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An Application of Artificial Neural Network for the Interpretation of Three Layer Electrical Resistivity Data using Feed Forward Back Propagation Algorithm

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Abstract

The Non-linear apparent resistivity problem of three layer case in the sub surface study of the earth is taken into account to get the model parameters in terms of resistivity and thickness of individual subsurface layers using the trained synthetic data by means of Artificial Neural Network toolbox in MATLAB software. Here we used a single layer feed-forward neural network with fast back propagation learning algorithm. So on proper training of back propagation networks it tends to give the resistivity and thickness of the subsurface layer model of the field resistivity data with reference to the synthetic data trained earlier in the appropriate network. During training the weights and biases of the network are iteratively adjusted to make network performance function level more efficient. On adequate training, errors will be minimized and get the better result using the artificial neural network .The network is trained with more number of VES data and this trained network is demonstrated with the field data. The accuracy of inversion depends upon the number of data trained. In the present study the interpretation of the vertical electrical sounding has been done successfully with more accurate layer model and presented in the text.

Keywords: Artificial neural network, Resistivity inversion, feed forward back propagation algorithm, Layer model.

Introduction
“Neural Network” (NN) is a mathematical model or computational model that tries to

simulate the structure and/or functional aspects of biological neural networks. It consists of as interconnected group of artificial neurons and processes information using a connectionist approach to computation. Artificial neural network (ANN) can play a major role to dig out the mystery of earth science by means of the previous learned examples used in Artificial Neural Network. These networks have self-learning capability and are fault-tolerant as well as noise-immune and have applications in various fields (Sreekanth et al.,2009).

A very important feature of these networks is their adaptive nature, whose 'learning by example' replaces "programming" in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data is readily available. ANNs are now being increasingly recognized in the area of classification and prediction, where regression model and other related statistical techniques have traditionally been employed. Here electrical resistivity data has been taken to interpret the layer model of the sub surface of earth using ANN.

Data acquisition using Schlumberger Vertical Electrical Sounding Method

Direct current resistivity methods of geophysical exploration are in extensive use globally for aquifer mapping and estimation of aquifer parameters viz., resistivity and thickness (Kosinky and Kelly, 1981; Sri Niwas and Singhal, 1981; Mazac et.al, 1985; Yadav and Abolfazli, 1998). The physical basis of the resistivity method is based on the relative distribution of impressed current in the earth controlled by subsurface resistivity distribution. Due to the excessive computational requirement and the interpretation of Vertical Electrical Sounding (VES) data remained confined to curve matching procedure through theoretical curves prepared using different computational methods. (Flathe, 1955; VanDam, 1964; Mooney et.al, 1966; Ghosh, 1971).

In general, the characteristic sounding curves illustrated in Fig.1 represent the multiple layers .On this assumption each of the four sets has particular properties that may be roughly classified. Types H and K have a definite minimum and maximum, indicating a bed, or beds, of anomalously low or high resistivity, respectively, at intermediate depth. Types A and Q show fairly uniform change in resistivity the first increasing, the second decreasing with depth. Obviously these curves also may be combined. It is generally possible to tell from the shape of the adjacent parts of the profile which layer corresponds to the maximum or minimum on the first two curve types. For H and K- type curves $\rho1 > \rho2 < \rho3$ and $\rho1 < \rho2 > \rho3$, respectively, and we may be able to draw some conclusions about relative values of $\rho1$ and $\rho3$ if the spread has been extended sufficiently. The A and Q-type curves corresponds to $\rho1 < \rho2 < \rho3$ and $\rho1 > \rho2 > \rho3$, respectively. Some idea of the relative bed thicknesses may be obtained from the horizontal extent of the maxima and minima as well as the flanking portions in all cases. The coordinates of the extreme points in curves of types H and K (i.e., maximum or minimum ρ_a and electrode separation) may be used with certain characteristic curves for three layers employing a particular electrode spread (Telford 1990).

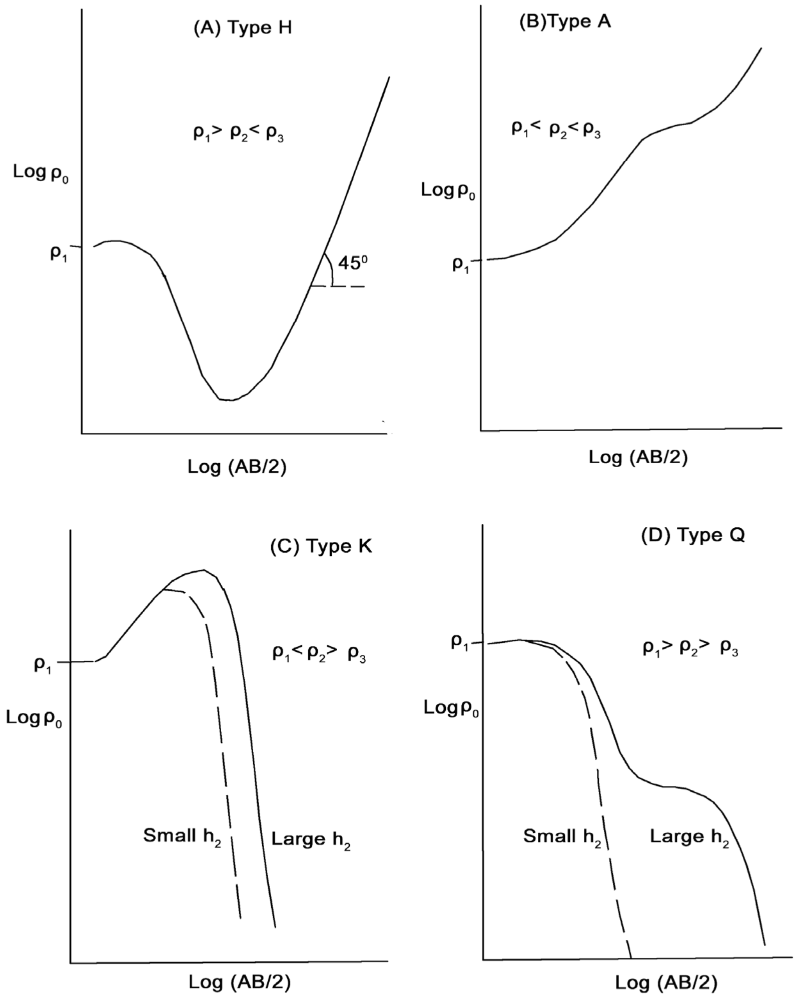

Figure 1. Characteristic Sounding Curves representing the four types of sub surface layers.

Artificial Neural Network application on Electrical Resistivity method

Interpretation of the electrical resistivity data is necessary to understand the concept of reality behind the earth sub surface system and there should be an efficient tool to estimate and predict the parameters which are close relevant to the system. Thus computational method involves the intelligent network to justify all the non linear problem is necessary. Neural network can have the power to understand the factors related to the cause of earthquake and the variations of the sub surface geology. Conventional mathematical analysis is difficult when there are uncertain and partially defined systems with a degree of vagueness. The use of intelligent systems to evaluate such complex system is ideal. An adaptive network consists of a structure of nodes and the directional links through which these nodes are connected. The outputs of the nodes depend on the parameters associated with these nodes. The change in these parameters is brought about by a learning rule to minimize the error. The learning techniques can automate this process and substantially reduce development time and cost while improving performance. For neural networks, the knowledge is automatically acquired by the backpropagation algorithm and will be a more efficient tool used for the interpretation of Geophysical data extensively.

Artificial neural networks have been successfully applied to a number of geophysical problems in this way, including parameter estimation, classification, filtering and optimization (Poulton etal., 1992;Sheen,1997;Vander Baanand Jutten,2000;Calderon-Mac ias etal.,2000; El-Qady and Ushijima,2001). The adoption of the neural network approach holds several advantages over more conventional modeling techniques, allowing the effective solution of non-linear problems from complex, incomplete and noisy data. The computational expense of the inversion using neural networks, being dependent upon the dimension of the space of unknown parameters rather than the physical dimensions of the model space, is also comparatively low.

Feed forward Back propagation Algorithm

Back-propagation learning algorithm works for feed-forward networks with continuous output. Training starts by setting all the weights in the network to small random numbers. Now, for each input example the network gives an output, which starts randomly. We measure the squared difference between this output and the desired output—the correct class or value. The sum of all these numbers over all training examples is called the total error of the network. If this number was zero, the network would be perfect, and the smaller the error, the better the network This has been projected in Fig 4 (a), 5 (a), 6 (a), 7 (a) by checking the synthetic data and it exactly matches with the trained layer model and thus error has been made nearly zero. By choosing the weights that minimize the total error, one can obtain the neural network that best solves the problem at hand. This is the same as linear regression, where the two parameters characterizing the line are chosen such that the sum of squared differences between the line and the data points is minimal. This can be done analytically in linear regression, but there is no analytical solution in a feed-forward neural network with hidden units. In back-propagation, the weights and thresholds are changed each time an example is presented, such that the error gradually becomes smaller. This is repeated, often hundreds of times, until the error no longer changes.

The advent of Back propagation algorithm (BP), the adaptation of steepest descent method, opened up new avenues of application of Multilayered ANN for many problems of practical interest. A multilayer ANN contains three basic types of layer: input layer, hidden layer (s), and output layer. Basically the Back propagation learning involves propagation of error backwards from the output layers to the hidden layers in order to determine the update for the weights leading to the units in the hidden layer(s).

The non-linear relationship between input and output parameters in any network requires a function, which can appropriately connect and/or relate the corresponding parameters. In operation, each unit of an ANN receives inputs from other connected units and/or from an external source. A weighted sum of the inputs is computed at a given instant of time. The activation value determines the actual output from the output function unit i.e., the output state of the unit. Input element vectors with layer of neurons are shown in Fig.2. The output values and the other external inputs in turn determine the activation and output states of the other units.

The feedforward neural network was the first and arguably simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network.

Back propagation learning involves propagation of the error backwards from the output layer to the hidden layers in order to determine the update for the weights leading to the units in a hidden layer. The error at the output layer itself is computed using the difference between the desired output and the actual output at each of the output units. The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data (Yegnanarayana 2005). A trained multilayer feedforward neural network is expected to capture the functional relationship between the input-output pattern pairs in the given training data. It is implicitly assumed that the mapping function corresponding to the data is a smooth one. The function approximation interpretation of a single layer feedforward neural network enables us to view different hidden layers of the network performing different functions. Feedforward backpropagation algorithm is used here to invert the Vertical Electrical Sounding Data. Backpropagation learning emerged as the most significant result in the field of artificial neural networks. In fact it is this learning law that led to the resurgence of interest in neural networks, nearly after 15 years period of lull due to exposition of limitations of the perceptron learning by Minsky and Papert (1969). Backpropagation learning involves propagation of the error backwards from the output layer to the hidden layers in order to determine the update for the weights leading to the units in a hidden layer. The error at the output layer itself is computed using the difference between the desired output and the actual output at each of the output units. The actual output for a given input training pattern is determined by computing the outputs of units for each hidden layer in the forward pass of the input data. A trained multiplayer feedforward neural network is expected to capture the functional relationship between the input-output pattern pairs in the given training data. It is implicitly assumed that the mapping function corresponding to the data is a smooth one. But due to limited number of training samples, the problem becomes an ill-posed problem, in the sense that there will be many solutions satisfying the given data, but none of them may be the desired/correct one [Tikhonov and Arsenin, 1977; Wieland and Leighton, 1987]. Fig 3 illustrates the basic idea of an ill-posed problem for a function of one variable. Given the samples marked ‘x’, the objective is to capture the function represented by the solid curve. But depending on the size of the network, several solutions are possible, including the overtraining situations (shown by dotted curve) in which for all the training data the error is zero. In fact there could be several functions passing through the given set of points, none of which is the desired one. This happens if the number of free parameters (weights) of the network is very large. Such a situation results in a large error when some other (test) samples are given to validate the network model for the function. This is called ‘poor generalization’ by the network. On the other hand, fewer number of the free parameters may result in a large error even for the training data, and hence a poor approximation to the desired function. The function approximation interpretation of a multiplayer feedforward neural network enables us to view different hidden layers of the network performing different functions. For example, the first hidden layer can be interpreted as capturing some local features in the input space. The second hidden layer can be interpreted as capturing some global features. This two-stage approximation has been shown to realize any continuous vector-valued function [Sontag, 1992b]. The universal approximation theorem of Cybenko seems to suggest that even a single layer of nonlinear units would suffice to realize any continuous function [Cybenko, 1989]. But this result assumes that a hidden layer of unlimited size is available, and that the continuous function to be approximated is also available. Thus Cybenko’s theorem gives only an existence proof, but it is not useful to realize the function by training a single hidden layer network. It is also possible to view that the hidden layers perform a nonlinear feature extraction to map the input data into linearly separable classes in the feature space. At the output layer the unit with the largest output is considered as the class to which the input belongs.

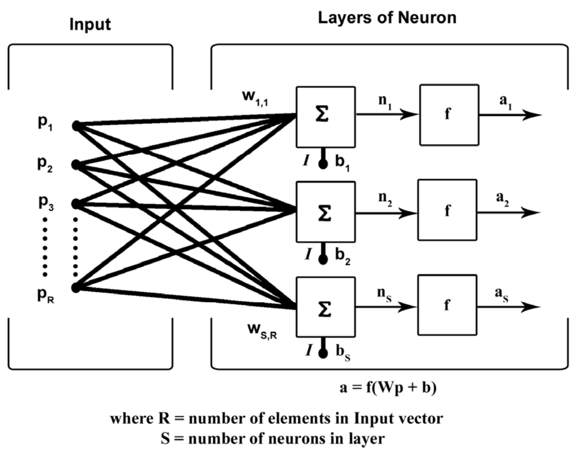

Figure 2. Input element vectors with layer of neurons having certain weights and bias.

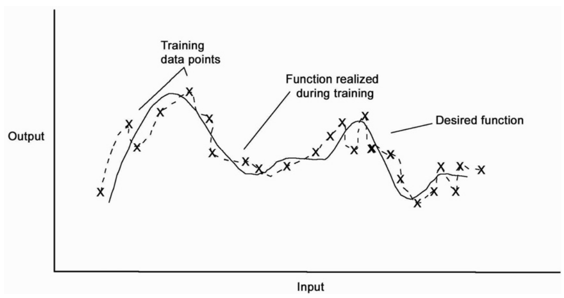

Figure 3. Neural network realized the function during training and fixes the appropriate function for the respective data.

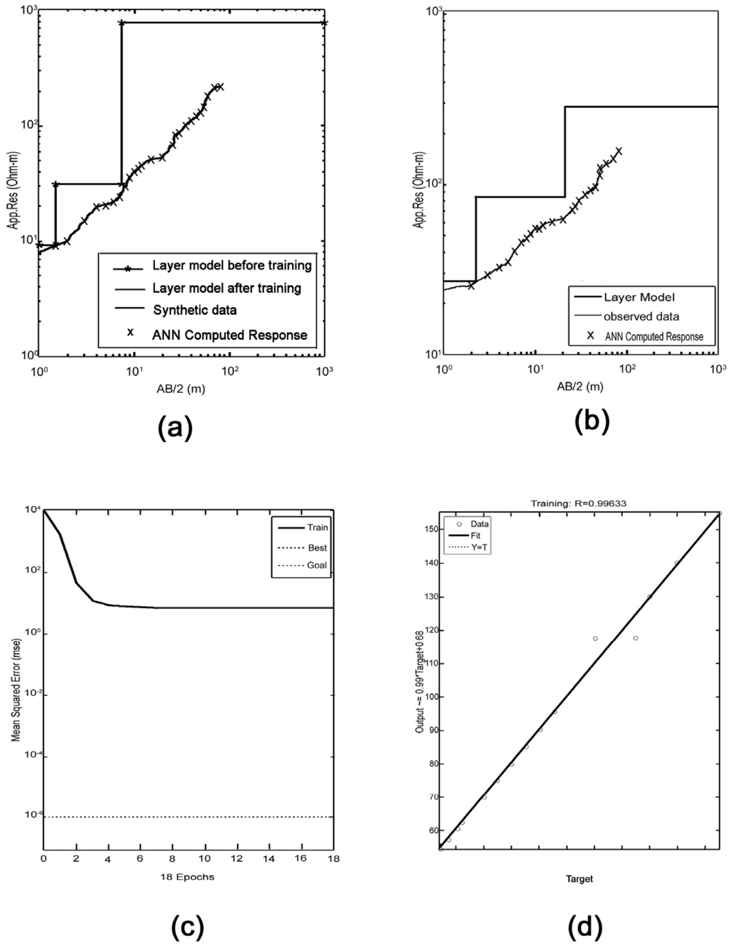

Figure 4. VES 1 sounding curve with (a) Layer model of synthetic trained data. (b) Layer model of observed data. (c) Performance plot of trained synthetic data. (d) Regression plot of trained synthetic data.

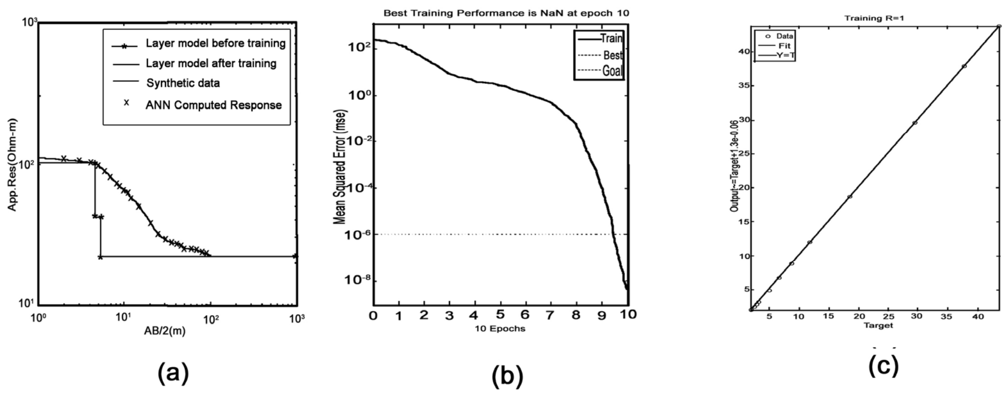

Figure 5. VES 2 sounding curve with (a) Layer model of synthetic trained data. (b) Performance plot of trained synthetic data. (c) Regression plot of trained synthetic data.

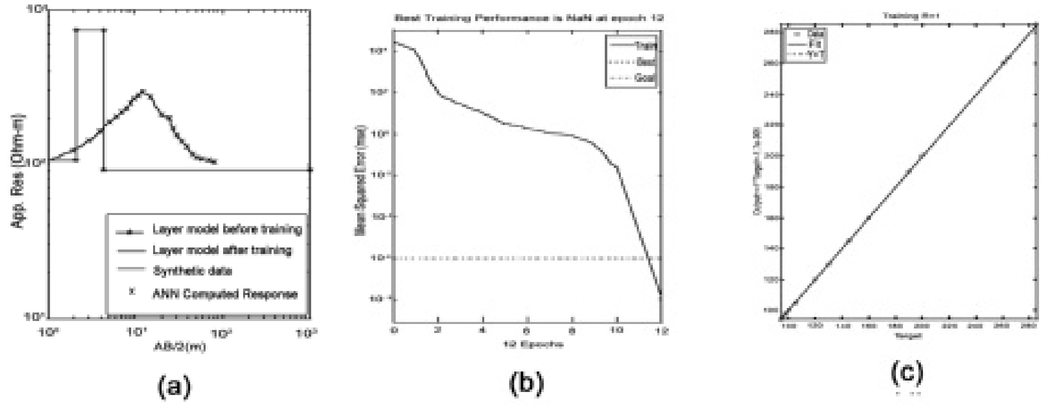

Figure 6. VES 3 sounding curve with (a) Layer model of synthetic trained data. (b) Performance plot of trained synthetic data. (c) Regression plot of trained synthetic data.

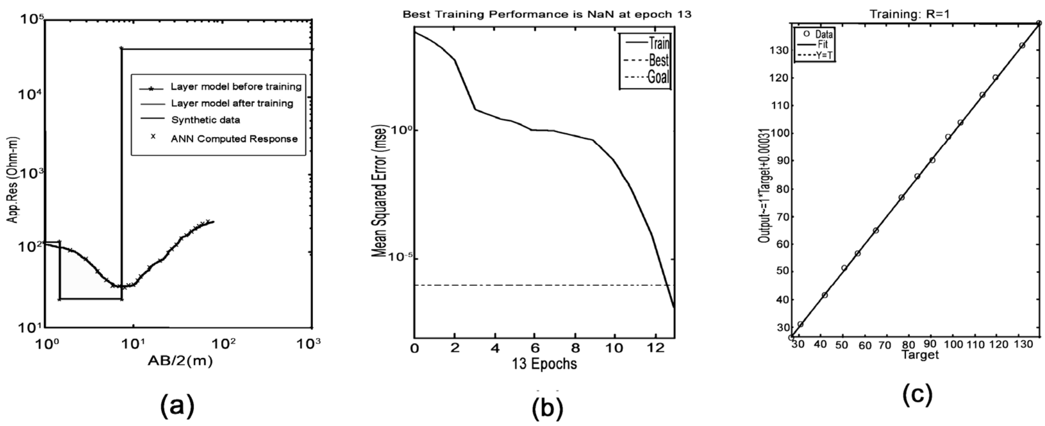

Figure 7. VES 4 sounding curve with (a) Layer model of synthetic trained data. (b) Performance plot of trained synthetic data. (c) Regression plot of trained synthetic data.

Results and Discussions

Linear transfer function (purelin) is used to make the nonlinear data to linear by adjusting certain weights used as the parameters in the program. Network training function trainlm (Levenberg-Marquardt optimization) is used to updates weight and bias values. Feed-forward layer network is constructed to analyze the observed field data and while analyzing it will make changes to the data by means of updating weights and biases of subsequent layers. Specified transfer function will affect the changes in training and the optimization of the observed data will be then adapted to the network and fits with the activation function of the network. We can able to see the performance of the network using the perform function. The number of epochs will be of the range that the training completed the network to be fitted with the activation function.

Best training performance can be achieved after the iterations has been successfully completed the goal using the number of epochs for the synthetic data. The training stops whenever the goal has been achieved in a particular number of epochs. The regression plot of the synthetic and trained data will be well fitted in the graph to achieve the target. The test using trained data indicates that the ANN system can converge to the target rapidly and accurately. According to The study of 1D resistivity inversion procedure using the ANN system was carried out because the procedure works well for the observed data. The synthetic and ANN trained data along with layer model is plotted and the layer model for the field data also predicted with the performance and regression plots. After testing the data the network has to interpret the layer model of the sub surface. For the interpreting the layer model the network will call the associative memory linked with the layer parameters. If the model parameters, on comparison, matching with the memory of the synthetic trained data already stored in the network it produces the corresponding model parameters with respective error percentage. Associative memory recall is the most important function to extract the suitable model parameters that has been trained by the feed forward back propagation algorithm of the network. Well trained network will increases the performance level of the output parameters. Moreover the network parameters weighted the output enhancement of the network.

Figs.4(a) shows the A type layer model parameters for the trained data. The performance and regression plots correspond are also shown in the same graph (Figs.4c and 4d). Similarly, Fig.5, Fig.6. and Fig.7. show the layer model for the Q Type, K Type and H Type respectively along with performance and regression plots. This inversion thus represents the layer parameters of subsurface geology viz., thickness and resistivity. Successful interpretation was produced only after the training and determines the model parameters with the trained data. The results of interpretation of the near-sub surface features by means of this ANN technique is satisfactory and are more efficient and the error has been checked with the synthetic trained data. The interpreted synthetic data along with error percentage is presented in Table.1 for A type of three layer resistivity data.

Table 1 : Interpreted Layer Model of field data along with Error Percent

S.No	Sounding No.	MODEL PARAMETERS (ρ=True resistivity of sub-surface layers, T=Thickness of layers)	ERROR PERCENT
1	VES1	$\rho1=27.1$ $\rho2=84.7$ $\rho3=285$ T1=2.27 T2=21	2.999

2	VES2	ρ1=31.87 ρ2=108.3 ρ3=809.9 T1=28.9 T2=44.64	0.683
3	VES3	ρ1=41.34 ρ2=95.64 ρ3=797.24 T1=16.5 T2=31.94	14.24
4	VES4	ρ1=39.15 ρ2=125.5 ρ3=983.5 T1=2.14 T2=22.3	0.555

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