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Prediction of Electron Flux Environment at Geosynchronous Orbit using Neural Network Technique

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Abstract: In this study a neural network technique is adopted to a prediction of the electron flux at the geosynchronous orbit using several solar wind data obtained by ACE spacecraft and magnetic variations observed on the ground as input parameters. The parameter tuning for back-propagation leaning method is attempted to the feed-forward neural network. As a result, the prediction using the combined data of solar wind and ground magnetic data shows the highest prediction efficiency of 0.61, which is enough to adapt the actual use of the space environment prediction.

Keywords: Neural Network. Spacecraft, Internal charging

I. INTRODUCTION

From 1950's many spacecrafts have been launched into the near earth space and over 300 artificial satellites are operated as the significant infrastructure today. However such satellites are exposed in the sever environment on their orbits. In particular, the orbit in the range from 2 to 7 R_E (Earth Radii) which include the geosynchronous orbit is well known as "Radiation Belt" filled with the high-energy particles. The high-energy ($>10^6$ eV) electrons are thought to be a cause of internal charging which give rise to the serious troubles on the electric circuit onboard the spacecraft.

In order to avoid the significant problems on the satellite systems, it is important to predict the space environment especially for the high-energy particles. The physical element process of the high-energy electrons flux variations has not been understood well though much number of observations have been conducted by many investigators. Thus, it is difficult to predict the electron flux variations by the computer simulation based on the theoretical models, so that some studies of the electron flux predictions using the empirical models based on the statistical analysis were attempted. In the previous observations, it is well known that the electron flux shows the large enhancement during the magnetic storm which is driven by the disturbance of the solarwind (that is the high-speed plasma stream flowing out from the sun).

Some investigator tried to predict the electron flux variations by the linear prediction filter using the observed space environment data [1][2]. In these studies, the accuracy of the prediction was not enough to adopt the actual operations, though enhancement itself was well reproduced in 24hours-later predictions.

Fukata et al. [3] first attempted the prediction of the electron flux variations using the neural network model. This model well predicted the variation of the electron flux during the disturbance period of the space environment. However, this model was developed by the statistical learning using only disturbed-days data, so that the transition from the quiet days to disturbed days (commencement of the electron flux enhancement) was not reproduced well.

The objective of this study is to establish the prediction system to be applied to an actual space operation. We first attempt the prediction of the high-energy electron flux enhancement by means of the neural network using the much amount of the data obtained by the spacecraft and ground network observations. Then we validate the accuracy of the prediction by using the prediction efficiencies (*PE*) for the various combinations of the input parameters.

II. DATA SET

The electron flux enhancement generally occurs during the magnetic storms which have some precursor variations in the other monitored data.

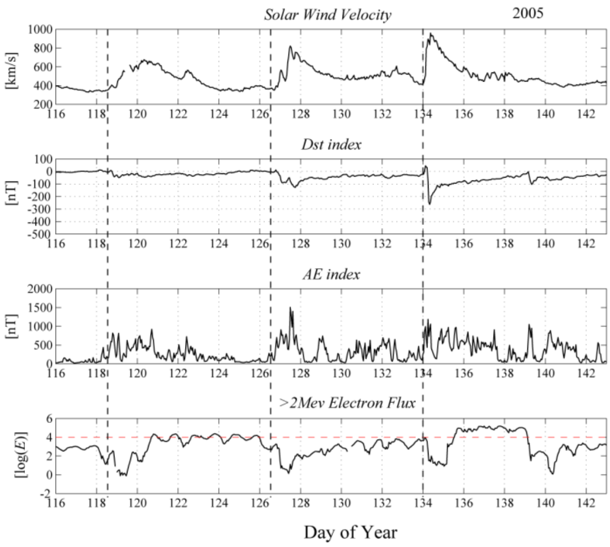

Fig1. Example data of the electron flux enhancement

The bottom panel of Fig.1shows the electron flux variations for 27days in 2005. The horizontal axis is Day of year (Jan. 1 = 1 and Dec. 31 = 365). The electron flux increases in 121 and 136 days and exceeds the horizontal dashed line which indicates the alert level for the spacecraft's interference. On the other hand, the obvious precursor could be seen (in the vertical dashed lines), that is, the increasing of the solarwind velocity (top panel) and AE index (third panel) precede the electron flux enhancement by 2days. The Dst index (second panel) shows the sudden decreasing preceding the electron flux enhancements.

In this study, we use the solarwind data which is observed by Advanced Composition Explorer (ACE) space craft. The dataset of the solarwind consists of the velocity (V_{sw}), north-south component of the magnetic field (B_z) and 3-days integration of epsilon parameter ($\Sigma\varepsilon$) (which is calculated from the velocity and magnetic field and is consistent with the electromagnetic poynting flux from solar wind to the earth). The (Auroral Electrojet) *AE* index is determined from the magnetic field variations observed on the high-latitude ground observatories and is proxy of the Auroral activity due to the solarwind disturbances. The Disturbed field during Storm Time (*Dst*) index is also determined by the ground magnetic variations. Since the magnetic observatories used in calculation for the *Dst* index are not at high latitude but at low latitude, the *Dst* index is generally utilized for the definitive scale of the magnetic storms (which is major electromagnetic disturbances in the space environment). The high-energy (>2MeV) electron flux (E) at the geosynchronous orbit is observed by the GOES 10 satellite operated by National Oceanic and Atmospheric Administration (NOAA). In the preparation for the analysis, we removed the error data from the hourly data for each observed data in the interval from 1998 to 2006, and got 74376 samples for each hourly data.

III. Neural Network

In this study, since the output data of the model is 24-hours-later prediction, the output data could not physically affect the past data used as the input parameter in actual causality. Thus, we adopted the feed-forward neural network model with the back-propagation leaning method to predict the 24-hours-later electron flux variations. Fig.2 represents the schematic illustration of the network model used in this study. The network consists from arbitrary number of middle layers which also consist from arbitrary number of neurons.

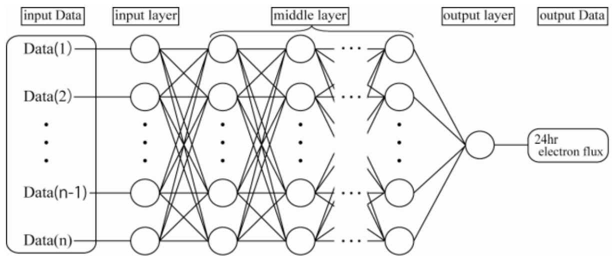

Fig.2 schema of neural network

All the data obtained from 1998 to 2006 were normalized in the range from -1 to 1 to be used as input parameters. In each neuron, input parameters are weighted with an appropriate weight and a sum of the weighted input is send to the transfer function of transient sigmoid. As a result, one output data can be obtained through the reiteration of above mentioned scheme. Then output parameter (O_P) for the input parameters with the arbitrary pattern ($_P$) is compared with the observed 24-hours-later electron flux (T_P)

which is supervised data, and validate the following error function (E).

$$E = \frac{1}{2}\sum_{P}(O_P - T_P)^2$$

The appropriate weight for each neuron is determined by the steepest descend method to minimize E. In this analysis the reiterating calculation stopped under the condition that the error function E reaches less than 0.01.

IV. Result of the analysis

In the training process, various combinations of input parameters were attempted to evaluate the accuracy of the prediction. In order to quantitatively evaluate the accuracy of the prediction, we calculated the prediction efficiency (*PE*) which was adopted by NOAA Space Weather Prediction Center (SWPC) [4] as

$$PE = 1 - \frac{MSE}{VAR}$$

$$VAR = \frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x}_i)^2$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(f_i - \bar{x}_i)^2$$

where x_i and f_i are observed and predicted values of electron flux, respectively. Thus *PE* is based on the mean square error which is normalized by variance of the observed values.

We classified the input parameters into three cases, that are, (1)data basically obtained in the space (E, V_{sw}, B_z, $\Sigma\varepsilon$, UT), (2)data basically obtained on the ground (E, Dst, AE, UT), (3)combination data obtained both in the space and on the ground (E, V_{sw}, Dst, AE, UT), here UT means Universal Time. For each case, the training was conducted using the data from 1998 to 2006 except 2003. It is known that the solarwind had been much disturbed in 2003 due to the large coronal hole appeared on the surface of Sun, so that we attempted the validation of the prediction to calculation of *PE* for the predicted electron flux with the observed data in 2003.

We attempted the various combination of the number of middle layers and neurons for above three cases. The result is shown in Fig3. In cases 1 and 2, the relationship between the number of neurons and middle layers are not clear and the maximum *PE* is less than 0.58. On other hand, in case 3, the dependence of *PE* on the number of neurons and middle layers is in the orderly manner. The maximum *PE* of 0.61 is shown under the condition that number of neurons is more than 6 and number of middle layers is less than 4. This result means that the prediction of the electron flux shows the best performance using the both data observed in the space and on the ground.

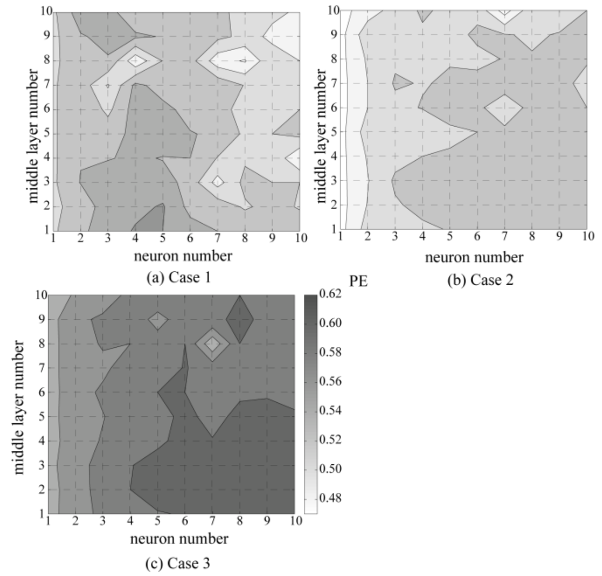

Fig3. Result of the network turning for 3 cases

For the case 3, the comparison between the predicted electron flux and observed electron flux is shown in Fig4. The enhancement of the electron flux is well predicted in entire variations though predicted line (solid line) sometimes shows the over estimation comparing to the observed line (dotted line).

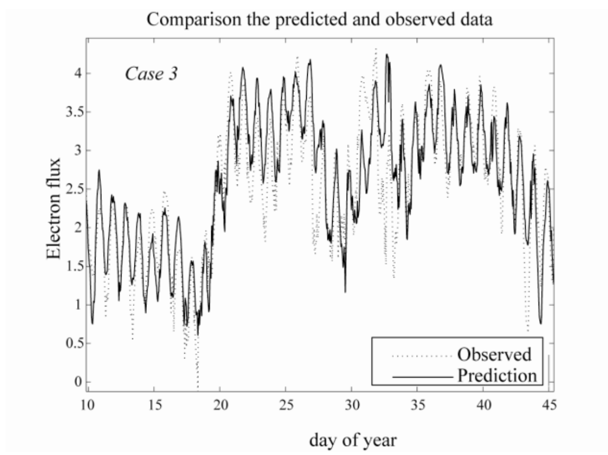

Fig4. Comparison between the predicted and observed variations

The both predicted and observed values for all data in 2003 are shown in the scatter plot of Fig4 to validate the prediction accuracy in more details. The vertical and horizontal axes are the observed and predicted values, respectively. The plots are fairly scattered in the condition that the flux is less than 4, which means the predicted values sometimes deviate from the observed values. In the condition that flux is more than 4, the plots become to concentrate on the dashed line, though the distribution of plots shows the overestimate tendency of ~10%. In terms of the application of the electron flux prediction to the actual space operation, ~10 % of the overestimation could be acceptable to avoid the risk, by contrast the underestimation of the predictions connotes a significant risk for real operations.

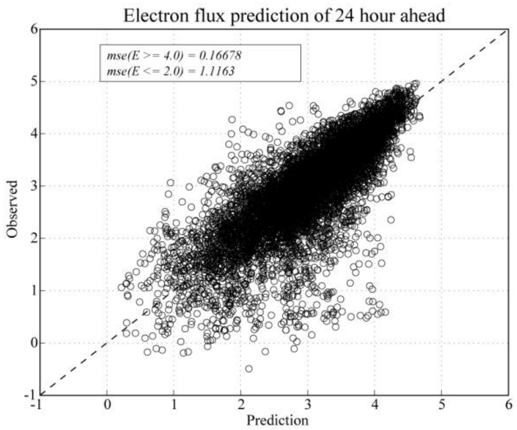

Fig5. Scatter plot of the predicted and observed values

VI. CONCLUSION

In the present study, we attempted the high-energy electron flux variations using the feed-forward neural network with back-propagation learning method. We could summarize the present study as follows. (1) The maximum *PE* shows 0.61 with input parameters obtained both in the space and on the ground. (2) The accuracy of the prediction increases with increasing an amount of the electron flux and tends to be an overestimation of ~10%. These results indicate that the present neural network model could be adopted in the real space environment forecast operation.

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