Forecasting the Earth Atmosphere's Ozone Layer Conditions Using Neuronic Networks

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Abstract – The study performed has proven a high degree of effectiveness of using neuronic networks for simulating the dynamics of the Earth's ozonosphere. A real opportunity to design local prognostic models using neuro-networks is revealed. The study is focused upon revealing the precursors of the spontaneous "ozone hole" (areas of the lowered concentration of ozone) formation in the stratosphere and based on neuronic network models allowing to forecast the ozone layer dynamics with limited information available, according to satellite data (time TOC – total ozone concentration – rows).

Keywords: Ozone, ozone layer, stratosphere, neuroinformatics, ozone prediction, atmospheric models.

1. INTRODUCTION

One of the major tasks today is preserving the Earth's ozonosphere, - because the ozone layer serves as a screen, filtering a part of harmful solar ultraviolet radiation. During the recent decades, some scientists of different countries have paid their attention to significant decrease of ozone density in the atmosphere above certain points of the Earth's surface. If the average ozone concentration in the atmosphere is about 300-350 D. u. (Dobson units), its annual drop above the Antarctic continent follows to the values of concentration even of 90 D. u. Such – and similar – publications have triggered widespread public interest (tied to the global environmental crisis); the phenomenon has been named "an ozone hole" and followed by an explosion of scientific interest to ozonospheric studies. There are quite a limited number of atmospheric and ozone layer dynamic quantitative models, - because this scientific trend is very young; in addition, there are some difficulties, related to the process of collecting the data, necessary for model designing and verification. The investigated atmospheric processes are multi-dimentional, non-linear and dynamic (unbalanced) and therefore sometimes are too complicated for full-scale analytic descriptions, – that is also true (though to a esser degree) for quantitative models. Universal and flexible apparatus of approximating complex non-linear interrelations, based upon "artificial neuronic network" methodology, seems to be very usable here.

2. NEURONIC NETWORK MODEL

For the purposes of the quantitative experiment, a neuronic network program ("Model") has been used. The latter is represented by the formula:

$$Y_i = \sum_{j=1}^{N} a_j \sin\left(\sum_{k=1}^{M} b_{kj} X_k\right), \text{ where}$$

Y_i – output of the i neuron; N – number of neurons in the neuronic network; M – length of the input vector; $X_1, \dots, X_5$ – input vector, represented by TOC time series' components; a, b – subscripting coefficients of the neuronic network. The program is based upon a supervisory algorithm3 that employs a method of conjugated gradients for minimizing the evaluation functional. The most famous version of the algorithm is known as "back-propogation"4. In addition to the "Model" program effectiveness, another reason of such a choice is that it is organized as an Excel electronic table. This is very convenient for the purposes of intermediary calculating as well as preliminary and final data processing. The choice of a far-out type of neuronic non-linearity is not a principal characteristic of this neuronic network. It is shown in the article5 that, independently on a type of non-linearity, the neuronic network (after being appropriately trained) is capable to fulfill a transformation, corresponding with any contiguous function.

3. MEAN HOURLY FORECAST

In order to simulate hourly TOC (total ozone concentration) oscillations, the ground observation data (City of Tomsk, Russia - 56° N and 84° E) has been used (March 16-31, 1996-99). In order to design a forecast for each of the four years, Mach was selected. There were 6-22 measurements a day. The forecast was designed for the period of March 30-31. 1996: March 30 – 6 measurements (6.06 – 6.45 p.m.), March 31 – 8 measurements (4.42-5.38 p.m.). 1997: March 30 – 12 measurements (4.25-7.26 p.m.), March 31 – 22 measurements (11.16 a.m. – 6.45 p.m.). 1998: March 30 – 13 measurements (11.10 a.m. – 7.57 p.m.), March 31 – 12 measurements (10.33 a.m. – 6.43 p.m.). 1999: March 30 – 17 measurements (9.09 a.m. – 6.03 p.m.), March 31 – 14 measurements (9.38 a.m. – 4.53 p.m.). The neuro-network has been trained since March 16 to March 29. The Fig. 1 shows actual and forecasted TOC for March 28-31, 1996.

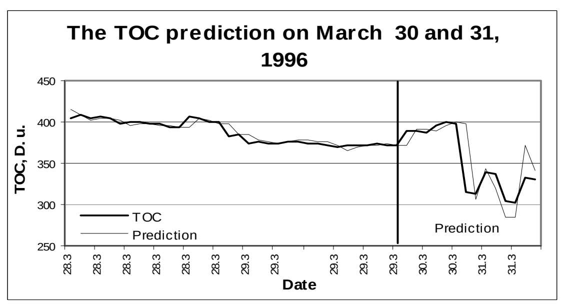

Figure 1. The hourly TOC prediction for period of March 30-31 (daylight) and learning sampling from March 28-29, 1996.

A significant decrease of TOC (approximately by 100 D. u.) has been measured in March 30. In spite of such a quantitative drop, the neuronic network was able to forecast it. Thus we can state that there are some prognostics in the teaching sample. R - a correlation coefficient (between the actual and forecasted data, Fig. 1) – is equal to 0.96. The neuro-network consists of 11 formal neurons. There were mentioned no such dramatic changes of TOC during those three years. Therefore a more accurate forecast was designed. The correlation coefficients (1997-1999) between the actual and simulated values are about 0.99.

4. MEAN DIURNAL FORECAST

In order to simulate 24-hour TOC oscillations, the ground observation data (City of Tomsk, Russia - 56° N and 84° E) has been used (January 1, 1996 – October 31, 1998). In the process of simulating, the neuro-network was using five past values for forecasting the future one. Training period was from January 1, 1996 to June 13, 1998. The modeled period was from June 14, 1998 to October 31, 1998. Despite the complexity of the studied object's behavior, the neuro-network model demonstrates a high degree of accuracy. The correlation coefficient (between the forecasted curve and the actual one) is 0.96.

5. MONTHLY MEAN TOC FORECAST

In order to design the model, three curves have been selected, – ones of average monthly ozone concentration above three spots, far from each other (Belsk, 52°N and 20°E, Poland; Leningrad, 60°N and 30°E, Russia; Edmonton, 52°N and 113°W, Canada). Such selection is, on the one hand, convenient for comparing the models based on the criterion of effectiveness, and, on the other hand, preconditioned by the lack of quantitative data. The graphs were scanned and then quantitatively represented using the GRAFULA program. Minor inaccuracy of drawing is unimportant. The apparatus of model designing (neuronic networks) in use is very flexible. If necessary, the final models could be renovated ("taught"). This feature of neuro-network simulators is very valuable for studying dynamic regularities of the processes in nature. Flexibility of the system-adaptive models allows easily modify the models either way without following verification. The teaching sample is created based upon the data of the Feb. 1963 – Aug. 1975 period. The forecast has been designed using the actual data of several past measurements, not included into the teaching sample. A good degree of correlation between the model and actual data is reached, though additional factors of influence have not been taken into account. In Belsk, four past values were used for simulating the fifth one (six-neuron network). In Leningrad, the fourth value was modeled based upon the three previous ones (nine-neuron network). In Edmonton, two values have been used for calculating the third one (ten-neuron network). The correlation coefficients R = 0.99.

6. MEAN ANNUAL CCO FORECAST

In order to design the model, a curve selected was one of average monthly ozone concentration above Aroza Station, °N and 46°, Switzerland). These data are represented by the Graph13. Education was based upon the data of 1926-74 period. The forecast has been formulated for the period of 1975-82. Four past values have been used in predicting the fifth one. The teaching sample consisted of 45 TOC values. Eight values were forecasted. The network included 11 neurons. The correlation coefficient between the actual and modeled curves was about 0.98. A good quality of simulation is obvious, though additional factors of influence (upon the concentration of the stratospheric ozone) have not been taken into account.

7. REVEALING "THE PREDICTORS" OF CHANGING TIME SERIES REGULARITIES

In order to analyze the time row forecasts two major approaches (theoretical and practical) are used. The theoretical approach accumulates models, hypotheses, theories that idealize the general features of the phenomena studied. Such works do not design concrete models for time row simulations but formulate certain recommendations for such a design. The practical approach is in actual time row simulation as representing a certain complex relationship of the unknown type. The major if this approach is that the designed model must be suitable for simulation (its type is not important). On the other hand, it is desirable for better understanding the relationship that the method of the time row value calculations is to be of physical sense. The model is chosen, as a rule, by the empirical method based upon certain given, universal family of predictors. The properties of the family allow describing any time row. The choice of one or another family of models reflects the specifics of the goal of forecasting. Recently, regression and neuronic network methods (as well as ones based upon Wavelet-transformation) are widespread. The common feature of both the approaches is in an attempt of designing the unitary model of a time row, but such simulation is tied with a number of difficulties defined by a complex nature of a time row. In order to resolve the problem the work offers an approach based upon a "peacemeal" simulation of a time row. The idea is the following: The study shows that the same predictor (Predictor 1) models different spans of a time row with different degrees of precision. On the other hand, there is another predictor (Predictor 2) that predicts better than Predictor 1 does at certain spans (and worse or similarly – at the other spans of a time raw). So, a series of predictors with certain properties may be given. For the goals of forecasting, the chosen is the predictor better suitable for a certain span of a time raw. The most often it consists of some the last values of the raw. The optimal tune-up of the system presupposes the best quality of prediction (compared with the one, based on any individual predictor of the given series). Using the approach described presupposes a certain methodology of revealing the moments of "disorder" of the time raw, i.e. the moments when a predictor has to be changed. The most convenient for neuronic network models is the method of removing individual values of the time raw, used to predict the following value. In this case, the difference between the standard forecast and the one created after removing certain values is an indicator of serious time raw property change at the following span. It is clear that a neuronic network used for evaluating this difference has to be "trained" in advance.

8. TOC VALUE-REMOVING PROGNOSTIC EXPERIMENTS

Ozone concentration curve consists of "calm" and "complex" curves. "Calm" periods are characterized by the difference between maximal and minimal D. u. values up to 75. The forecast accuracy here is always good. Training the neuronic network is easier than the one for "complex" spans. The correlation coefficient between the forecasted and real TOC curves is 0.95-0.98. For instance, such a situation takes place on Summer. If for a short period of time (2-5 TOC) this difference is more than 100 D. u., such spans could be characterized as "complex" ones (Fig. 2, Sept. 26-30, 1996).

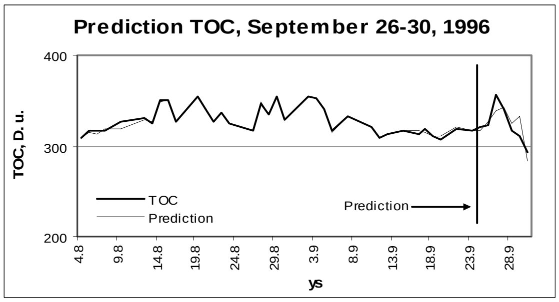

Figure 2. The prediction TOC of mean diurnal values on period since September 26-30, 1996 on learning sampling since August 1 till September 25, 1996 (Tomsk).

Significant changes of time series regularities are detected at those intervals. Such intervals have to be revealed in advance; the appropriate neuronic network predictors are to be chosen (as stated above). Modeling the "complex" intervals has been performed for the following periods: August-September 1996, October-December 1996, February 1997, July-August 1998, March-April 1999. In this case, the designed three-consecutive-value prognostic models (three-day TOC values at the neuronic network input) have been used for forecasting the ozone concentration value for the forth day (at the output of the neuronic network). Then, in accordance with the procedure described above, some isolated values have been removed from the input vector. An example of the results, obtained by the aforementioned way, is given (Fig. 3).

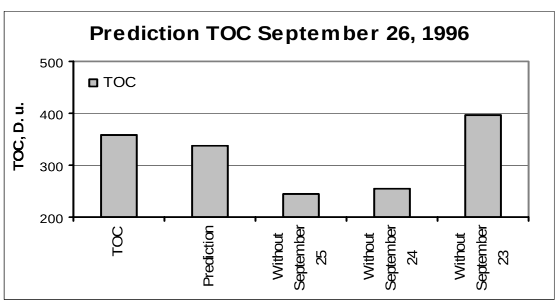

Figure 3. The prediction TOC of mean diurnal values on September 26, 1996 (Tomsk).

Columns of the histogram (from the left to the right) show: a real TOC value; a value, simulated by a previously trained neuronic network (predictor); results of forecasts after consecutive removal of the first, second, and third value out of the neuronic network's input vector. Fig. 3 demonstrates that the simulated TOC value fits neither real value nor the one, modeled without removing individual spots. The spot, modeled with removing Sept. 25 TOC value, differs from actual and forecasted (second column) ones more than the ones, modeled with removing Sept. 23 and Sept. 24 TOC values. This situation is typical. For all the investigated periods, there is an ozone concentration value that maximally differs from the real and prognostic ones. For the August-September 1996 period, it is September 25. For the October-December 1996, it is November 27. February 1997 – February 20, July-August 1998 – August 21, March-April 1999 – April 23. According to the proposed hypothesis, an attempt to reveal the beginnings of "complex" intervals has been performed (based on the difference between the 'usual' forecast of the neuronic network predictor and the forecast, designed after removing one of the input neuronic network values, – one giving the largest error).

9. ANALYZING THE EXPERIMENTAL DATA

A preliminary findings on possibility of dividing a TOC time series by "calm" and "complex" intervals are based upon estimating error dispersion of the prognostic model for each of them (without removing individual values of the input vector) according the formula:

$$S_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - x_m)^2 \text{ , where}$$

x_i – prognostic error for the studied interval, x_m – mean error for the studied interval, N – volume of the sample. Assessments, based on Pearson's criterion and performed at the value level of 0.05, show that the errors, generated by the prognostic models, normally disperse at both types of intervals. At the same time, error dispersion for "calm" and "complex" intervals differs a lot:

$$F_{ob} = S_x^2 \big/ S_y^2 = 5.67.$$

The obtained preliminary result lets distinguish one type of intervals from the other. However, the comparison of errors for these intervals with removing individual spots from the TOC prognostic neuronic network's input vector gives a different value of F_{ob} = 1.18. An attempt to correlate the difference of modeled values of the complete input vector with the situation of removing individual spots of the input vector (the way described above) leads to F_{ob} =1.082. So, the quantitative experiments did not let univocally divide "calm" and "complex" intervals of the TOC time series. At the same time, quality of the neuronic network forecast at "complex" intervals appears to be relatively good. That fact evidences about certain differences between economic series (characterized by the possibility of quasi casual fluctuations derived by a human factor) and the dynamics of natural ozonospheric processes (characterized by quasi stationary parameters). This is supported by the existed publications on the subject. Therefore, the proposed hypothesis on the applicability of the method of defining the time series' disorder intervals cannot be conformed. Though there some differences in dispersion for "calm" and "complex" intervals, it looks impossible to divide them by the described method. At the same time, there are other helpful results, given in the next paragraph.

10. PHYSICAL INTERPRETATION OF THE RESULTS

As it was shown above, influence of the certain values of a neuronic network input vector upon the forecast is detected by the represented models. For each model, different spots may exercise the maximal influence upon the result. (Values of the input vector are ones of TOC time series, preceding the forecasted spot). It is important to define mechanisms of this influence. Let's turn to results of satellite monitoring the studied territory. Comprehensive day-to-day data on the ozone concentration is obtained by NASA satellites (TOMS/EP, GOES, etc.). They are represented in the worldwide web. TOC maps for Siberia are created using these data. Comparing TOC maps for two consecutive days, it is possible to define a speed of air mass (degrees of latitude and longitude) and the direction of ozone layer (and stratosphere as a whole at the height of maximal ozone concentration – 18-25 km) moving. Correlation coefficient between today's TOC field and the dislocated, turned to a definite degree, yesterday TOC field could be calculated. The maximal value of the sampling correlation coefficient (0.95 - 0.98) correlates with the daily mean field's turn and shift. The given method of calculating the speed of air masses (rotational speed of ozone in a circumpolar vortex defined) is described in the article (Kashkin, 2003). Removing 25 Sept. TOC values from the neuronic network input vector is the major reason of the forecast error, compared with removing the Sept. 23 and Sept. 24 values. This error correlates with the maximal speed of air mass moving (and the maximum of ozone concentration). So, it is possible to state the existence of predictors of principal changes of ozone concentration time series' properties, "caught" in the proposed models. At the same time, being applied to the studied object, the models demonstrate insufficient (for the purposes of clear identifying the aforementioned principal changes) stability.

11. CONCLUSION

It is important to state that the results obtained differ from the ones, typical for financial time series. Differing from jumplike changes of currency exchange rates that look like casual, – backgrounded by smooth preceding series (1998), TOC dynamics is of quasi stationary character. Actually, it is impossible to detect the intervals of ozone concentration time series that completely deny the forecast of a neuronic network predictor. Though the quality of forecast worsens at "complex" intervals, it remains, as a whole, quite good. At the same time, the relationship between the conduct of neuronic network predictors and physical characteristics of atmosphere is revealed. Accelerated moving of air masses influences ozone concentration change in the stratosphere. The values of the correlated spots of the TOC time series (a part of the neuronic network input vector), being modified, intensively influence the outcome of forecasting. This let us conclude that certain relationship between atmospheric perturbations and the following significant changes of the TOC time series' regularities takes place. However, the frame of our study does not allow univocal forecasting of these changes. It is important to state that the goal of assessing the prognostic capabilities of neuronic networks required no preliminary processing the time series. In particular, trend removal has not been practiced. Therefore, there are certain reserves; being utilized, they could make the described method more applicable.

12. REFERENCES

V.B. Kashkin, J.P. Lankin, I.Yu. Sakash, and S.V. Smirnov, "Predicting the Earth atmosphere's ozone layer conditions using neuronic networks for various time lags", SPIE, vol 5027, p.p. 207-216, 2003.