Solar Cycle 24 Forecasts

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The forecasts of the solar cycle 24 activities using the neural network method were made. For the sunspot relative number, June 2006 as the next minimum epoch with a value around 18 and, December 2009 as the next maximum epoch with a value of around 145 were obtained. For the 2800 MHz solar radio flux, the next minimum epochs with an approximate value of 75, on May 2006, and the next maximum epoch with a value of about 195, on December 2009, were forecasted. The time phase of both minima and maxima agrees very well which gives us a hope in a good behaviour of our approach. The forecasts of the geomagnetic aa, Dst, Ap and Kp indices were also done with the same pre-processing (gaussian monthly smoothed mean) and the same neural net for the same forecast horizon.

Introduction

A large range of forecasting methods is used to predict the occurrence and amplitude of solar cycles (SCs). They have changed from simple statistical (linear/nonlinear) to complex physical (precursor), based on the understanding of the dynamo process that generates the solar magnetic field and its evolution ([6]). Most favoured are the precursor methods. They invoke a solar dynamo concept where the polar field in the declining phase and at minimum is the seed of future toroidal fields within the Sun that will cause a solar activity. Criticisms of long-term solar cycle prediction focus however, on the thin physical foundation beneath such predictions and the limitations of the data used to define and extend solar and geophysical variability. The dramatic variability from one cycle to the next in these sunspot and geomagnetic records shows the difficulty in making empirical predictions of both types of activity. The issue is further complicated by the lack of a successful quantitative, theoretical model of the Sun's magnetic cycle. Waiting for a fundamental understanding of the solar cycle that would provide the basis for physical prediction methods we must relay on the present empirical ones.

This paper presents our forecasts of some SC 24 solar (R_i , F_o) and geomagnetic (aa, Dst, Ap, Kp) indices using the neural network method. The neural network method is described in the second section. Our forecast results on the solar as well as on the geomagnetic indices are presented in the third section. A short comparison with other forecasting data is made in the last section.

Neural Network Method

A neural network is a computational model that is loosely based on the neuron cell structure of the biological nervous system. Given a training set of data, the neural network can learn the data with a learning algorithm. At this time neural networks still suffer from basic problems such as data preprocessing, architecture selection and parameterization. Until a more theoretic foundation on which are to be build emerges a particular choice is more art than science

A neural network can have any number of *layers*, *units* per layer, *network inputs*, and *network outputs*. The feed-forward neural network depicted in Fig. 1 has four inputs, four units in the first layer (layer A) and three units in the second layer (layer B), which are called *hidden layers*, and one unit in the third layer (layer C), which is called the *output layer*.



Fig.1. A three-layer feed-forward neural network.

Each unit has the same number of inputs as there are units in preceding layer (or network inputs) and, the same number of outputs as the number of units in the succeeding layer (or network outputs). Each network input-to-unit and unit-to-unit *connection* is modified by a *weight*. In addition, each unit has an extra input called the *bias* (Fig. 2). All data propagate along the connections in the direction from the network inputs to the network outputs, hence the term *feed-forward*.



Fig. 2. Weights and bias of a specific unit.

Each

hidden layer unit performs a weighted sum of inputs, applies the *activation function* (h) of the unit, and transfers the result (O_c) to the next layer as in equation below:

$$O_c = h_{Hidden} \left(\sum_{p=1}^{P} i_{c,p} w_{c,p} + b_c \right)$$
(1)

Then, the neural network has to be trained on an appropriate data series. The *back propagation* training consists of the following steps:

- Take an input vector and compute activation functions sequentially forward from the first hidden layer to the output layer.
- Compute the difference between the desired output for that example and the actual network output.
- Propagate the error sequentially backward from the output layer to the first hidden layer.
- For every connection, change the weight modifying that connection in proportion to the error.

When these three steps have been performed for every example from the data series, one *epoch* has occurred. Training lasts until a predetermined maximum number of epochs (*epochs limit*) is reached or the network output error (*error limit*) falls below an acceptable threshold.

The typical method for training a network is to first partition the data series into three disjoint sets: the *training set*, the *validation set*, and the *test set*. The network is trained directly on the training set, its *generalization ability* is monitored on the validation set, and its ability to forecast is measured on the test set. A network's generalization ability indirectly measures how well the network can deal with unforeseen inputs, in other words, inputs on which it was not trained.

When consistently the *validation error* increases, while the *training error* decreases, the network has over-learned or over fitted the data and training should stop.

In choosing the neural network we faced some usual difficulties. First comes from the limited quantity of data not in terms of values but of patterns covered. If you are to predict a certain pattern (SC) you better have at least two such patterns. As the work was targeted at the investigation of SC 23 end with extension to SC 24 we limited ourselves at January 1976 (beginning of SC 21). All the indices used were

338 pseudo-gaussian smoothed monthly mean obtained from daily values from January 1976 to February 2004. Forecasts were performed 94 steps ahead that is December 2012.

The second drawback is the inherent noise. We encountered heavy difficulties in treating daily data. Even for the monthly data the standard smoothing procedure is not very successful so we used a pseudo-gaussian smoothing window. This worked well for solar data but not so well with the geomagnetic data. Moreover it gave a different look to the data plots that may look unfamiliar to the trained eye.

Even in choosing a particular neural net structure much too many ways exists. As concerning the architecture we found by trial and error that we need at least a cycle span long number of inputs so we choose 128. This approximates 10 years of 12 months of data and accommodates the addiction induced by years of spectral analysis. One hidden layer took us nowhere so we throw it in the second one. They were chosen to be 64 and 34 as explained before. With one cell output layer as we process time series we ended up with a neural network of 128-64-32-1 structure.

With 128 out of the 338 values (months from January 1976 to February 2004) we have 210 points left for training and validating the neural network. Putting aside the testing we used the first 105 points for training and the last half for validating the net. To avoid over fitting we used the heuristic method (stops when training error lowers and validation error rises). Finally we do an iterative forecasting 94 steps ahead (December 2011).

Results

Solar indices forecast

First runs were done on the sunspot number (R_i) and the 10.7 cm observed solar radio flux (F_o) . After a tedious work of trial and error on choosing, training and validating the neural network we fall on the forecasts seen in Table 1 and Fig.3.



Fig. 3. Sunspot relative number (upper panel) and 2800 MHz solar radio flux (bottom panel) observed and predicted values (full line – observed values; dotted line – forecasted values).

TABLE 1

Forecasted extreme epochs and values of the solar indices

Index	Minimum	Maximum
R	June 2006; R _i =18	Dec. 2009; $R_i = 145$
F	May 2006; F _o =75	Dec. 2009; F _o =195

For the sunspot number R_i we obtained June 2006 as the date of the next minimum with a value around 18 and December 2009 as the date of the next maximum with a value of around 145. We note here that using the Max-Min precursor method a value of 18 for $R_{i, min}$ projects a value of 144 for the $R_{i, max}$ that follows. Much the same as the neural net forecasting predicts. Using the Ohl's method (similar to Min-Max but using *aa* instead of R_{min}) the predicted next maximum R_i is 138, not far from the previous forecast of 145.

For the solar radio flux F_o we obtained May 2006 as the date of the next minimum and December 2009 as the date of the next maximum.

The time phase of both minima and maxima agrees nicely which gives us hope in a good behaviour of our approach. Nevertheless both minima are a bit larger than expected. As concerning the maxima we have not yet the means to comment on their values.

Geomagnetic indices forecasts

Daily regular geomagnetic field variation arises from current systems caused by regular solar radiation changes. Other irregular current systems produce magnetic field changes caused by the interaction of the solar wind with the magnetosphere, by the magnetosphere itself, by the interactions between the magnetosphere and ionosphere, and by the ionosphere itself. Geomagnetic activity indices were designed to describe variation in the geomagnetic field caused by these irregular current systems.

We chose the *aa*, *Dst*, *Ap* and *Kp* indices for our forecasts. They were done with the same pre-processing (pseudogaussian monthly smoothed mean) and the same neural net for the same forecast horizon. Those much more noisy data did not seem to behave well for such a long forecast. The results of the *aa* and *Dst* indices are done in Fig. 4 and Table 2. The forecast of *aa* gives for mid 2006 (the next forecasted solar R_i minimum) a value around 18 and for late 2008 an absolute minimum value around 11.



Fig. 4. The observed and predicted values of the aa (upper panel) and Dst (bottom panel) geomagnetic indices (full line – observed values; dotted line – forecasted values).

TABLE 2

Forecasted extreme epochs and values of the *aa* and *Dst* indices

Index	Minimum	Maximum
aa	Mid 2006; aa=18 Late 2008; aa=11	Apr. 2005; aa=36 March 2010; aa=38
Dst	Jan. 2006; Dst=-29 Oct. 2010; Dst=-28	End 2006; Dst= -23 Mid 2008; Dst= -19

The *Dst* forecast gives for mid 2008 a local maximum around -19 but a higher maximum (-23) on the end of 2006, just after the next forecasted solar R_i minimum. The opposite

phase behaviour of the two indices is clearly maintained over the forecast interval.

The Ap and Kp forecasts are given in Table 3 and Fig. 5. The forecasted next minimum does not resemble the two previous ones but Ap and Kp are well correlated during the forecasted interval. The high geomagnetic activity in the beginning and the end of the year 2005 are seen in the *aa*, Apand, Kp forecasted values; this fact proves that our forecast is reliable.



Fig. 5. The observed and predicted values of the Ap (upper panel) and Kp (bottom panel) geomagnetic indices (full line – observed values; dotted line – forecasted values).

TABLE 3

Forecasted extreme epochs and values of the Ap and Kp indices

Index	Minimum	Maximum
Ар	Beg. 2009; Ap=6 Mid 2011; Ap=9	Beg 2005; Ap=22.5 Mid 2010; Ap=175
Кр	End 2008; Kp=2 ⁻ Mid 2011; Kp=2 ⁰	Beg 2005; Kp=3 ⁺ Mid 2010; Kp=3 ⁺

Result analysis (Conclusions)

Solar cycle 23 was originally predicted to reach a comparable magnitude as SC 21 with the monthly smoothed sunspot number reaching 160. The first peak of SC 23 at 120.8 was registered in April 2000 and the second one, smaller peak, at 115.5 in November 2001. This unverified forecast draws attention on a possible reduction of the solar activity level.

A lot of preliminary estimations for the 24th SC support the tendency towards a reduction in the intensity of solar activity ([4], [5]). Ref. [5] used both a nonlinear and a precursor method, giving a monthly SC 24 peak amplitude as $R_{i max} = 96 \pm 25$, occurring in April 2011 and a yearly peak as 115 ± 21 for 2011, respectively. Using the Ohl's method the predicted next maximum of the sunspot relative number is 138, not far from the previous forecast of 145. Another early nonlinear prediction ($R_{i max} = 87 \pm$ 23.5) was given in [1]. According to our empirical method of estimating the solar activity ([2], [3]), based on observing the flare energy release during the descendant phase of the precedent SC, the events from October – November 2003 as well as some active ones from the beginning of 2005 make us agree that the amplitude of SC 24 will be comparable to SC 23 or even lower.

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REFERENCES

- [1] S. Duhau, "An Early Prediction of Maximum Sunspot Number in Solar Cycle 24", *Solar Phys.*, Vol. 213, 2003, pp. 203–212.
- [2] G.Maris, M. D.Popescu, D. Besliu, "Solar Cycle 23: Forecasts and Observations", *Rom. Astron. J.*, Vol. 13, 2003, pp. 139–142.
- [3] G. Maris, M. D. Popescu, M. Mierla, "The North-South Asymmetry of Soft X-Ray Solar Flares", *Rom. Astron. J.*, Vol. 12, 2002, pp. 131–146.
- [4] S. Sello, "Solar cycle activity: A preliminary prediction for cycle #24", Astron. Astrophys., Vol. 410, 2003, pp. 691–693.
- [5] K.H. Schatten, W. K. Tobiska, "Solar Activity Heading for a Maunder Minimum?", *American Astronomical Society, SPD Meeting*, Vol. 34, 2003.