LARGE – SCALE SEVERE WEATHER PHENOMENA PARAMETERS RECOVERING AND MAPPING

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1. INTRODUCTION

Large-scale severe weather phenomena parameters (pressure, temperature, electralization, pollution, etc.) are recovered and mapped basing on satellite measurements in typical points. The new technology of fuzzy neural networks is proposed and checked. The effectiveness of that technology (Soft Computing) is demonstrated, especially in the early stage of modeling, when the information is uncertain and limited. Recovering is conducted on the basis of fuzzy-neural networks, mapping is realized by means of the new method based on Puankare's fundamental theorem "on return ability"

II. PRESENTATION OF RESEARCH

Various methods of recovery (by algebraic polynoms; filters; rational fractions; splines; geostatistical methods; search methods of nearest points: inverse distance, minimum curvature, etc; local and optimal approximation; fuzzy-neuro networks) have been analyzed (Gandin, 1963; Olea, 1975; Belov, 1975; Akima and Hiroshi, 1978; Berlyant and Ushakova, 2000; Yanalak, 2002; Pashayev, Sadiqov, Yildiz and Karabork, 2005; Sadiqov, 2006). Recommendation for correct choice of a method and its control parameters when preparing for surface modeling and mapping have been given. Advantages and disadvantages of these methods at different stages of large-scale severe weather phenomena parameters recovering have been revealed. For instance, at an early stage when information is limited fuzzy-neuro networks are more preferable.

It is therefore necessary to identify the parameters of a mathematical model of a multivariate fuzzy object described by the regression equation

$$\tilde{H}_m = \sum_{j=0}^{m}\sum_{k=0}^{m-j} \tilde{c}_{jk} \otimes \tilde{x}^j \otimes \tilde{y}^k \qquad (1)$$

$(j = \overline{0,m}; k = \overline{0,m}, j + k \le m)$,

where $\tilde{c}_{jk}$ are the desired fuzzy parameters.

We shall determine the fuzzy values of the parameters $\tilde{c}_{jk}$ of equation (1) using experimental fuzzy statistical data of the process, i.e., the input $\tilde{x}$, $\tilde{y}$ and output $\tilde{H}$ coordinates of the model. Let us consider a solution of this problem using fuzzy logic and neural networks.

A neural network consists of interconnected sets of fuzzy neurons. When an neural network is used to solve equation (3), the input signals of the network are the fuzzy values of the variable $\tilde{B}=(\tilde{x}, \tilde{y})$, and the output is $\tilde{H}$. The fuzzy values of the parameters $\tilde{c}_{jk}$ are the network parameters. We present the fuzzy variables in triangular form, the membership functions of which are calculated by the formula

$$\mu(x) = \begin{cases} 1-(\bar{x}-x)/\alpha, & if \quad \bar{x}-\alpha < x < \bar{x}; \\ 1-(\bar{x}-x)/\beta, & if \quad \bar{x} < x < \bar{x}+\beta; \\ 0, & otherwise \end{cases}$$

Neural-network training is the principal task in solving the problem of identification of the parameters $\tilde{c}_{jk}$ of equation (1). An α-section is used to train the parameter values.

We assume the presence of experimentally obtained fuzzy statistical data. From the input and output data we compose training pairs for the network $(\tilde{B},\tilde{T})$. To construct a model of a process, the input signals $\tilde{B}$ are fed to the neural network input; the output signals are compared with standard output signals $\tilde{T}$.

After comparison, the deviation is calculated:

$$\tilde{E} = \frac{1}{2}\sum_{i=1}^{l}(\tilde{H}_i - \tilde{T}_i)^2$$

When an α-section is used. the deviations for the left and right parts are calculated by the formulas

$$E_1 = \frac{1}{2}\sum_{i=1}^{l}\left[h_{i1}(\alpha) - t_{i1}(\alpha)\right]^2,$$

$$E_2 = \frac{1}{2}\sum_{i=1}^{l}\left[h_{i2}(\alpha) - t_{i2}(\alpha)\right]^2, \; E = E_1 + E_2,$$

where $\tilde{H}_i(\alpha) = [h_{i1}(\alpha), h_{i2}(\alpha)]$; $\tilde{T}_i(\alpha) = [t_{i1}(\alpha), t_{i2}(\alpha)]$

Training (correction) of the network parameters is concluded when the deviations E for all training pairs are less than the specified value (Fig.1). Otherwise, it is continued until E is minimized.

The network parameters for the left and right parts are corrected a-s follows:

$$c^n_{jk1} = c^o_{jk1} + \gamma\frac{\partial E}{\partial c_{jk}}, \qquad c^n_{jk2} = c^o_{jk2} + \gamma\frac{\partial E}{\partial c_{jk}} \qquad (2)$$

Here $c^o_{jk1}, c^n_{jk1}, c^o_{jk2}$ and c^n_{jk2} are the old and new values of the left and right pans of the neural network parameters $\tilde{c}_{jk} = [c_{jk1}, c_{jk2}]$, and γ is the training rate.

III. RESULTS AND CONCLUSIONS

Let us consider the mathematical model is described the equation of fuzzy a regression (consider a special case (1) at m=2):

$$\tilde{H} = \tilde{c}_{00} + \tilde{c}_{10}\tilde{x} + \tilde{c}_{01}\tilde{y} + \tilde{c}_{20}\tilde{x}^2 + \tilde{c}_{11}\tilde{x}\,\tilde{y} + \tilde{c}_{02}\tilde{y}^2. \qquad (3)$$

We shall construct a neural structure for solution of (3) in which the network parameters are the coefficients $\tilde{c}_{00}, \tilde{c}_{10}, \tilde{c}_{01}, \tilde{c}_{20}, \tilde{c}_{11}, \tilde{c}_{02}$. The structure has four inputs and one output (Fig. 2).

Using a neuro-network structure, we employ (2) to train the network parameters.

The network parameters were thus trained using the described fuzzy-neural network structure and experimental data. As a result, network-parameter values that satisfied the experimental statistical data were found (see Table 1):

$$\tilde{c}_{00} = (1.4124; 1.4223; 1.4275), \ \tilde{c}_{10} = (1.9884; 2.1131; 2.2339),$$

$$\tilde{c}_{01} = (-2.5353; -2.5349; -2.5326); \tilde{c}_{20} = (-1.1043; -1.1042; -1.1036)$$

$$\tilde{c}_{11} - (-0.8845; -0.8741; -0.8639); \tilde{c}_{02} = (1.3158; 1.3162; 1.3166).$$

These data were obtained as a result of 20-minute training of the neural network.

The coefficients $\tilde{c}_{00}, \tilde{c}_{10}, \tilde{c}_{01}, \tilde{c}_{20}, \tilde{c}_{11}, \tilde{c}_{02}$ regression equation (3) were evaluated by a program written in Turbo Pascal on an IBM PC.

The use of fuzzy neural networks (Soft Computing) advantages over traditional statistical-probability approaches. Primary is the fact that the proposed procedure can be used regardless of the type of distribution of the parameters. The more so because, in the early stage of modeling, it is difficult to establish the type of parameter distribution, due to insufficient data.

IV. AKNOWLEDGMENTS

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V. REFERENCES

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Mohamad H, 1995: Fundamentals of Artificial Neural Networks, MIT Press, Cambridge, Mass., London.

Table 1

$\tilde{y}$ / $\tilde{x}$	3,7,11	17,21,25	31,35,39	45,49,53	59,63,67	73,77,81
28,31,35	0.77,0.81,0.85	1.08,1.13,1.17	1.28,1.33,1.44	1.43,1.47,1.51	1.49,1.53,1.57	1.48,1.50,1.54
50,54,58	0.48,0.52,0.56	0.68,0.72,0.76	0.81,0.85,0.89	0.89,0.93,0.97	0.93,0.97,1.01	0.91,0.95,0.99
68,72,76	0.37,0.41,0.45	0.53,0.57,0.61	0.63,0.67,0.71	0.69,0.73,0.77	0.72,0.76,0.60	0.71,0.75,0.79
82,86,90	0.30,0.34,0.38	0.43,0.47,0.51	0.52,0.58,0.60	0.57,0.61,0.65	0.60,0.64,0.68	0.59,0.63,0.67
92,96,100	0.27,0.31,0.35	0.39,0.43,0.47	0.46,0.50,0.54	0.51,0.55,0.59	0.54,0.58,0.62	0.53,0.57,0.61
96,100,104	0.23,0.27,0.31	0.34,0.38,0.42	0.41,0.45,0.49	0.46,0.50,0.54	0.47,0.51,0.55	0.47,0.51,0.55

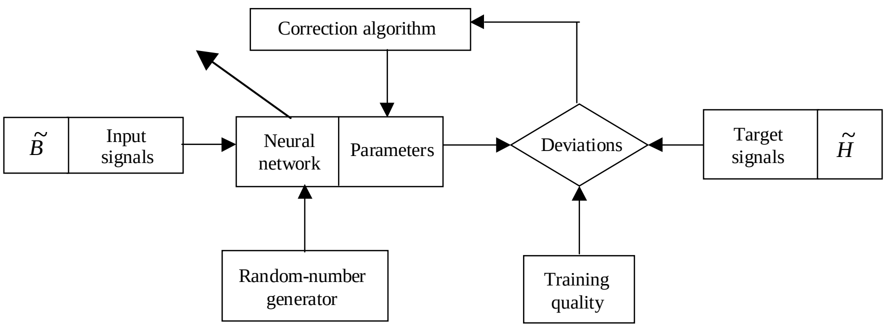

Fig. 1. System for network-parameter training (with backpropagation)

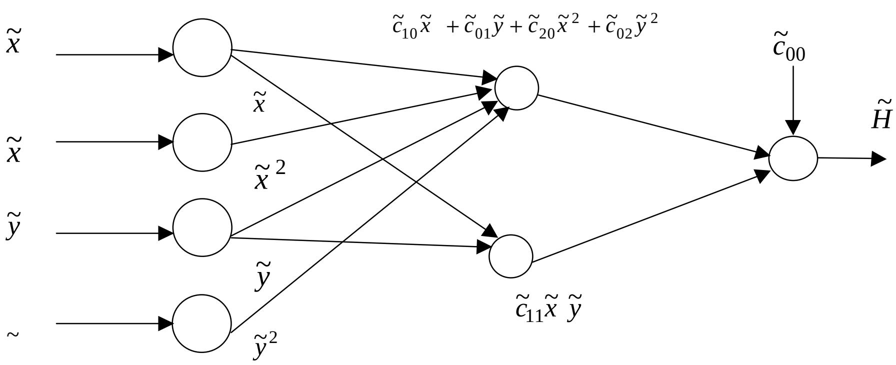

Fig. 2. Structure of neural network for second-order regression equation