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Estimation of interval times in the profile of Cambrian and Silurian sediments by means of the neural networks method

The goal of this paper is to present the use of the neural networks method for the estimation of interval times. An important parameter for shale formations is the Total Organic Carbon content (TOC). Acoustic logging constitutes the data necessary in methods assessing the TOC (CARBOLOG, Passey). Newly drilled boreholes feature a complete set of geophysical logging. Nevertheless, there are archival boreholes for which acoustic logging is usually missing or was performed only for a limited depth interval. In such cases it is impossible to perform the quantitative assessment of the TOC parameter using the above mentioned methods. Therefore, in order to calculate the TOC parameter, the neural networks method can be used for the estimation of interval times in archival boreholes. Many types of networks were tested for various input variables constituted by the borehole data, obtaining high values of the correlation coefficients R (0.95÷0.97) between acoustic logging and logging resulting from the use of neural networks.

Key words: neural networks, acoustic logging.

Określenie czasu interwałowego w profilu osadów kambryjsko-sylurskich metodą sieci neuronowych

Celem pracy jest zastosowanie metody sztucznych sieci neuronowych do wyznaczania czasu interwałowego skał na podstawie profilowań geofizycznych. Ważnym parametrem dla formacji łupkowych jest zawartość substancji organicznej TOC. Niezbędnymi danymi w metodach do określenia zawartości substancji organicznej TOC (CARBOLOG, Passeya) jest profilowanie akustyczne. Nowe wiercenia posiadają komplet profilowań geofizycznych. Niemniej jednak istnieją otwory archiwalne, w których na ogół brak jest profilowania akustycznego lub wykonanie jest w ograniczonym interwale głębokościowym. W takim przypadku niemożliwe jest przeprowadzenie ilościowej oceny parametru TOC powyższymi metodami. Stąd, aby wyliczyć parametr TOC, do estymacji czasu interwałowego w odwiertach archiwalnych można wykorzystać metodę sieci neuronowych. Przetestowano kilka typów sieci, dla różnych zmiennych wejściowych, które stanowiły dane otworowe, uzyskując wysokie współczynniki korelacji R (0,95÷0,97) pomiędzy profilowaniem akustycznym a profilowaniem uzyskanym przy wykorzystaniu sieci neuronowych.

Słowa kluczowe: sieci neuronowe, profilowanie akustyczne.

Introduction

An increased interest in the subject of hydrocarbon prospecting in shale gas formations has been observed in recent years. Therefore there is a growing need for archival geophysical data. Most of such data is of low quality, resulting from the technology of geophysical logging in Poland, based on equipment, which quality differed considerably from the standards set by western geophysical companies. Moreover some kinds of geophysical logging, like for example acoustic logging were conducted sporadically.

The methodology, which for many years has been used in solving the problem of the low quality or absence of acoustic logging in archival logging sets [1], was developed by J. Nowak in the Centre for Interpretation and Methodology – the Geofizyka Kraków Company.

The use of the artificial neural networks method for estimation of acoustic time in the profiles of three selected boreholes from the studied area has been described in the presented paper.

Development of neural networks for the estimation of interval times

Neural networks are used increasingly often when solving numerous problems in the fields of geology and geophysics [2–5]. In the present paper, the STATISTICA Neural Networks (SNN) software has been used for the simulation of artificial neural networks, enabling the use of such network types which currently constitute a state of the art problem solving tool. A database including examples of input variables and proper solutions is the primary source of information for neural networks. The input database comprises:

- gamma ray logging (GR),
- neutron porosity in the limestone scale corrected for the borehole diameter and the density of the drilling fluid (NPHI),
- bulk density logging (RHOB).

Geophysical logging from three boreholes: X, Y and Z, having a complete set of borehole data, has been used for the study. Among the numerous tested types of network, the best ones were networks with radial basis functions (RBF). The results obtained for the analysed boreholes are presented in form of tables and figures.

The X borehole

The results of simulation of the interval times DT by means of neural networks for two and three input variables for the X borehole are presented in Table 1. The correlation coefficients *R*, listed in the table for the whole set of data, and taking into account its division into the training, validation and test sets, are the indicators of the method's correctness. Input loggings are presented and the interval times from the acoustic logging DT (marked by the red colour) with those determined using the neural networks method DT_SNN (marked by the black colour) are compared on Figure 1. Table 2 contains the range of variation and the average values of interval times obtained using the above mentioned methods.

The presented analysis indicates that the RBF type neural networks constructed basing on borehole data estimate the interval times DT correctly. High values of coefficients *R* have been obtained for the correlation between the values of interval times from acoustic logging DT and those determined by means of the neural networks method DT_SNN for both three and two input variables (*R*: 0.97; 0.95) (Fig. 2). The interval times estimated using the SNN method (DT_SNN) are characterised by a slightly smaller range of variation compared to the DT logging times (Table 2). The resulting

Table 1. Results of simulation of the interval times DT by means of neural networks in the X borehole

Type of network	Input data	Correlation coefficient *R*			
		training set	validation set	test set	total
RBF	GR, NPHI, RHOB	0.97	0.97	0.97	0.97
RBF	GR, NPHI	0.95	0.95	0.95	0.95

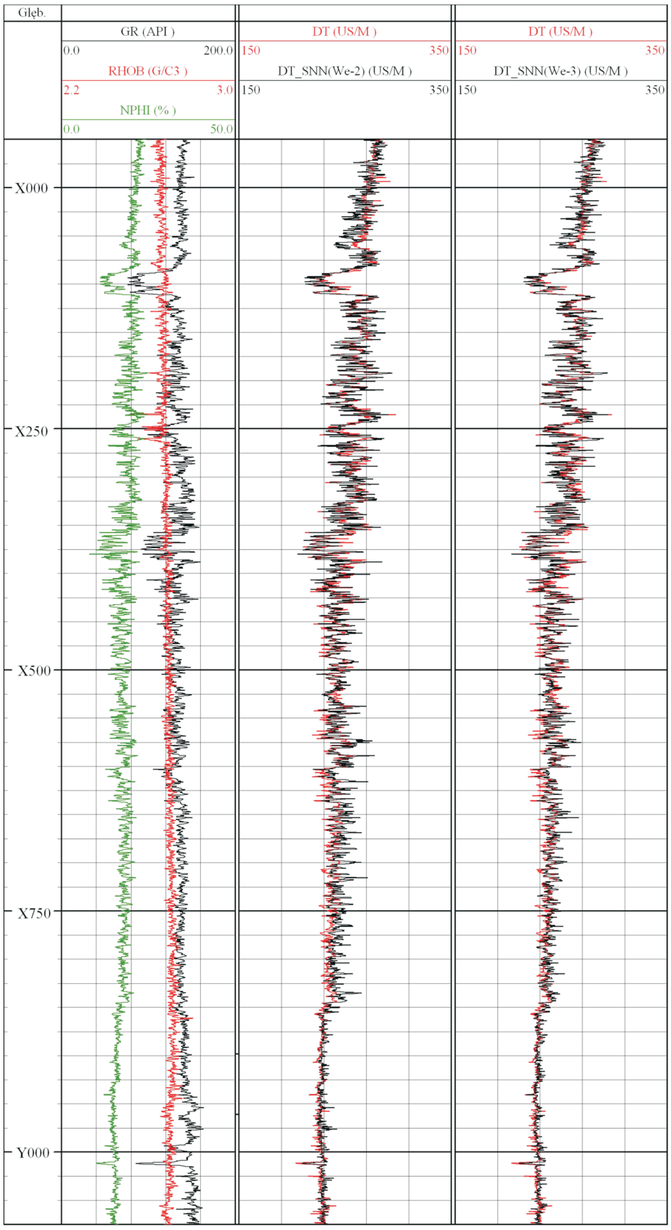

Fig. 1. Comparison of interval times from acoustic logging DT and those determined using the neural networks method DT_SNN for two and three input variables in the X borehole

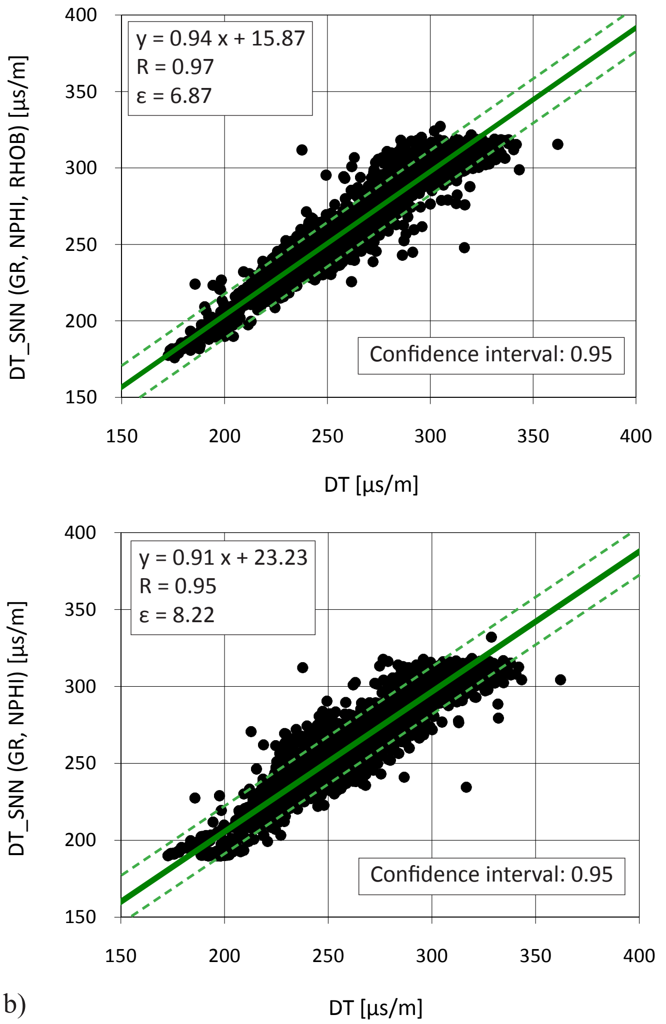

Fig. 2. Correlation between the interval times from acoustic logging DT and those determined by means of the neural networks method DT_SNN (a – for three, b – for two input variables) in the X borehole, (*ε* – the standard error of estimation)

Table 2. Ranges of variation and the average values of interval times obtained by means of different methods in the X borehole

Parameter	Range of variation	Average value
DT [μs/m]	172.7÷362.0	259.3
DT_SNN (GR, NPHI, RHOB) [μs/m]	175.9÷327.1	259.4
DT_SNN (GR, NPHI) [μs/m]	189.5÷332.1	259.4

trends of variation for the interval times are usually compatible with each other.

The Y borehole

The results of estimation of the DT times using the neural networks method are presented in Table 3 and on Figures 3 and 4. Table 4 contains the range of variation and the average values of interval times calculated using different methods.

The presented analysis indicates that the RBF type neural networks generalise properly. The coefficients *R* of correlation between the values of interval times from the acoustic

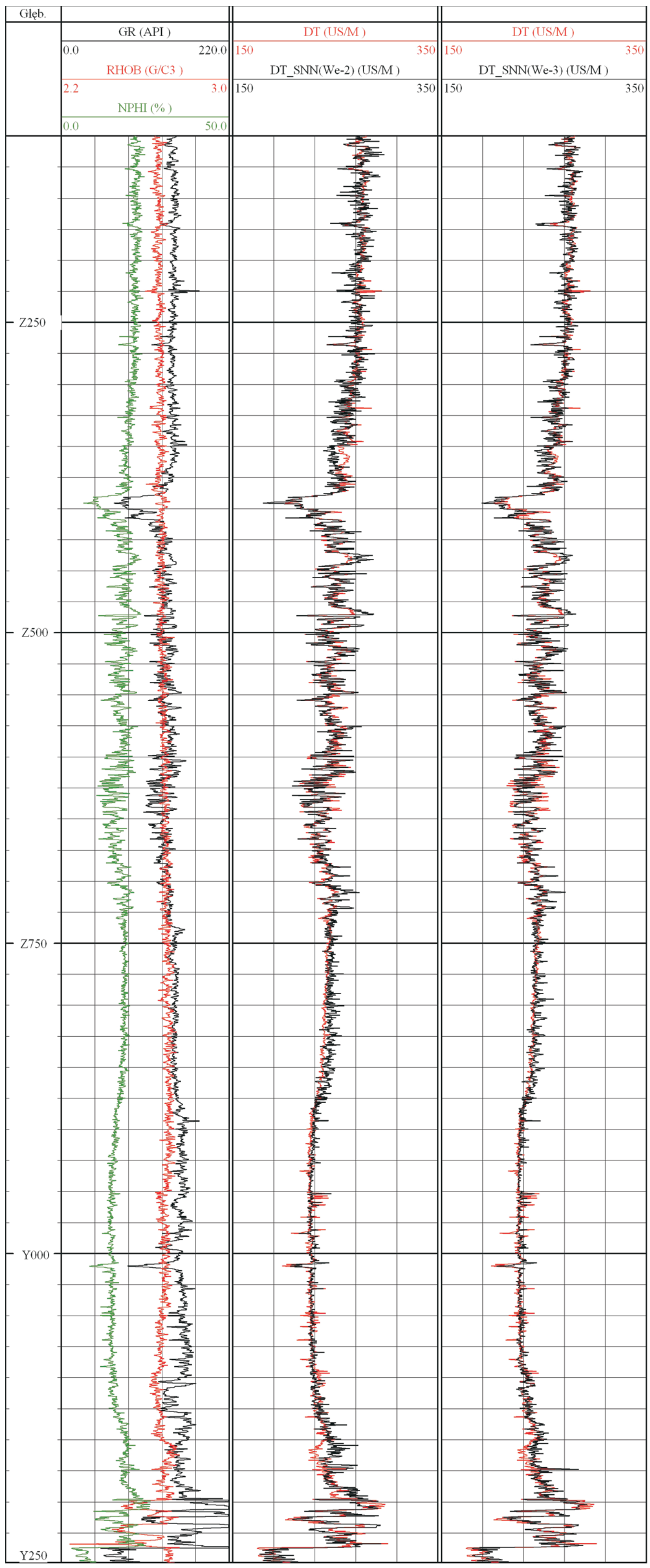

Fig. 3. Comparison of interval times from acoustic logging DT with those determined using the neural networks method DT_SNN in the Y borehole

Table 3. Results of simulation of the interval times DT by means of neural networks in the Y borehole

Type of network	Input data	Correlation coefficient *R*			
		training set	validation set	test set	total
RBF	GR, NPHI, RHOB	0.97	0.97	0.97	0.97
RBF	GR, NPHI	0.95	0.95	0.96	0.95

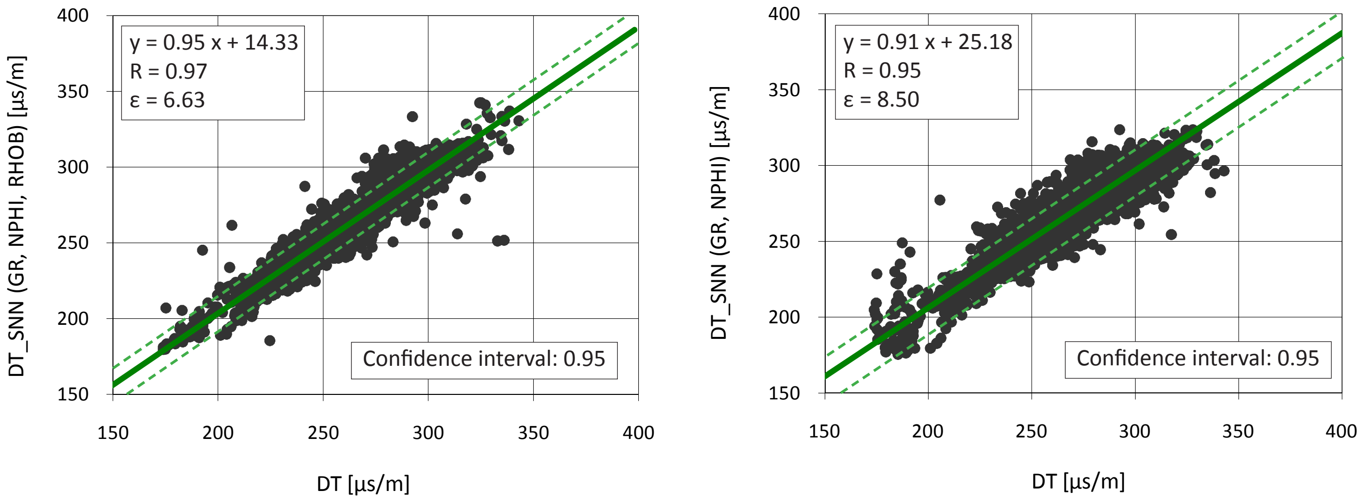

Fig. 4. Correlation between the interval times from acoustic logging DT and those determined by means of the neural networks method DT_SNN (a – for three, b – for two input variables) in the Y borehole (*ε* – the standard error of estimation)

logging DT and those determined using the neural networks method DT_SNN amount to 0.97 and 0.95 for three and two input variables, respectively (Fig. 4). The interval times determined by means of the above mentioned methods are characterised by similar ranges of variation and average values (Table 4). The trends of variation for the interval times are usually compatible with each other.

Table 4. Ranges of variation and the average values of interval times obtained by means of different methods in the Y borehole

Parameter	Range of variation	Average value
DT [µs/m]	173.8÷343.0	265.2
DT_SNN (GR, NPHI, RHOB) [µs/m]	179.7÷342.6	265.1
DT_SNN (GR, NPHI) [µs/m]	175.6÷323.6	265.2

The use of the developed neural networks for the estimation of interval times in a borehole profile

The examples of the use of neural networks constructed for the given borehole in the estimation of interval times in the profile of another borehole in the examined region are presented below.

The neural networks developed for three and two variables for the X borehole have been used to determine the interval times in the profile of the Y borehole, and the ones from the Y borehole – for the Z borehole in the studied area. The obtained results are presented in Figures 5–8.

The use of the artificial neural networks constructed based on the borehole data from the X and Y boreholes for prediction of interval times in different boreholes (Y, Z) usually gives positive results. High correlation coefficients *R* have been obtained for the interval times determined by means of various methods. In both boreholes, for a network with three input variables the *R* coefficient equals 0.95, and for two variables *R* = 0.93. The trends of variation for the interval times are usually compatible with each other. Nonetheless, in some depth intervals a slightly worse compatibility of the interval times obtained by means of the neural networks method is observed. Such a situation is visible above the depth of Z350 m and within the interval of (Z750, Z850) m (Fig. 5), as well as above the depth of Z350 m and within the interval of (Z700, Z900) m (Fig. 6) in the Y borehole.

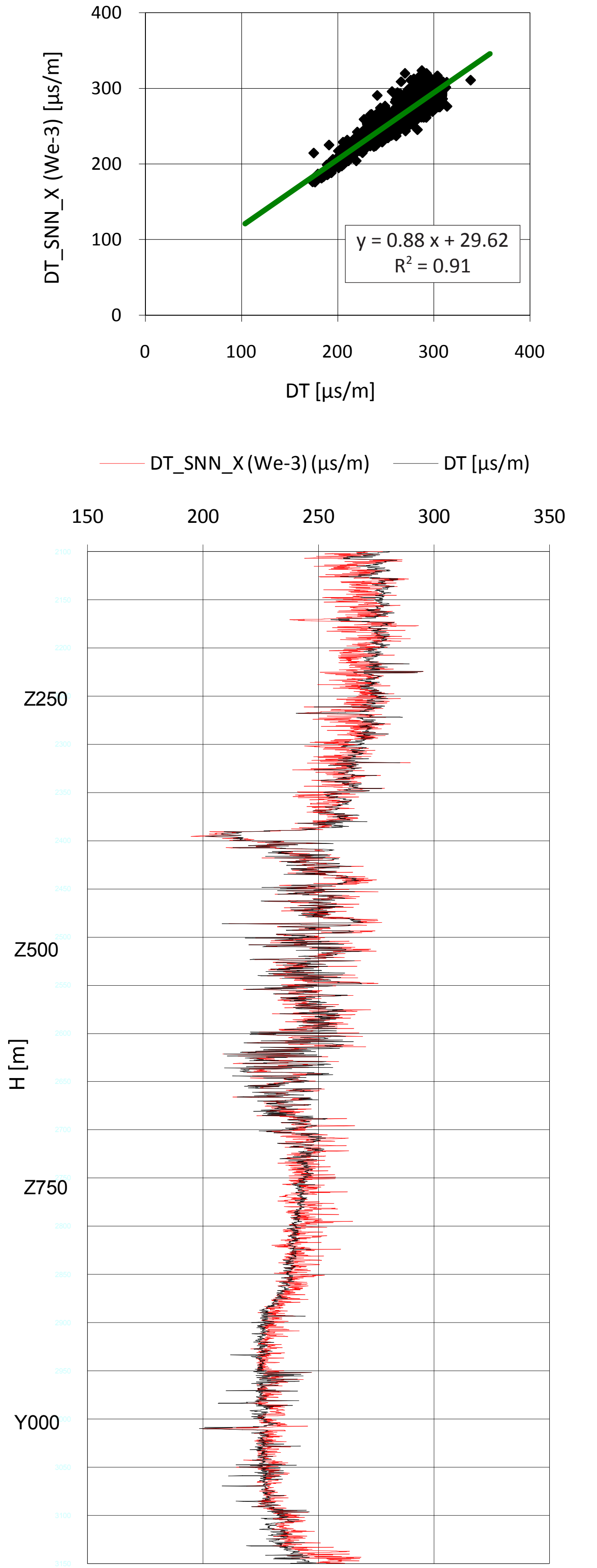

Fig. 5. Comparison of the interval times determined using the method of neural networks constructed for the X borehole (for 3 input variables) with the interval times from the acoustic logging DT in the Y borehole

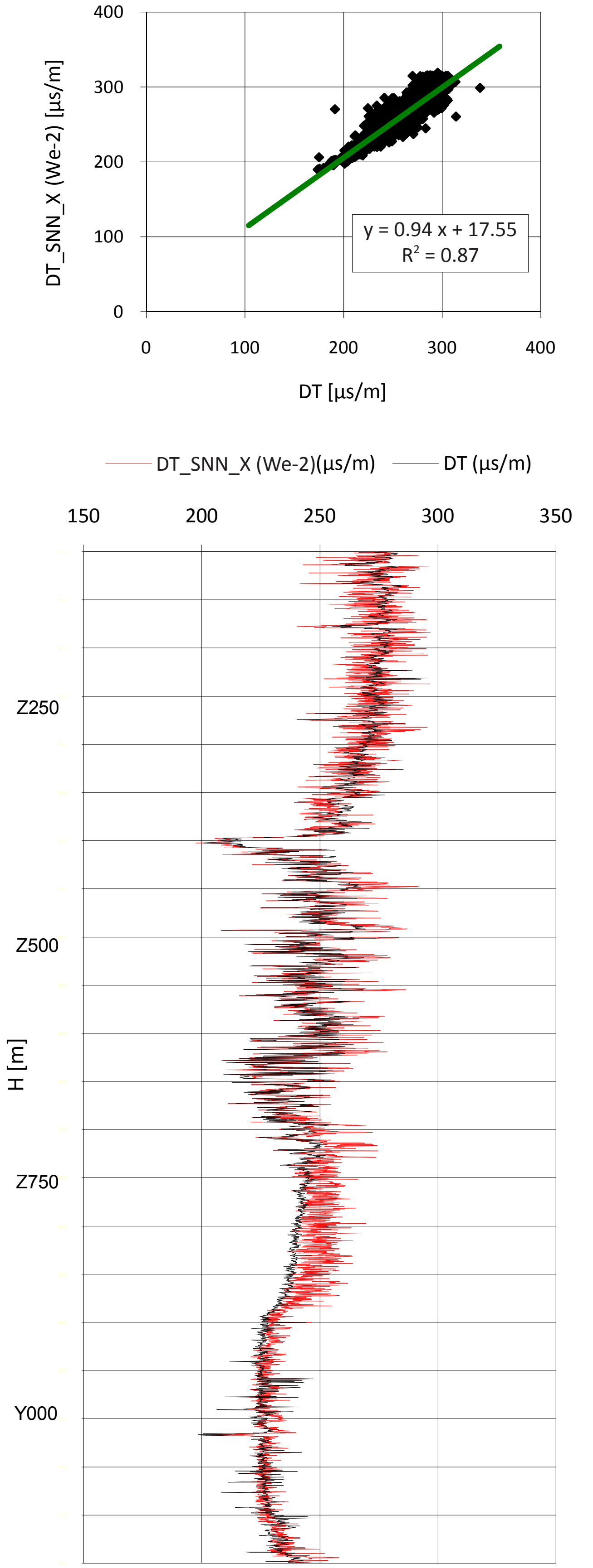

Fig. 6. Comparison of the interval times determined using the method of neural networks constructed for the X borehole (for 2 input variables) with the interval times from the acoustic logging DT in the Y borehole

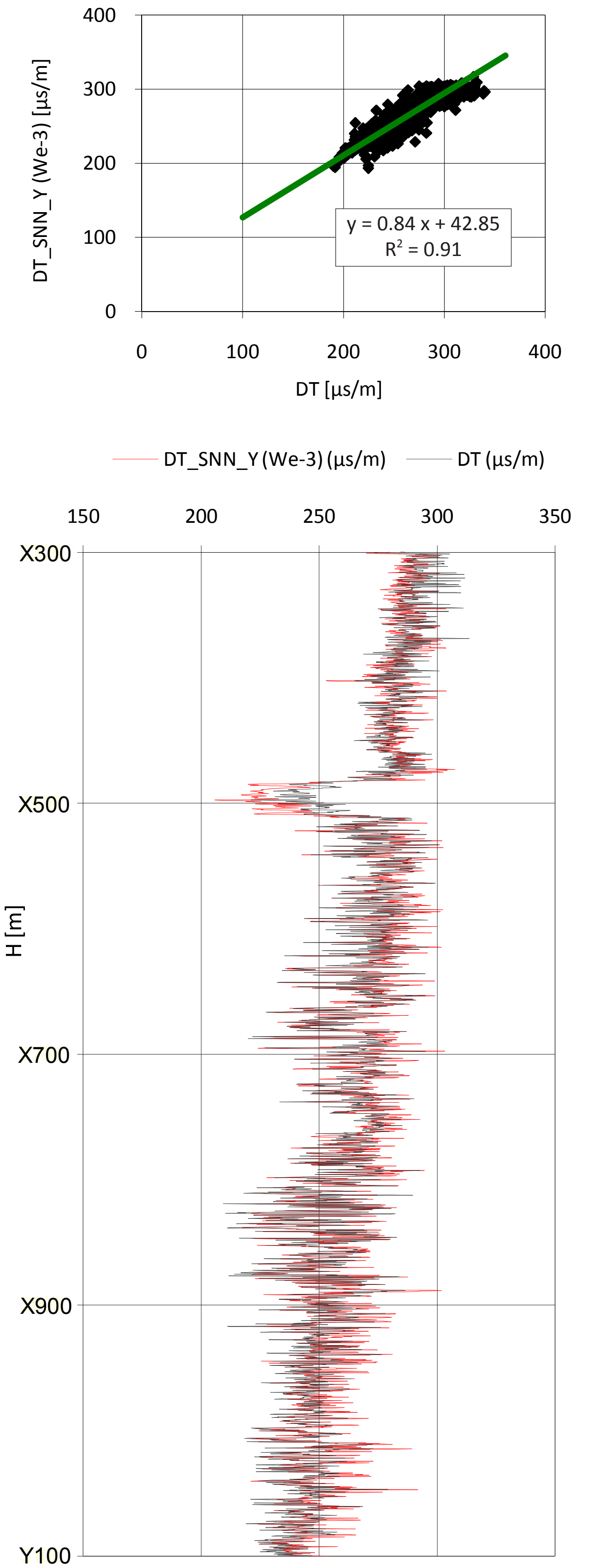

Fig. 7. Comparison of the interval times determined using the method of neural networks constructed for the Y borehole (for 3 input variables) with the interval times from the acoustic logging DT in the Z borehole

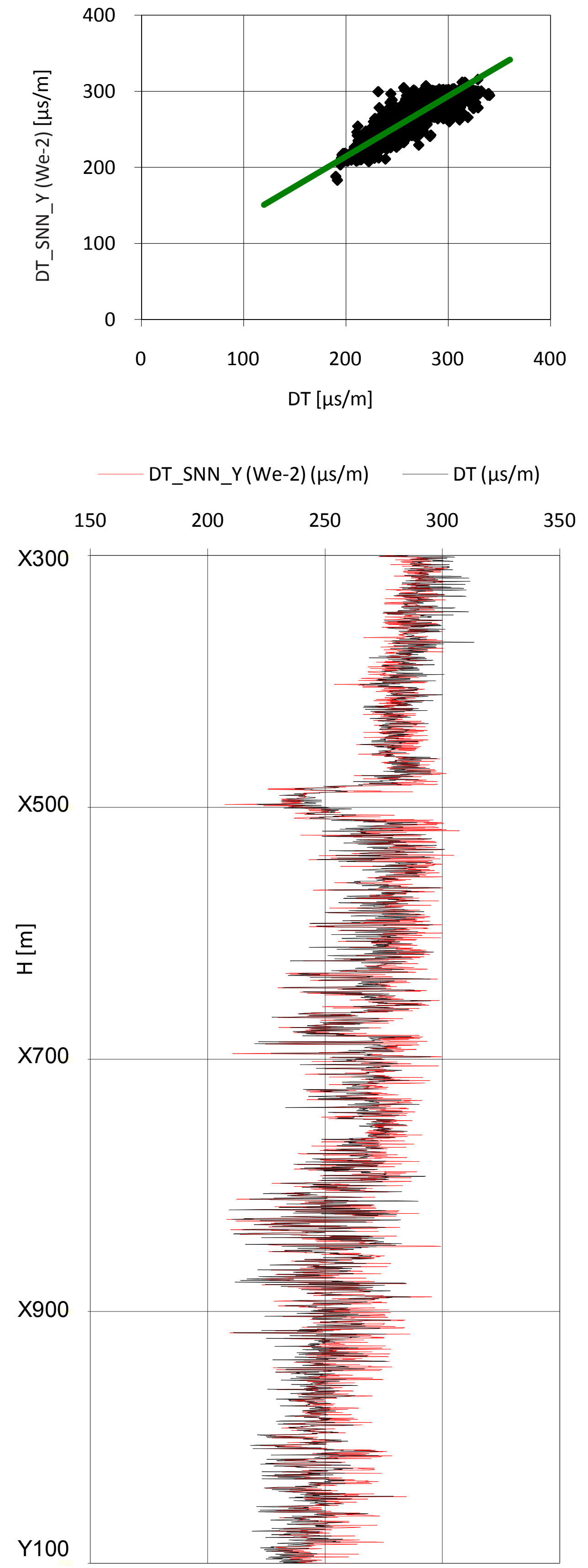

Fig. 8. Comparison of the interval times determined using the method of neural networks constructed for the Y borehole (for 2 input variables) with the interval times from the acoustic logging DT in the Z borehole

Conclusions

The neural networks method has been used for the estimation of acoustic time logging based on the borehole data. Neural networks have been developed for two and three input variables for two boreholes: X and Y. Numerous network types have been tested, and the best among them turned out to be the networks with radial basis functions (RBF). High coefficients *R* of correlation between the values of interval times from logging and those determined by means of the neural networks method have been obtained (*R*: 0.95÷0.97). It should be pointed out that neutron logging performed prior to 1990 was usually not calibrated and corrected, which is why there was a necessity to conduct such calibration before using the neural networks method for the interval times estimation. During those times, the density logging RHOB was not conducted either. In the presented paper, one of the input variables used for the construction of the networks was the bulk density from RHOB logging. In the case of the absence of such data, the neural network constructed for the three input variables: GR, NPHI, RHOB cannot be used to predict the interval times in a borehole profile. In the present paper, the neural networks for the two parameters: GR and NPHI have also been developed, and can be used for the estimation of interval times in all boreholes within the analysed area.

The artificial neural networks developed for the examined boreholes were used to predict the interval times in the profiles of other boreholes. High correlation coefficients *R* were obtained between the interval times determined by means of the neural networks method and those from acoustic logging (*R*: 0.93÷0.95). In some depth intervals, especially in the Y borehole (Figures 5 and 6), a slightly worse compatibility of the interval times obtained using the neural networks method with the ones from the acoustic logging is observed. This is probably connected to the slightly different lithology of the Y borehole from the lithology of the X borehole for which the neural network has been developed and trained.

The constructed neural networks may be used in boreholes from the given region (investigated as part of the BLUE GAS – POLISH SHALE GAS programme).

The results presented in the present paper show that the neural networks technique can be used to estimate the interval times for archival boreholes, in which no acoustic logging was performed, or it was performed for an incomplete profile.

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