Although the existing research on intelligent identification and prediction of volcanic rock is very rich, there are still some limitations in real practice.

Lithology identification of volcanic rocks is the basic work of volcanic rock reservoir evaluation. Because of the variety of volcanic rocks and complex mineral composition, it is difficult to accurately identify the lithology of volcanic rocks. Conventional logging data mainly reflect the composition characteristics of volcanic rocks, while imaging logging data provide the structural information of volcanic rocks. Therefore, this paper combines the two kinds of data and summarizes a set of intelligent identification and prediction process of volcanic rock under the fusion of artificial neural network. The lithology identification of volcanic rock strata of three Wells in the study area is carried out through experiments, and good results are obtained. The identification rate of three volcanic rocks, mudstone, siltstone and argillaceous siltstone, is above 90%.

2. Intelligent Identification and Prediction of Volcanic Rock Based on Artificial Neural Network

2.1. Artificial Neural Network

Artificial neural networks mainly rely on neural network learning algorithms [4]. Neural network algorithm belongs to algorithm ∂ (also known as error correction rule algorithm), first introduce ∂ learning rule:

If $v_x(r)$ is used to represent the recognition and prediction result of neuron x at time r for volcanic rock sample $u(r)$, and $f_x(r)$ is the actual lithologic output of the sample, the error of recognition and prediction can be written as follows:

$$k_x(r) = f_x(r) - v_x(r) \tag{1}$$

The purpose of correcting errors is to minimize the objective function based on $k_x(r)$, so that the training results of each level of output recognition prediction in the model are the most close to the expected results [5]. The most common objective function is the mean square error criterion, which is defined as:

$$G = D\left\{\frac{1}{2}\sum_{x=1}^{m}(f_x - v_x)^2\right\} \tag{2}$$

In Equation (2), D is the expected value of recognition prediction. When G is directly used as the objective function, it is necessary to know the statistical characteristics of the whole recognition prediction, and replace G with the instantaneous value $G(r)$ of G at time r, namely:

$$G(r) = \frac{1}{2}\sum_{x=1}^{m}(f_x - v_x)^2 = \frac{1}{2}\sum_{x=1}^{m}k_x^2(r) \tag{3}$$

The problem of lithology identification and prediction becomes to find the minimum value of $G(r)$ against the weight ϖ_{xy}. According to the steepest gradient descent method, the following can be obtained:

$$\Delta\varpi_{xy}(r) = \mu\cdot\partial_x(r)\cdot u_y(r) = \mu\cdot k_x(r)\cdot w'(\varpi_x u)\cdot u_y(r) \tag{4}$$

2.2. Lithology Classification of Volcanic Rocks

Volcanic rock belongs to a class of igneous rocks, which refers to rocks formed by magma overflow along volcanic channels or condensation and consolidation on the surface during volcanic activities, including volcanic lava and pyroclastic rock [6].

(1) Volcanic lava

1) Basalt is a representative of basic volcanism lava, rich in calcium, magnesium and ferric magnesium, so the color of the rock is dark and the ratio of material to hardness is large [7]. The rock mass on the rock core is generally dark gray, gray black and gray green, and the wind erosion layer is purple red to dark brown. The rock mass is generally a porphyry structure, and a dense mass structure is also common [8].

2) Andesite is a typical representative of calc-alkaline series of neutral volcanic lava [9]. Color to reddish-brown, gray brown, weathered surface gray green or gray purple, mainly for the porphyry structure, no spot hidden crystal structure is rare, the main block structure. The content of porphyry in Andesite is high [10].

3) Ansan basalt

The mineral phenocrysts of the basalt in Ansan are mostly basic plagioclase, ordinary pyroxene or xanthopxene, and the matrix is mostly neutral plagioclase, which has obvious intergranular structure, interwoven structure and glassy interwoven structure [11].

(2) Pyroclastic rocks

Pyroclastic rock is a kind of pyroclastic rock that is similar to sedimentary rock after a series of diagenesis such as "compaction and consolidation" of various pyroclastic materials produced during volcanic activity [12]. Pyroclastic rocks are divided into tuff and volcanic breccia according to the content of detritus and the size of particles [13]. Breccias are mainly basic, neutral and moderately acidic volcanic lava debris and crystal debris [14].

3. Investigation and Research on Intelligent Identification and Prediction of Volcanic Rock Based on Artificial Neural Network

3.1. Regional Profile

The application of the identification and prediction model in this study is the igneous strata of Yingcheng Formation in Songnan Gas Field [15]. Classification according to igneous mineral composition, clastic grain size, proportion and structural characteristics: on the basis of the principle of first and second class classification, six specific rock types were determined. For example, the tertiary classification of igneous rocks in Yingcheng Formation of Songnan Gas Field is shown in Table 1 [16].

Table 1. Tertiary classification of igneous rocks in Yingcheng Formation of Songnan Gas Field

Structure categories	Component category	Rock types
Volcanic lava class	basic	Compact basalt, stomatal basalt, brecciated basalt
	Neutral	Trachyte, brecciated trachyte
Pyroclastic lava	Neutral	Coarse breccia lava
	Basic	Basaltic aggregates, breccia, tuff
Pyroclastic rocks	Neutral	Coarse grained aggregates, breccia, tuff
Sedimentary pyroclastic rocks	Clastic < 2 mm	Low limestone
Shallow and subvolcanic rocks	Basic	Diabase
Plutonic	Basic	Gabbro

3.2. Volcanic Rock Data Analysis

(1) Logging response characteristics of volcanic rocks

By means of comparative analysis, cross-plot analysis and statistical analysis, the logging curves of multiple Wells in Yingcheng Formation of Songnan Gas Field are analyzed. It is found that the logging response of volcanic rocks in the study area has the following characteristics in general, and the electrical characteristics of some volcanic rocks are shown in Table 2.

Table 2. Log response characteristics of some rocks

The lithology	Natural gamma	Acoustic time	Neutron	The resistivity
Sandstone	70-150	220-280	0-19	13-70
Mudstone	120-160	250-280	12-30	6-15
Basalt	0-65 190	190-240	12-25	>70
Basaltic tuff	0-65	>225-320	7-26	6-50
Andesite	65-100	185-240	9-31	>70

(2) Texture feature extraction of volcanic rocks from electrical imaging logging

The lithologies with different structures and structures can be identified by using the image information features of microresistivity imaging logging data.

1) Characteristics of dissolved rock structure: the overall characteristics are dense, massive, non-layered electrographic images, and relatively developed fractures. The lithology is uniform without granular characteristics [17].

2) Characteristics of volcanic block structure: the particles inside the rock are of different sizes, disorderly arrangement, mutual support between the blocks, mixed accumulation, clear edges and corners.

3) Pour-ash structure: The outstanding characteristics of pour-ash structure are coarse sugar and pitted, similar to fine and coarse sandstone in clastic rocks, and can be classified as layered and massive type II according to the stratification of rocks [18].

4. Application Research on Intelligent Identification and Prediction of Volcanic Rock Based on Artificial Neural Network

4.1. Intelligent Identification and Prediction Model of Volcanic Rock Based on Artificial Neural Network

The establishment process of artificial neural network is integrated and applied to the intelligent identification and prediction of volcanic rock lithology. The realization of the model includes the following basic processes, whose flow chart is shown in Figure 1.

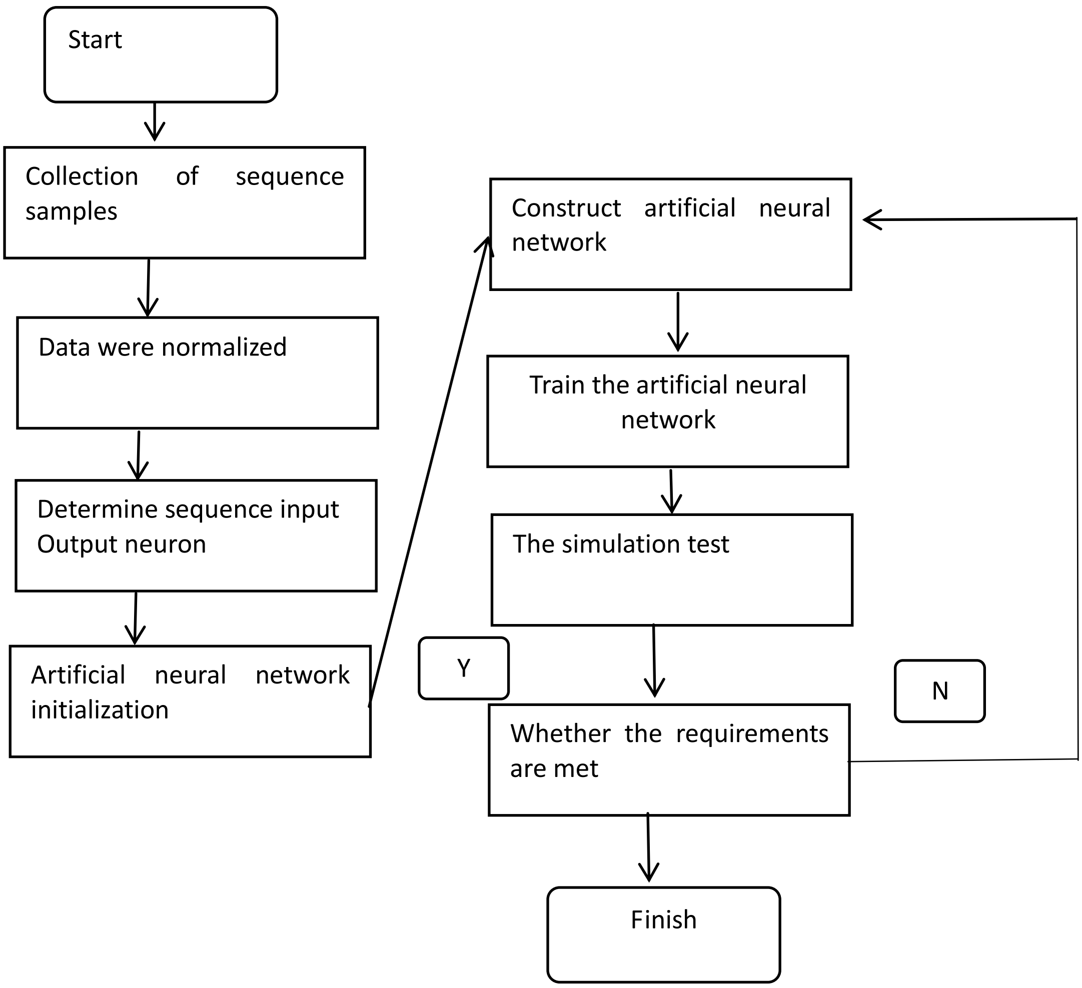

Figure. 1. Intelligent identification and prediction model of volcanic rock with artificial neural network

The realization process of intelligent identification and prediction of volcanic rock based on artificial neural network includes the following aspects:

(1) Collection of sequence samples First, the classification and sequence data of igneous strata in Songnan Oil and Gas field are collected and sorted, and the initial classification of existing igneous

strata is made according to the classification rules of mature igneous strata.

(2) Data preprocessing According to the needs, data normalization and other related preprocessing work.

(3) To determine the sequence input and output neurons, select the single sequence parameters with obvious characteristics of igneous strata, and calculate the initial parameter values of three logging curves of all igneous strata sequence samples as input neurons, and the category attribute of igneous strata sequence as output neurons.

(4) The artificial neural network is constructed by determining the number of layers of the artificial network model and the number of neurons in each layer, and selecting activation function, initial weight, learning rate and expected error.

(5) The artificial neural network is trained by training samples, so as to establish the mapping relationship between the sequence characteristic parameters of igneous strata and lithology differentiation, so as to classify and identify and predict the lithology of igneous rocks.

4.2. Intelligent Identification and Prediction Application of Volcanic Rock With Artificial Neural Network

Through the analysis of conventional logging data and imaging logging data, ILD, GR and DE3 logging curves are selected as the input units of the network. The lithologies to be identified are mudstone, siltstone and argillaceous siltstone, and a three-layer forward network is established. The typical samples with core data were selected as the input samples of BP neural network for learning and training, and the lithology identification of the whole well segment was carried out in Well 20 of Yingcheng Formation in Songnan Gas Field by using the established neural network model. 152 lithologic samples were selected for identification and prediction, and the test results are shown in Table 3.

Table 3. Lithologic identification and prediction data

Number of training	Mudstone	Siltstone	Argillaceous siltstone
50	90.9%	92.1%	93.4%
100	93.5%	92.8%	91.5%
150	96.2%	97.4%	94.9%
200	95.7%	96.3%	92.4%

According to the data in Figure 2, when the number of iterations is 50, the accuracy of mudstone identification and prediction is as high as 90.9%, the accuracy of siltstone lithology identification and prediction is as high as 92.1%, and the accuracy of muddy siltstone lithology identification and prediction is as high as 93.4%. When the number of iterations is 100, the accuracy of identification prediction for mudstone is up to 93.5%, for siltstone is up to 92.8%, and for argillaceous siltstone is up to 91.5%. When the number of iterations is 150, the accuracy of identification prediction for mudstone is as high as 96.2%, for siltstone as high as 97.4%, and for argillaceous siltstone as high as 94.9%. When the number of iterations is 200, the accuracy of recognition and prediction is as high as 95.7% for mudstone, 96.3% for siltstone and 92.4% for argillaceous siltstone.

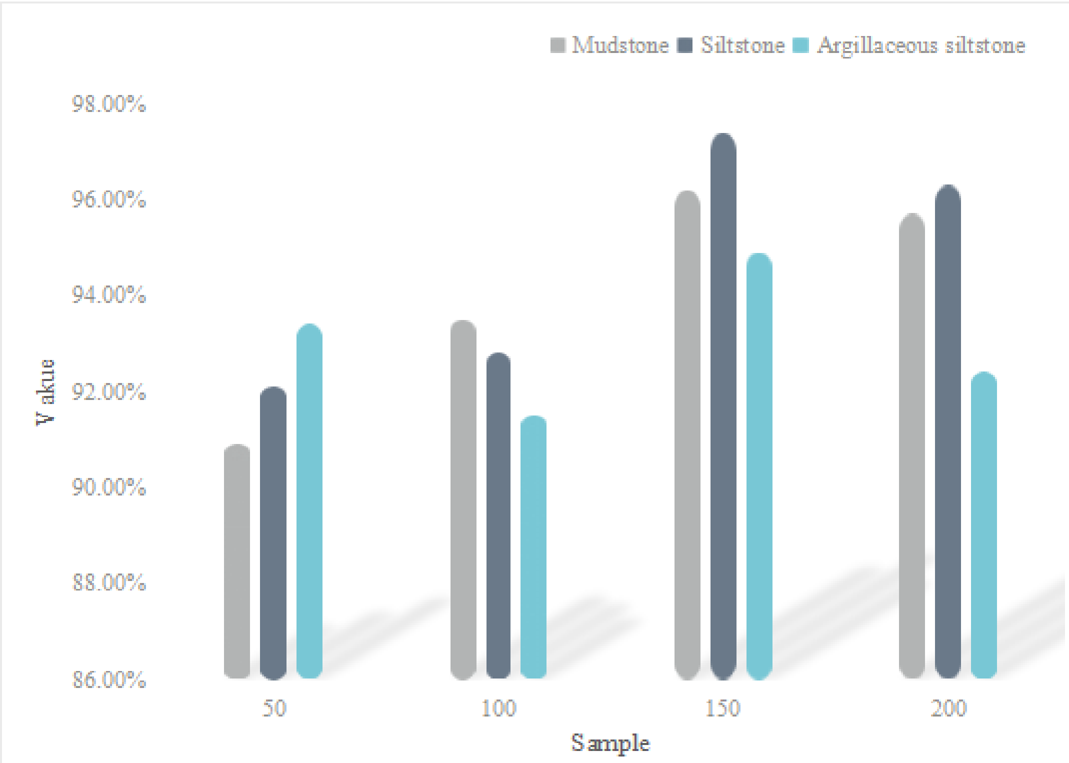

Figure 2. Comparison of lithology identification and prediction results

5. Conclusion

The lithology of volcanic rock reservoir is diverse and its components vary greatly, so the logging interpretation of volcanic rock reservoir is far more complicated than that of clastic rock reservoir and carbonate rock reservoir. Based on the realization process of artificial neural network algorithm and the basis and characteristics of volcanic rock classification, this paper aims at the difficulties faced by logging lithology identification and prediction of volcanic rock reservoir. Based on the analysis and summary of the logging response characteristics of volcanic rocks and the texture characteristics of the electric imaging logging of volcanic rocks in various regions, the establishment of the intelligent identification and prediction model of volcanic rocks is taken as the fundamental starting point. In order to accurately obtain the parameters of each part of the volume model, a widely used prediction and identification method based on the fusion of artificial neural network for volcanic reservoir is established.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Osimobi J C, Avwiri G O, Agbalagba E O. Radiometric and Radiogenic Heat Evaluation of Natural Radioactivity in Soil Around Solid Minerals Mining Environment in South-Eastern Nigeria. Environmental Processes, 2018, 5(4):859-877. https://doi.org/10.1007/s40710-018-0336-1

[2] Cramer R, Lu J, Shultz M, et al. Use of Environmental Sequence Stratigraphy (ESS) as an Environmental Forensic Tool to Identify Chlorinated Solvent Sources at a Complex Site in Silicon Valley, California,2018, 9(5):554-566. https://doi.org/10.4236/jep.2018.95035

[3] Caggiano A, Nele L. Artificial Neural Networks for Tool Wear Prediction Based on Sensor Fusion Monitoring of CFRP/CFRP Stack Drilling. International Journal of Automation Technology, 2018, 12(3):275-281. https://doi.org/10.20965/ijat.2018.p0275

[4] Valero, D, Bung, et al. Artificial Neural Networks and pattern recognition for air-water flow velocity estimation using a single-tip optical fibre probe. Journal of hydro-environment research, 2018, 19(Mar.):150-159. https://doi.org/10.1016/j.jher.2017.08.004

[5] Muhammad, Kamran, Malik. Urdu Named Entity Recognition and Classification System Using Artificial Neural Network. ACM Transactions on Asian and Low-Resource Language Information Processing, 2018, 17(1):2.1-2.13. https://doi.org/10.1145/3129290

[6] Schulte H, Gauterin E. Adaptive GLOH with PSO-trained NN for the recognition of plastic surgery faces and their types. Bio-Algorithms and Med-Systems, 2019, 15(1):1-7. https://doi.org/10.1515/bams-2018-0033

[7] Kalanidhi K, Vinodkumar D, Sridharan P. Transmission power line fault detection based on deep leaning methods. Indian journal of power and river valley development, 2019, 69(3-4):35-38.

[8] Bhavani N, Sujatha K, Ponmagal R S. Pollution Control by Monitoring of So_X and No_X Emissions Using Smart Sensors. Pollution research, 2018, 37(3):678-683.

[9] Andrew, Tzer-Yeu, Chen, et al. Convolutional neural network acceleration with hardware/software co-design. Applied Intelligence: The International Journal of Artificial Intelligence, Neural Networks, and Complex Problem-Solving Technologies, 2018, 48(5):1288-1301.

[10] Lima R, Suriamin F, Marfurt K, et al. Convolutional Neural Networks. AAPG Explorer, 2018, 39(10):22-23.

[11] Subject-Independent Emotion Recognition of EEG Signals Based on Dynamic Empirical Convolutional Neural Network. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2021, 18(5):1710-1721. https://doi.org/10.1109/TCBB.2020.3018137

[12] Mohd, Yawar, Ali, et al. Artificial neural network simulation for prediction of suspended sediment concentration in the River Ramganga,Ganges Basin,India. International Journal of Sediment Research, 2019, v.34(02):14-26. https://doi.org/10.1016/j.ijsrc.2018.09.001

[13] V, Prema, K, et al. Interactive Graphical User Interface (GUI) for Wind Speed Prediction Using Wavelet and Artificial Neural Network. Journal of The Institution of Engineers (India), Series B. Electrical eingineering, electronics and telecommunication engineering, computer engineering, 2018, 99(5):467-477. https://doi.org/10.1007/s40031-018-0339-3

[14] Delafrouz, Hadi, Ghaheri, et al. A novel hybrid neural network based on phase space reconstruction technique for daily river flow prediction. Soft computing: A fusion of foundations, methodologies and applications, 2018, 22(7):2205-2215. https://doi.org/10.1007/s00500-016-2480-8

[15] Kanat, Z, Evrim, et al. Application of artificial neural network (ANN) for the prediction of thermal resistance of knitted fabrics at different moisture content. The Journal of the Textile

Institute, Part 3. Technologies for a New Century, 2018, 109(9):1247-1253. https://doi.org/10.1080/00405000.2017.1423003

[16] Hm A, Ns A, Pg A, et al. Clayey soil stabilization using alkali-activated volcanic ash and slag - ScienceDirect. Journal of Rock Mechanics and Geotechnical Engineering, 2022, 14(2):576-591. https://doi.org/10.1016/j.jrmge.2021.08.012

[17] Alistair, Schofield. The newer volcanics 'hyaloclastite', melbourne: geology, geotechnical properties and engineering implications. Australian Geomechanics, 2018, 53(2):39-51.

[18] Rocholl A, Schaltegger U, Gilg H A, et al. The age of volcanic tuffs from the Upper Freshwater Molasse (North Alpine Foreland Basin) and their possible use for tephrostratigraphic correlations across Europe for the Middle Miocene. International Journal of Earth Sciences, 2018, 107(2):387-407. https://doi.org/10.1007/s00531-017-1499-0