Reported on EGS XXIV General Assembly, 22 April 1999, The Hague, The Netherlands

Solar Activity Forecasting on 1999-2000 by Means of Artificial Neural Networks

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Geomagnetic conditions are controlled effectively by solar activity. Three representative parameters characterizing the solar activity are sunspot number (W), 10.7cm radio solar flux (F10.7) and mean solar magnetic field value (SF). These parameters are responsible for different sides of solar activity manifestation and influence on the Earth. Sunspot number is associated with solar flares strongly affecting on Earth's magnetosphere and radiation environment. Earth's ionosphere conditions are tightly related to the F10.7 solar radio flux reflecting solar ultraviolet radiation. Mean solar magnetic field value is related to the interplanetary magnetic field controlling the averaged Earth's magnetosphere conditions. Practically persistent time series of these parameters are appropriate data sets for modelling and forecasting by means of Artificial Neural Networks (ANN). Methods of optimization of ANN input data sets and selection of training, testing and examination sets are discussed in the paper. The dynamical models of the mentioned above parameters are developed by means of ANN. The results and reliability of ANN forecasting for period 1999-2000 are presented and discussed.

Introduction

For modeling of self-consistent time series the recurrent ANN is very powerful method. These models take the information about prehistory of the system dynamics into account and hence they may be used for forecasting. The models forecasting sunspot number and average solar wind conditions are excellent examples of this kind of ANN applying. The prognoses of time-series of geomagnetic indexes (Dst, Kp, AP, etc.) are generated using Recurrent Neural Networks (RNN) [e.g. *Wu*, 1996]. Last report by *Conway et al.* [1998] presents the results of the feed forward neural networks applying for the long-term prediction of sunspot number. The authors estimate the maximum and the duration of the present XXIII solar cycle as 130±30 (in 2001) and 11 years respectively. Nevertheless the solar activity is realized by different ways that affect to the Earth in different manners. The most representative time series of parameters that characterized some sides of solar activity are sunspot number (Wolf number) W, 10.7cm radio solar flux (F10.7) and mean solar magnetic field value (SF). In this study we try to forecast these parameters on 1999-2000 by means of RNN.

Initial Data

As initial data of sunspot number W we use the database on daily Wolf number on ftp-directory ftp://ftp.ngdc.noaa.gov/STP/SOLAR_DATA/SUNSPOT_NUMBERS/. We use only regular data of sunspot number that begins from 1850 (13 last solar cycles). The www-archive www.drao.nrc.ca/icarus/data/current.txt is used for obtaining daily 10.7cm radio solar flux values recorded by the National Research Council's Solar Radio Patrol since 1947. We use regular F10.7 flux adjusted to 1 Astronomical Unit since 1949. Daily means of mean solar magnetic field value (SF) for period 1975-1998 is obtained from NOAA NGDC Data base ftp://ftp.ngdc.noaa.gov/STP/SOLAR_DATA/SUN_AS_A_STAR/STANFORD/.

As shown in [Veselovskiy et. al., 1998] usually the best correlation of sunspot number with other parameters are obtained with annular averaged values of these parameters. The best correlation of W with F10.7 and SF are shown in the Table 1 where the first line is the correlation coefficient, the second line is averaging time and the third line is shifting time. Using these facts we used for ANN modeling the annular averaged sunspot number and mean solar magnetic field values and 100 day averaged 10.7 radio solar flux value.

Table 1.

	F10.7	**SF**
W	0.84 100 days 0.55 Y	0.9 1 Year 0.00

RNN Description

Recurrent Neural Networks (RNN) with Error Back-Propagation [NeuroShell 2] are known of their ability to generalize in a wide range of diverse problems. These networks are trained with "teacher", i.e. during the training, besides inputs, desired values of outputs are required. There are different kinds of RNN, but the most famous of them are RNN with a feedback from hidden or output layer. These networks perform well on time series data. Some disadvantage of RNN is significant time of training.

Standard feed-forward ANN responds to a given input pattern with exactly the same output pattern every time the input pattern is presented. RNN may respond to the same input pattern differently at different times, depending upon the patterns that have been presented as inputs just previously. Thus, the sequence of the patterns is as important as the input pattern itself.

RNN are trained the same as standard feed-forward ANN except that patterns must always be presented in the same order; random selection is not allowed. The one difference in structure is that there is one extra recurrent layer that is connected to the hidden layer just like the input layer (Fig.1). This recurrent layer holds the contents of one of the layers as it existed when the previous pattern was trained. In this way RNN sees previous knowledge it had about previous inputs. This recurrent layer is sometimes called the network's "long term" memory.

The “long term” memory is formed in the following way. Current State Feedback Link copies some proportion of the neuron values into the recurrent layer from itself. Prehistory Feedback Link copies some proportion of the neuron values in the current pattern from either the input, hidden, or output layer (depending upon the network type) into the recurrent layer. The sum of both proportions is equal to 1. If we want to put more emphasis on historical patterns, we set a higher proportion of neuron values on Current State Feedback Link. If we want to put more emphasis on more recent patterns, we set a higher proportion of neuron values on Prehistory Feedback Link.

We use in our study one of the most powerful RNN with feedback from the hidden layer. In this RNN the long-term memory keeps in mind the condition of a hidden layer, which contains features, extracted from previous examples.

The number of hidden neurons for 3-layers RNN was calculated using the following formula: N of hidden neurons = 1/2 (N of inputs + N of outputs) + the root square of the number of examples in training set.

Results

Wolf number modelling

The results of modeling of Wolf number W are presented on Fig. 2 and Fig. 3. The initial data set of annular averaged monthly running sunspot numbers is shown as solid lines. The RNN results on training and testing sets are shown as dashed lines. The forecasting on 1999-2000 is presented as hard solid lines. Both models are developed by means of standard RNN models. We use 12 input (one year before) and 12 output (one year after) nodes in RNN. The number of neurons in the hidden layers was 49 and in the recurrent layer - 12. First model has 10 first solar cycles in training set, 2 cycles in testing set and 1 last solar cycle (XXII) in examination set. In Fig. 2 we present the results of RNN modeling. Left panel presents ANN results on training set (dashed line). Right panel presents ANN results on testing set (dashed line), examination set (hard dashed line) and forecasting on 1999-2002 (hard line). Thin line on the right panel is monthly averaged sunspot number.

The correlation coefficient of the model on examination set is better than c=0.96. The second model has 12 solar cycles in the training data set and 1 cycle in testing set. The correlation coefficient of the second model on the testing set is better than c=0.9.

As we see in Fig. 2 and Fig. 3, the forecasting Wolf numbers are similar in both models: about 110 in the solar maximum at beginning of 2000. This result shows the stability of RNN model solution at least for three years foreword. Therefore the maximal sunspot number forecasted for XXIII solar cycle is ~40% less than for the previous solar maximum (W=160) in XXII solar cycle.

10.7 radio solar flux modelling

The result of RNN modelling of 10.7 radio solar flux is presented in Fig. 4. The initial data set of 100 day averaged F10.7 is presented by solid line. Monthly averaged mean of F10.7 flux is presented by thin line. Initial data set was divided on training data set (from 1949 to 1989) and testing data set (from 1990 to 1998). Like in sunspot modelling RNN has 12 input and 12 output nodes. The hidden and recurrent layers contain 23 and 12 neurons respectively. RNN results on training and examination sets are shown in Fig. 4 as thin dashed and hard dashed lines respectively. The correlation coefficient on testing set is better than 0.8. Forecasting of 100 days averaged means of solar radio flux F10.7 on 1999-2005 is presented by hard line. The forecasted flux in maximum at 2001 is 10% less than in maximum of XXII solar cycle. This result does not contradict to forecasting of sunspot numbers.

Mean solar magnetic field SF modeling

Due to poor statistics of the mean solar magnetic field SF RNN for this model contains 12 input nodes and 1 output node. The training data set includes annular averaged monthly running values of SF from 1978 to 1995. The testing data set contains data from 1996 to 1998. The hidden and recurrent layer contain 24 and 6 neurons respectively. Fig. 5 shows the result of RNN modeling of annular monthly running mean values of the mean solar magnetic field (*SF*) (solid line). ANN results on training set are shown by thin dashed line. SF forecasting on 1999-2000 is presented by hard line. We can indicate the distortion of RNN solution. The reason of the distortion is obviously due to insufficient volume of initial data for RNN training - only 2 solar cycle and only one 22-year solar cycle.

Conclusion

We have obtained three RNN producing predictions that agree well with each other. The results of modeling of sunspot number *W* and *F10.7* radio solar flux by means of RNN show that the maximum of XXIII cycle will be in 2000-2001 and the maximal Wolf number will be about *W*=110. The long-term forecasting (~10 years) is difficult due to changing of fractal dimension of the sunspot time series at the time scale about 8 year [*Zhang Qin, 1998*]. We need the additional statistics for successful modeling of the mean solar magnetic field value SF.

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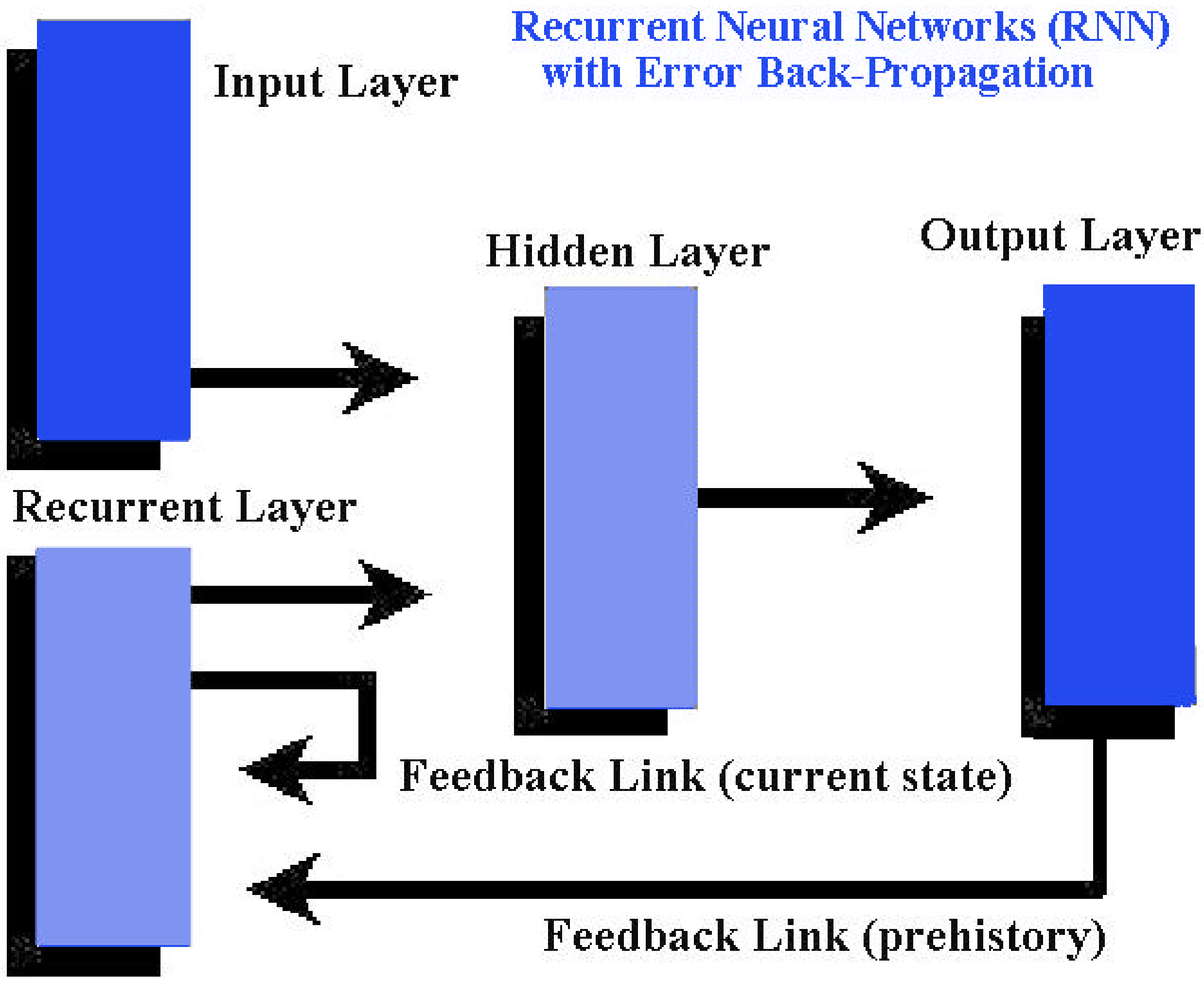

Fig. 1. Recurrent Neural Network with Feedback Error Propagation (RNN). The relation between weigh of Reverse Link (prehistory) and weigh of Reverse Link (present) defines the relative importance of the prehistory impact on the out nodes of ANN.

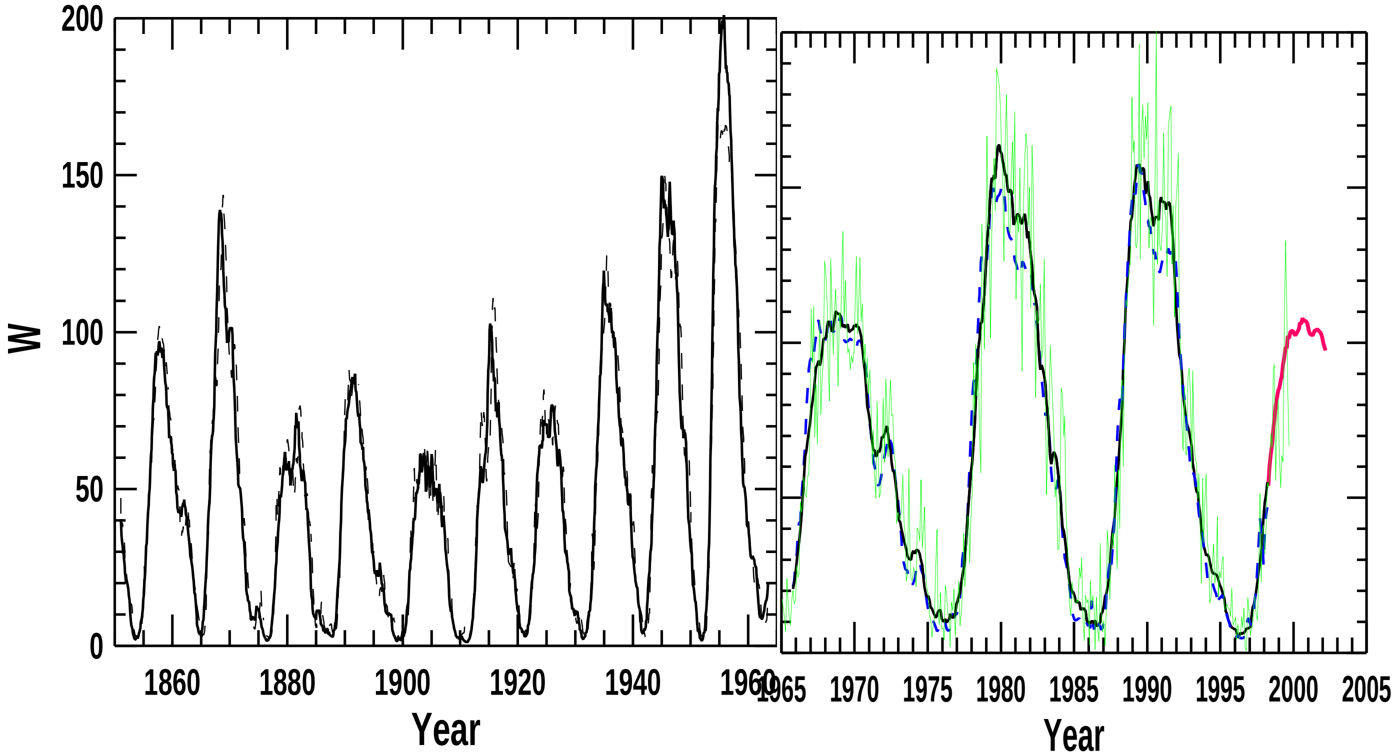

Fig. 2 RNN modeling with examining set of annular monthly running sunspot number *W* (solid line). Left panel is ANN results on training set (dashed line). Right panel - ANN results on testing set (dashed line), examining set (hard dashed line) and forecasting on 1999-2002 (hard line). Thin line on the right panel is monthly averaged sunspot number.

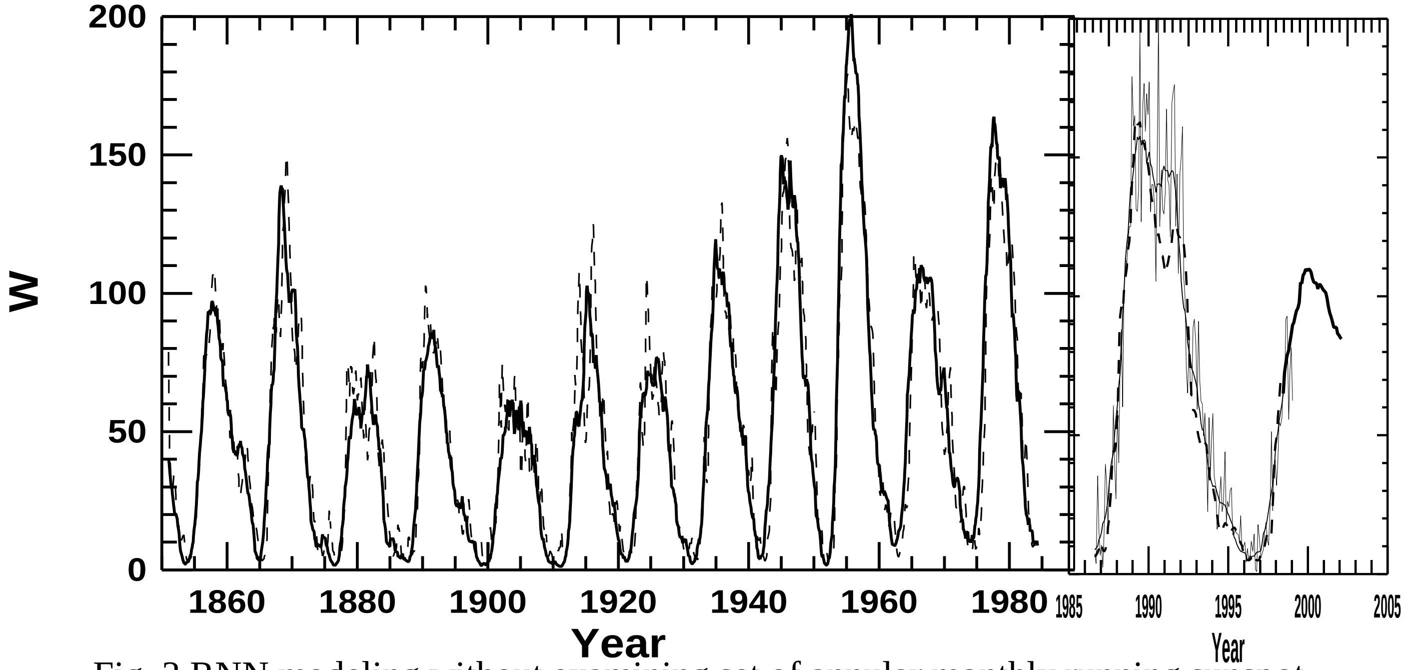

Fig. 3 RNN modeling without examining set of annular monthly running sunspot number *W* (solid line). Left panel is ANN results on training set (dashed line). Right panel - ANN results on testing set (dashed line) and forecasting on 1999-2002 (hard line). Thin line on the right panel is monthly averaged sunspot number.

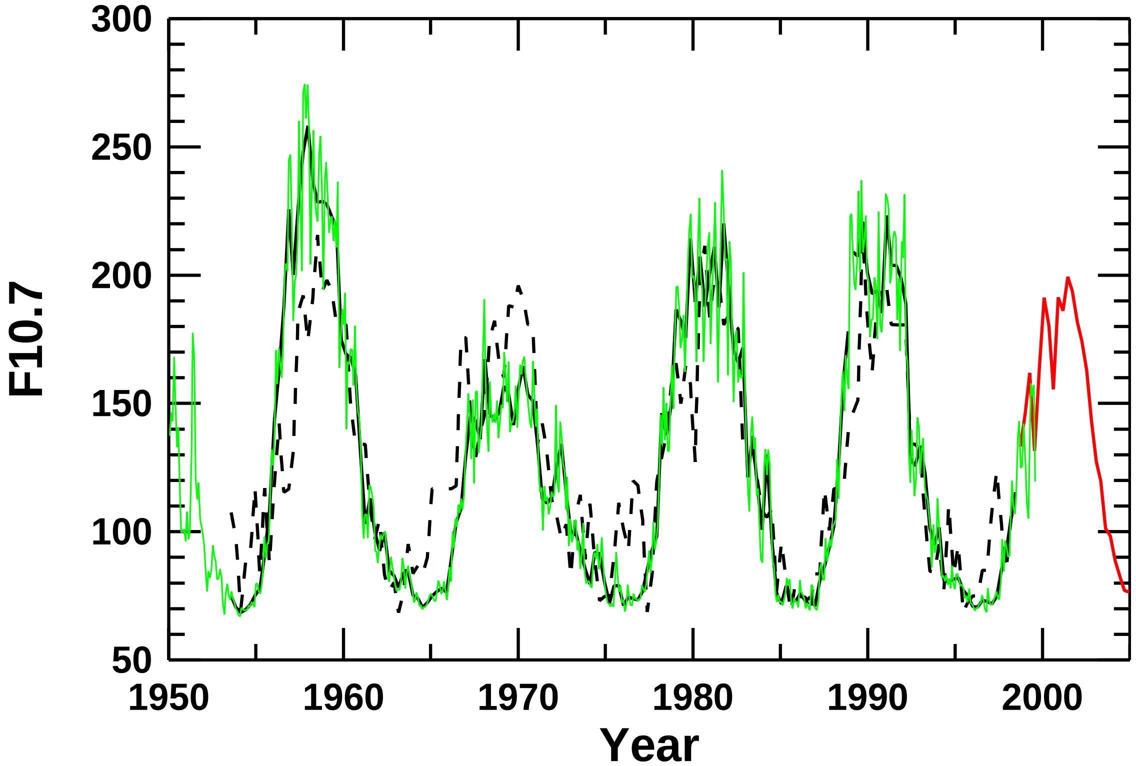

Fig. 4 RNN modeling without examining set of 100 days averaged means of solar radio flux *F10.7* (solid line). ANN results on training and examining sets are shown by thin dashed and hard dashed lines respectively. *F10.7* flux forecasting on 1999-2005 is presented by hard line. Thin line is monthly averaged mean of *F10.7* flux.

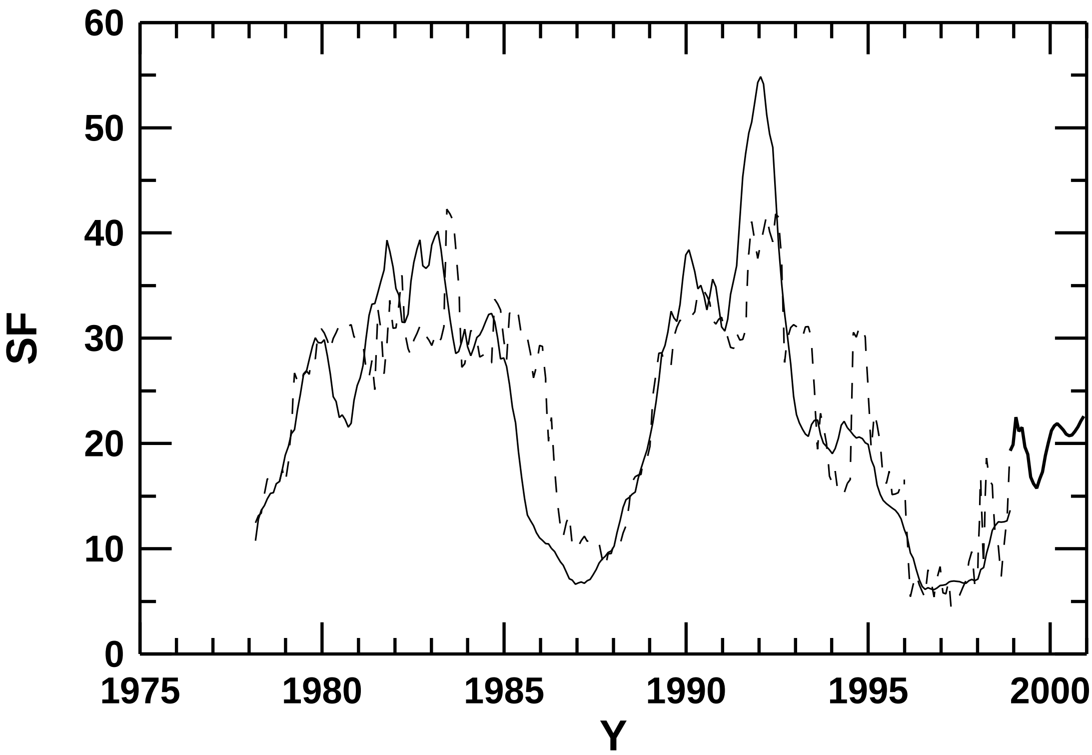

Fig. 5 RNN modeling without examining set of annular monthly running means of the mean solar magnetic field *SF* (solid line). ANN results on training set are shown by thin dashed line. *SF* forecasting on 1999-2000 is presented by hard line.