ARTIFICIAL NEURAL NETWORK APPLICATIONS TO THE SPACE RADIATION ENVIRONMENT MODELLING AND FORECASTING

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ABSTRACT

The paper presents a short review of various directions of Artificial Neural Network (ANN) applications to modelling of near Earth space radiation distribution and dynamics and to the development of some methods of space weather forecasting. ANN models may be based on well-known physical laws or on some empirical rules. We can present four main directions of ANN applications. The first one is the development of strong non-linear quasi-stationary models with large number of input nodes. The examples of results in the first direction are: 3D model of the Earth's magnetopause and mapping of the near Earth high energy particle (electrons and protons) distribution. The second direction is modelling of cumulative and time shifted effects in the time series. The main problem in these models is searching the most significant measured physical parameters as input nodes and determination of the most appropriate time intervals for averaging or shifting parameter values. This direction permits to develop dynamical models of physical processes in multi-parametric time series. One of the models developed in the second direction is the model of the slot region of Earth's radiation electron belt dynamics depending on the solar wind conditions. The third direction is modelling of self-consistent time series by means of recurrent ANNs. These models take into account the information about prehistory of the system dynamics and hence they may be used for forecasting. The models forecasting sunspot number and average solar wind conditions are excellent examples of investigations in the third direction. The fourth direction is combination of the described directions by means of global ANN on the base of some classification rules which may be used in future for the development of an expert system for the space weather forecasting.

INTRODUCTION

Artificial Neural Networks (ANN) are very powerful algorithms that may be used to construct empirical computer models of non-linear physical phenomena. These algorithms successfully operate with large volumes of noisy data. ANN are used in solar-terrestrial physics very efficiently. Self-Organising Maps (SOM) [*Lippman*, 1987] are applied for classification of data to distinguish independent processes in complex dynamics of physical systems [e.g. *Wintoft*, 1993]. The prognoses in time-series of geomagnetic indexes (Dst, Kp, AP, etc.) are generated using Elman Recurrent Neural Networks (ERNN) [e.g. *Wu*, 1996]. Multi Layer Perceptrons (MLP) [e.g. *Liszka*, 1993; *Lundstedt*, 1996] or General Regression Neural Network (GRNN) [*Dmitriev*, 1997b] are used to develop complex multy-parameter models in the solar wind magnetosphere coupling system. Group Method of Data Handling (GMDH) [*Dolenko*, 1996] presents ANN models in analytical form.

This paper presents the overview of ANN applications for the development of expert system for modelling and prediction of the space radiation environment - firstly the fluxes of high energy electrons and protons that strongly affect the near Earth satellite's operation. We use in this work the software ANN package *Neuroshell* 2 [1996].

1. MAPPING OF THE ENERGETIC PARTICLES DISTRIBUTION IN THE MAGNETOSPHERE

A lot of experimental data about fluxes of energetic particles at low altitudes (350-1000 km) is accumulated in SINP MSU during the last two decades. The main part of the data is loaded to the Low Altitude Space Radiation Environment Data Base (LASRE DB) (http://dec1.npi.msu.su/english/data/lasre/index.html) which contains experimental information obtained during five space experiments performed from 1979 to present time. The data from one active experiment "Riabina" onboard MIR station is loaded regularly in the real time regime till now.

A large volume of accumulated experimental data permits us to develop the models of low altitude energetic particle distributions and dynamics of particle fluxes. The intensity of low altitude radiation is controlled both by the atmospheric density co-varied with solar activity (long time variations) and by the solar wind (SW) and interplanetary magnetic field (IMF) conditions (short time variations). So the model has to take into account many parameters with different characteristic times varied from hours to years. The model also has to describe the spatial and temporal variations of particle fluxes up to four orders of magnitude. It is important that the magnetosphere is strongly non-linear system with current state depending on its previous states (or prehistory). Therefore we have to develop a multy-parameter non-linear model. In this case ANN is the best tool to solve this problem.

As a first step we use GRNN network to develop the stationary model of the particle distribution under certain conditions in SW and IMF and at a certain level of solar activity. In the output node of ANN we use logarithm of particle intensity to decrease the dynamic range of variations in the flux magnitude. The input nodes of ANN are the geomagnetic coordinates of the point, local time of the measurements, and energy of the particles. The level of geomagnetic activity is determined via Dst-variation. The example of ANN model calculation for >0.5 MeV electron intensity under quite geomagnetic conditions (Dst>-50) is shown on Figure 1 [*Dmitriev*, 1997a]. Different intensity is presented by different density of shadow in the magnetic longitude (mLon) - magnetic latitude (mLat) coordinate system. The outer radiation belt is seen in the Figure 1 as a practically strait line at mLat~±60°. The inner radiation belt is located on the middle latitudes between mLon~0° and mLon~90°. The slot region is clearly seen at mLat~-50°. ANN model allows to describe up to four orders of magnitude of spatial variations of electron intensity. The correlation coefficient of ANN model on the examination set (20% of initial data set containing 13860 examples) is 0.96.

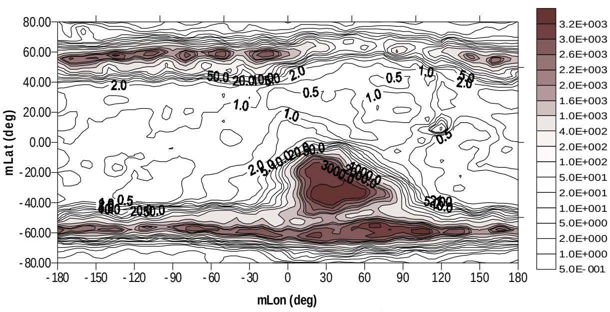

Fig. 1 ANN model simulation of >0.5 MeV electron intensity distribution at altitude 500 km under quite geomagnetic conditions (CORONAS-I satellite data).

2. 3D ARTIFICIAL NEURAL NETWORK MODEL OF THE DAYSIDE MAGNETOPAUSE

The precise knowledge of the shape and size of magnetopause is very important for the description of dynamics of the magnetosphere and particle distribution inside. The dynamics of the shape and size of Earth's magnetopause (MP) have not been studied yet by means of ANN. We have used GRNN [*Caudill*, 1993] and GMDH to develop a complex 3D model of the dayside magnetopause [*Dmitriev*, 1997c]. At the first stage the empirical MP model with a large number of input parameters was created by means of GRNN. At the second stage GRNN model is parameterised - the number of input parameters is reduced in order to obtain optimum between number of inputs and accuracy of the model. At the third stage GMDH was used to represent the model solution in the form of analytical expression. We have to emphasise that our model was developed without any a-priori assumption about the magnetopause shape and about kind of its dependence on the input parameters. ANN model permits to represent the influence both of traditionally used dynamics pressure P and Bz and of By IMF component on three-dimensional geometry of the magnetopause surface. The model may be applied in the extend ranges of SW and IMF parameter values: B_y=-20÷20 nT; B_z=-20÷20 nT; *P*=0.5÷40 nPa. The average relative deviation is better than ≈11% in the wide range of the model parameter variations. Figure 2 shows the magnetopause shape both in meridian and in equatorial sections. The model describes rather well the following main features of MP surface: the cusp region, erosion "dimple" near equator plane at B_z<-10 nT and dawn-dusk asymmetry of MP shape.

We can see in Figure 2 that the minimal distance to MP may change significantly from ~11 Earth's radii (R_E) to ~6 R_E. The magnetosphere boundary defines the last closed magnetic line therefore ANN model describes how the boundary of trapped radiation is controlled by the interplanetary conditions.

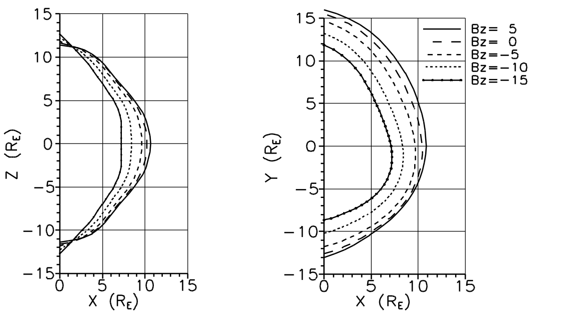

Fig. 2. ANN magnetopause surface simulations in solar-ecliptics coordinate system (GSE). Left panel is magnetopause section in meridian plane (*XZ*); right panel is section in ecliptic plane (*XY*). The model is computed for B_y=0, *P*=2, B_z=5, 0, -5, -10, -15.

3. DYNAMICAL MODEL OF THE SLOT REGION OF EARTH'S ELECTRON RADIATION BELT

The short time (hours) dynamics of relativistic electrons in the slot region (SR) on recovery phases of recurrent magnetic storms is modelled by means of GRNN [*Dmitriev*, 1998]. The strong latitudinal shifts of the slot location (from L=3 to L=2) and variations of electron fluxes up to two order of magnitude in this region are modelled by ANN as function of heliospheric parameters. The initial data was obtained on low altitude (500 km) highly inclined (82°) CORONAS-I satellite during its operation in March-May 1994 (crosses on the third and fourth panels of Figure 3).

Table 1 shows best correlation coefficients and corresponding integration times. The shaded values in the Table were used as input nodes of ANN. This selection of input nodes may be not the best one, but it was done because of the limited data set available for us (116 measurements). The output node in ANN model of SR location is logarithm of L-location of SR (ln(L)). The input layer of ANN contains 11 nodes: local time and magnetic field strength in the points of measurements, IMF components (in GSM system), solar wind velocity, logarithms of density, variations of dynamical and thermal pressures (dPd and dPt), IMF strength and solar radio flux (F10.7) (shaded in Table 1). The heliospheric parameter values are integrated in 91-hour interval preceded the moment of measurements, the solar radio flux value is integrated in 10-hour interval. The output node in ANN model of electron intensity is logarithm of electron intensity in SR (ln(I)). The input ANN layer contains 7 nodes: local time, magnetic field strength and L-shell in the points of measurements, logarithms of IMF components and solar wind velocity with 157-hour averaged values. The training, testing and examination data sets contain 72, 22, and 22 examples respectively. Therefore the hidden layer of GRNN contains 72 neurons. The results of ANN training are shown by rectangles on two bottom panels in Figure 3. As one can see we have obtained close agreement between ANN model and measurements. The correlation coefficient on examination set for SR location model is c=0.96 and for the electron intensity model it is c=0.94.

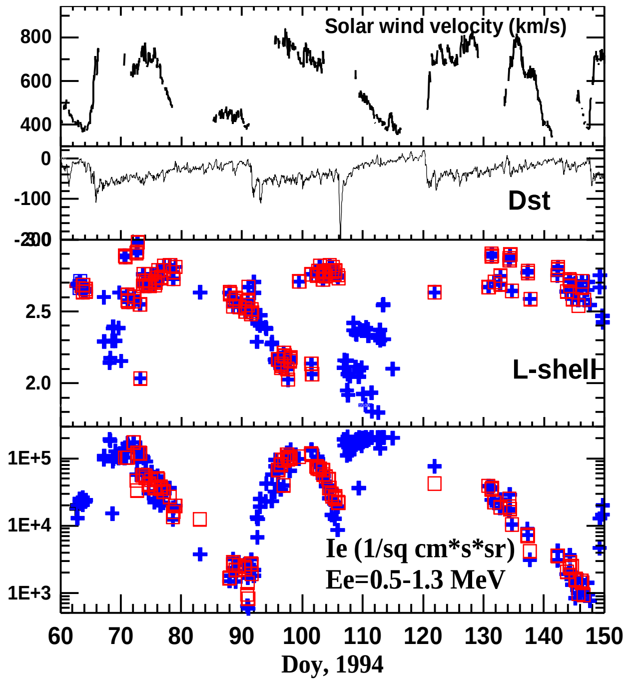

Fig. 3. Time profiles of (up to low) solar wind velocity (first panel), Dst-variation (second panel), L-location and >0.5 MeV electron intensity in the slot region (crosses on the third and forth panels respectively). The rectangles on the third and forth panels are the results of GRNN calculations.

Table 1. Integration Time and Correlation Coefficients

Parameter	ln(L)		ln(I)	
	C	T(h)	c	T(h)
Bx	-0.2	10	0.85	134
By(GSM)	0.25	10	-0.81	159
Bz(GSM)	0.23	10	-0.82	140
ln(V)	-0.33	25	0.843	125
ln(n)	-0.32	108	-0.58	102
ln(dB)	-0.33	92	0.64	161
ln(dPd)	-0.57	91	0.26	96
ln(dPt)	-0.61	91	0.28	139
ln(F10.7)	0.5	11	-0.32	144

ANN model represents the influence of fluctuations of IMF components and plasma parameters of the fast solar wind streams on the electron fluxes at low L-shells (L~2÷3) on the recovery phase of geomagnetic storms. Close agreement of developed ANN models with experimental data allows us to conclude that the dynamics of energetic electrons at low layers of magnetosphere may be defined by the variations of interplanetary medium conditions accumulated during 4-6 days.

4. SELF- CONSISTENT ANN MODEL OF HELIOSPHERIC PARAMETERS

Elman Recurrent Neural Network (ERNN) is used to model the dynamics of the heliospheric parameters: Wolf number, F10.7 flux, solar magnetic field and IMF, SW velocity, temperature and density measured on the Earth's orbit during 1975-1997. The heliospheric data is considered as self-coincident time profiles. To model such kind of data we have to use information about prehistory of parameter behaviour. Furthermore, we have to take into account the influence of one heliospheric parameter on the other, for example well-known dependence of solar wind and IMF properties on the sunspot number. To model this multy-parameter non-linear dynamics the ERNN is most appropriate. ANN used in our study has the feedback link from hidden or output layer to input layer. The initial data set contains monthly averaged values of the above mentioned seven parameters. The data set was divided subsequently into training, testing and examination data sets contain 200, 40 and 39 examples respectively that corresponded to following time intervals of data: 1975-1990, 1991-1994(April) and 1994(May)-1997. So using the ANN trained on the data from time period 1975-1994(April) we try to describe the behaviour of parameters in the minimum of XXII and beginning of the XXIII solar cycle. The developed ANN model permits to predict the monthly averaged values of the parameters for the next month. The results of ANN forecast of sunspot number W and SW velocity V are shown in the Figure 4. The correlation coefficients on the examining set are: 0.67 for the sunspot number, 0.65 for F10.7 flux, 0.86 for the solar magnetic field, 0.47 for IMF strength, 0.81, 0.56, 0.6 for the SW velocity, temperature and density respectively.

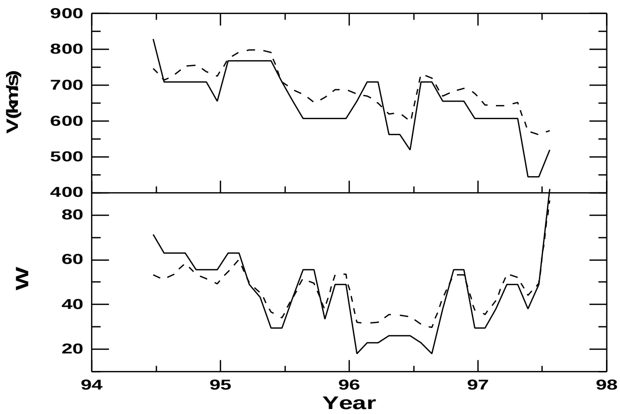

Fig. 4 Comparison of experimental data (solid lines) on solar wind velocity (upper panel) and sunspot number (bottom panel) with ANN model simulation (dashed lines) on examining set.

DISCUSSIONS

We have presented and discussed four ANN models of different space physics systems that may be joined in the global system of Space Weather. These models were developed using different types of ANN. On this way we have a problem: how to use the results of the different ANN calculations to forecast the near Earth radiation distribution. Figure 5 shows the scheme of ANNs combination for this purpose. First, experimental data about solar characteristics (W, solar magnetic field, F10.7 flux) are used for prediction of SW and IMF parameters by means of ERNN. Second, MP, SR and probably some other magnetospheric parameters (if necessary) may be obtained from calculations of ANN models based on these predictions. Finally the results are analysed by SOM network in order to select the most appropriate map of the near Earth radiation distribution.

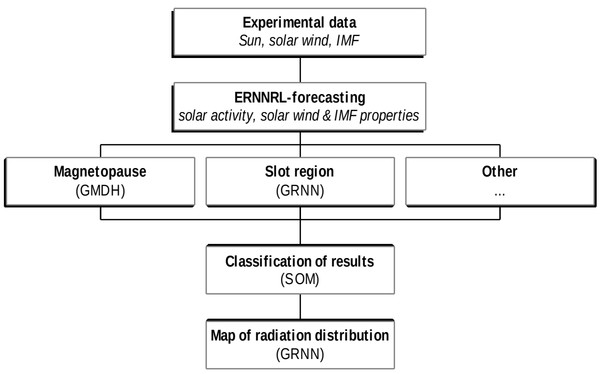

Fig. 5. Scheme of ANNs joining for forecasting of low altitude space radiation distribution.

ACKNOWLEDGEMENTS

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