# Capabilities of the neural network method for retrieval of the ozone profile from lidar data

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The paper describes a possibility of using lidar data for ozone concentration profile retrieval based on the neural network method. The capabilities of this method for profile retrieval at different schemes of the neural network learning, as well as the solution algorithm are considered. The results of retrieving the ozone concentration profile from lidar sensing data are presented.

## Introduction

In the lidar sensing, the following methods are commonly used for retrieving vertical distribution of the gas concentration from the lidar data: difference schemes, spline functions, Tikhonov regularization, optimal parameterization, and others.[1–6] Each of these methods has some limitations (fail to retrieve the concentration profile in the troposphere or provide a sufficient accuracy) at the data processing in the automatic mode (routine measurements).

Our survey of the methods for processing lidar data has shown that the neural network (NN) method has not been earlier used for solving inverse problems of the laser sensing. Application of the NN method is now possible due to the modern computers and a wealth of data on ozone concentration profiles measured with lidars and radiosondes.

## Formulation of the problem

Determination of the vertical profile of gas content from lidar echo signals received by a two-wave lidar reduces to differentiation of the function $v(z)$ [Ref. 6]:

$$v(z) = \frac{1}{2}\ln\left(\frac{N_{\rm off}(z)}{N_{\rm on}(z)}\right) + \Psi(z); \qquad (1)$$

$$\Psi(z) = \frac{1}{2}\ln\left(\frac{\beta_{\rm on}(z)}{\beta_{\rm off}(z)}\right) - \left[\tau_{\rm on}(z) - \tau_{\rm off}(z)\right],$$

where $N_{\rm on}$, $N_{\rm off}$ are the echo signals from the height $z$ at the wavelengths $\lambda_{\rm on}$ and $\lambda_{\rm off}$; $\beta_{\rm on}$, $\beta_{\rm off}$ are the backscattering coefficients; $\tau_{\rm on}$, $\tau_{\rm off}$ are the total optical depths of molecular scattering and aerosol extinction at the corresponding wavelengths.

In Eq. (1) it is assumed that $N_{\rm on}$, $N_{\rm off}$ are free of background atmospheric radiation. The function $\Psi(z)$ is specified as model or determined from an independent experiment. If a pulse falls within a narrow spectral range occupied by some rotational-vibrational line, the function $\Psi(z)$ can be taken zero.

The gas concentration is determined from the equation

$$\rho(z) = \frac{1}{2\Delta K(z)}\varphi(z), \qquad (2)$$

where $\varphi(z)$ is the regularized analog of the derivative $v'(z)$ of $v(z)$; $\Delta K = K_{\rm on} - K_{\rm off}$ is the differential absorption cross section of the gas under study.

As is well-known,[7] differentiation of experimental information is classified as an ill-posed problem. The ill-posedness shows itself in the solution instability.[8,9] This means that small errors in initial data can lead to large errors in solution (the solution becomes unsteady) and, in some cases, to appearance of negative values for gas concentrations, which physically is a nonsense.

Just such a situation arises when applying the often used finite difference method for differentiation of the function $v(z)$. Before the differentiation procedure, the received signals (or the log signal ratio) are smoothed using various moving-average filters, polynomials, etc.[10] However, though these methods are computationally fast, they have some serious disadvantages. First, they are approximate, because they do not give an unambiguous answer to the question what is the efficiency of smoothing (selection between undersmoothing and oversmoothing). Second, each lidar signal, being unique, requires a fitting of smoothing parameters, which does not allow the profiles obtained at different time to be then unambiguously interpreted. Third, the accuracy of the gas concentration profile retrieval can be estimated only approximately.

## Neural network method

Describe a solution of this problem using the neural network method. The neural network is a set of interrelated simple neuron elements, and it is capable to give certain output information in response to the input perturbation. Mathematically, the neuron model can be presented as follows[11]:

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$$y(w) = f(\sum_{i=1}^{n} w_i x_i + w_0) = f(g), \qquad (3)$$

where $y$ is the output neuron signal; $f(g)$ is the neuron activation function; $w_i$ is the weighting coefficient of the $i$th input; $w_0$ is the initial state (excitation) of neuron; $x_i$ are input signals, $i = 1, 2, ..., n$ are numbers of neuron inputs.

The neuron can be also presented as a scheme depicted in Fig. 1.

**Fig. 1.** Formal neuron model.

The sigmoid function

$$f(g) = \frac{1}{1 + \exp(-ag)} \qquad (4)$$

serves as an activation function. The parameter $a$ determines a slope of the sigmoid function plotted in Fig. 2.

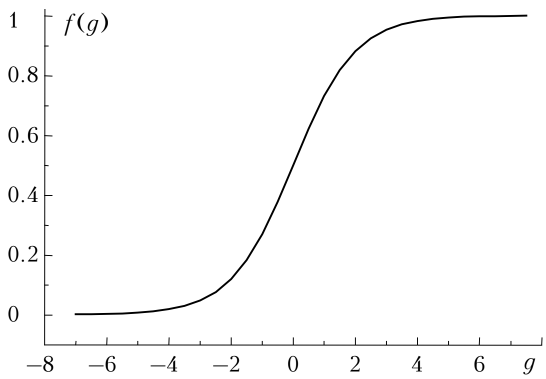


**Fig. 2.** Activation function.

The slope of the sigmoid function determines the neuron capability of distinguishing input signals. The steeper the slope, the lower is the neuron capability.

There are different types of neural networks. The use of a particular type depends on the problem to be solved. For example, pattern recognition involves Hamming and Hopfield neural networks, while in classification problems the Kohanen network is used. Fully connected multilayer network is best suited for solution of the inverse problem of lidar sensing. An example of a three-layer network is shown in Fig. 3.

To solve the problem formulated, the profile of the optical depth (1) was used as input for this network, while the concentration profile was its output. The profiles are reduced to the same vertical grid.

**Fig. 3.** Fully connected three-layer neural network.

In order for the network to solve a problem, it must be learned. There are self-learning neural networks and networks with a trainer. Learning with a trainer assumes that for every input vector there is a goal vector, which is just the needed output. Together they are called a training pair. Usually, the network is trained with a number of such pairs. After setting some input vector, the network output is calculated and compared with the corresponding goal vector, the difference (error) is returned to the network through a feedback, and the weights are changed in accordance with the algorithm aimed at minimization of the error. The vectors of the training set are sequentially inputted, the errors are calculated, and the weights are fitted for every vector until the error all over the training set achieves some acceptable low level.

There are several methods for learning the neural network[11]:

– *deterministic learning method* performing step-by-step correction of weights based on their current values and network outputs;

– *stochastic learning method* performing pseudorandom changes of the weights and saving those, which improve the results;

– *heuristic learning algorithms*, including the genetic search algorithm modeling the processes of natural evolution and allowing selection of the best solution from a variety (population).

The deterministic methods include the error back-propagation algorithm; stochastic methods involve the Boltzmann machine and the Cauchy machine.

To solve this problem, we have selected the error back-propagation algorithm, which allows rather fast learning of the neural network. The rate of learning is significant here, since it is necessary to re-learn the network as the conditions of modeling of the training pair change, for example, when solving the inverse problem for another gas. The stochastic algorithms, though allow overcoming the problem of local minima in optimization of solution and always converge to the global minimum, have too low rate of the convergence.

The error back-propagation algorithm[11] is the iteration gradient algorithm. The learning assumes minimization of the network error, which is determined by the least-square method:

$$E(w) = \frac{1}{2}\sum_{j=1}^{p}(y_j(w) - d_j)^2, \qquad (5)$$

where $p$ is the number of neurons in the output layer; $y$ is the current output of the $j$th neuron; $d$ is the desirable output of the $j$th neuron (the last layer [see Fig. 3] corresponding to the ozone concentration at the height $z$); $w$ are the weighting coefficients.

Neural network learning is performed by the gradient descent method, that is, the weight is changed at each iteration as follows:

$$w_{ij}(t+1) = w_{ij}(t) - h\frac{\partial E}{\partial w_{ij}}, \quad (6)$$

where $h$ is the parameter determining the learning rate.

We have selected a two-layer fully connected neural network with the vertical profiles of the optical depth as inputs and the gas concentration profiles as outputs (both input and output profiles are reduced to the same vertical grid). The number of inputs of every neuron in the network is equal to the number of elements in the vertical grid (vertical sensing range was 0–35 km with the strobe of 500 m, 70 dots).

As the examples for learning, we took the vertical profiles of the ozone concentration and the temperature profiles obtained by distorting the model profile[12] using a random number sensor. The ozone absorption coefficients for every height at a wavelength $\lambda_{on}$ = = 308 nm were calculated as[13]:

$$K_{ozone}(T) = A + BT + CT^2 \ [\text{cm}^{-1} \cdot \text{atm}^{-1}], \quad (7)$$

where $T$ is the temperature in the layer $z$; the model coefficients are $A = 1.32$, $B = 3.45 \cdot 10^{-3}$, $C = 2.18 \cdot 10^{-5}$.

The molecular and aerosol components of the optical depth were calculated by atmospheric models and kept unchanged during the calculation of different ozone concentration profiles.

For the neural network to be capable to retrieve the gas concentration in the troposphere from stratospheric optical data (based on the training pairs "optical depth–concentration profile"), additional training pairs were created, in which the concentration profile was the same, but the optical depth for the troposphere was set equal to –1 sequentially for the height ranges [$z_1$], [$z_1$, $z_2$],..., [$z_1$, $z_m$]. A total of $m$ pairs were created for each concentration profile, where $z_m$ is the lowest stratospheric height (12 km in our case). All the training samples were reduced to the interval [0,1].

We have realized a program for training the neural network by the error back-propagation method and checking its operation against the data not included in the training sample. To do this, an optical depth is simulated for some model ozone concentration profile, then the neural network retrieves the ozone profile from the optical depth, the result is compared with the initial data, and the relative error is calculated.

## Simulated results

Simulation was carried out in two stages. At the first stage, all 70 dots of the optical depth profile (0–35 km height range) at the 5-% noise were input, and the retrieved ozone concentration profile was compared with the model one (Fig. 4).

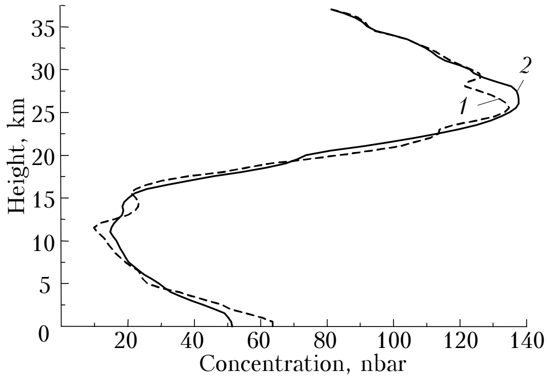


**Fig. 4.** Retrieval of the ozone concentration profile: model (*1*) and retrieved (*2*) profiles.

Figure 5 shows the relative error of retrieval of the ozone concentration profile at 5-% noise.

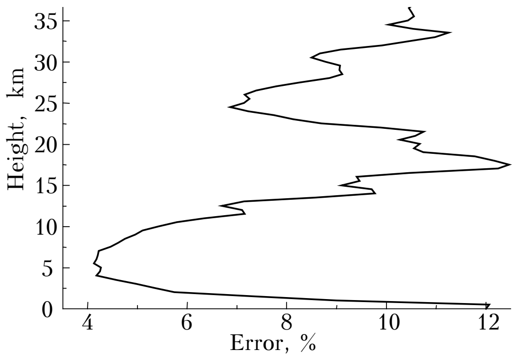


**Fig. 5.** Relative error of retrieval of the ozone concentration profile.

Figure 6 depicts the relative error of retrieval of the ozone profile at 15-% noise and the same measurement conditions. Comparison of Figs. 5 and 6 shows that a threefold increase of the measurement error (from 5 to 15%) does not cause a significant growth of the error in the ozone concentration profile retrieval. In our opinion, this is connected with the fact that the determined coefficients of the neural network weakly react to random changes in the optical depth (are not present in learning).

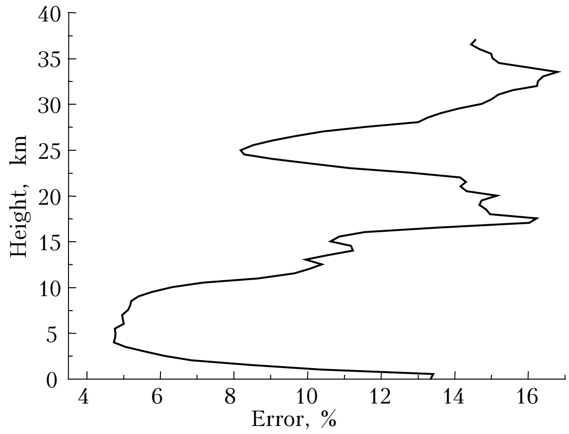


**Fig. 6.** Relative error of retrieval of the ozone concentration profile from the optical depth in the range of 0–35 km at 15-% noise.

At the second stage, only stratospheric measurements (12–35 km) are used for the ozone concentration retrieval in the entire range from 0 to 35 km. This model experiment is close to the actual stratospheric conditions. The results obtained at the second stage are shown in Figs. 7 and 8. Figure 7 compares the retrieved and model ozone concentration profiles, and Fig. 8 depicts the relative error of retrieval.

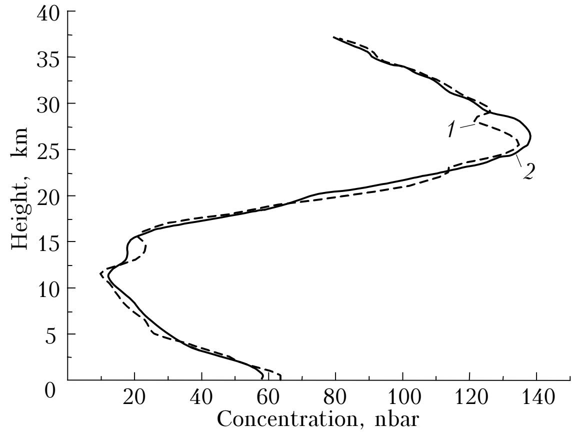


**Fig. 7.** Ozone concentration profile retrieved in the entire range from the optical depth in the range of 12–35 km at 5-% noise: model (*1*) and retrieved (*2*) profiles.

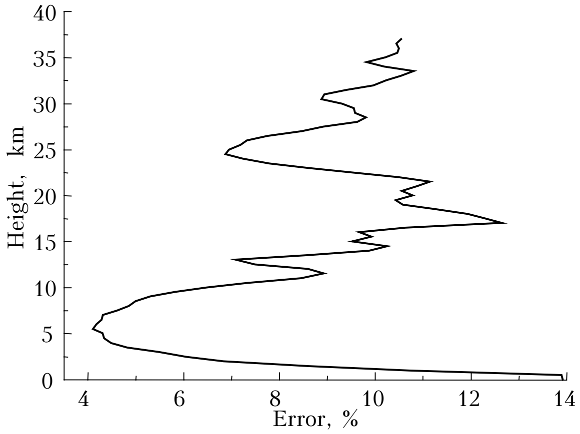


**Fig. 8.** Relative error of retrieval of the ozone concentration profile from the optical depth in the range of 12–35 km at 5-% noise.

Note that the error of retrieval at the first and second stages is almost the same. This is a property of the methods based on the use of statistical information, which is accumulated in this model in the form of model coefficients.

## Conclusion

The method of neural networks considered in this paper allows the ozone concentration profile retrieval from lidar data. The error of retrieval is almost insensitive to the experimental error up to 30%, it ranges nearby 10% and depends on the size and quality of the training sample. The material reported here form the basis for further investigation of the capabilities of the neural network method as applied to the lidar sensing problems.

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