Long-Term Datasets for the Understanding of Solar and Stellar Magnetic Cycles
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Prediction of future evolution of solar cycle 24 using machine learning techniques

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Abstract. Forecasting the solar activity is of great importance not only for its effect on the climate of the Earth but also on the telecommunications, power lines, space missions and satellite safety. In the present work, machine learning using Artificial Neural Networks (ANNs) called Nonlinear Autoregressive Network (NAR) with Exogenous Inputs (NARX) have been applied for the prediction of future evolution of the present sunspot cycle. NARX network is able to combine the performance of ANN algorithm with nonlinear autoregressive method to handle problems such as finding dependencies among solar indices and prediction of solar cycle evolution.

Keywords. Solar cycle, Machine learning

1. Introduction

Nonlinear Artificial neural networks have proven to be more effective for predicting sunspot number than classical linear predictors such as linear filters, linear autoregressive (AR) model, linear ARMA (Autoregressive moving average network), ARIMA (Autoregressive iterative moving average network) etc. In the present study an ANN-based model is used to perform the sunspot number (SSN) forecasting, according to multi-step ahead prediction approach, thus predicting 10-years ahead, from 2016-2026, also giving an indication of the evolution pattern of the next solar cycle (Qi & Zhang 2005, Petrovay 2010, Helal & Galal 2013).

2. Data and Method

The WDC-SILSO at Royal Observatory of Belgium, Brussels, provides the daily SSN (ver. 2.0) data. The SSN has been taken for the period of 1870-2016.

NARX (Nonlinear autoregressive with external input) networks can learn to predict one time series given past values of the same time series, the feedback input, and another time series, called the external or exogenous time series. NARX will act as NAR (nonlinear autoregressive) neural network if no exogenous inputs are provided, which can be directly trained to predict a time series from that series past values. The train function used is Levenberg-Marquardt algorithm. The NARX network can be described as

$$y(t) = f(y(t\text{-}1),...,y(t\text{-}n_y);\ u(t),....u(t\text{-}n_u)) + \epsilon(t)$$

where y(t) and u(t) are the past and present independent (exogenous) inputs of the model at a discrete time step t, $n_y \geqslant 1$, $n_u \geqslant 1$, $n_y \geqslant n_u$ are the input memory and output memory orders (delay) and f is a nonlinear mapping function. The multi-step-ahead forecast has been obtained using the NAR in closed-loop form. Multi-resolution analysis (MRA) using discrete wavelet transforms (Daubechies-db5) is used to decompose SSN during the period of 1870-2016. MRA yields both approximate and detail modes of which approximate mode at level 10 is used for predicting future values of SSN from NAR network (Di Piazza *et al.* 2016).

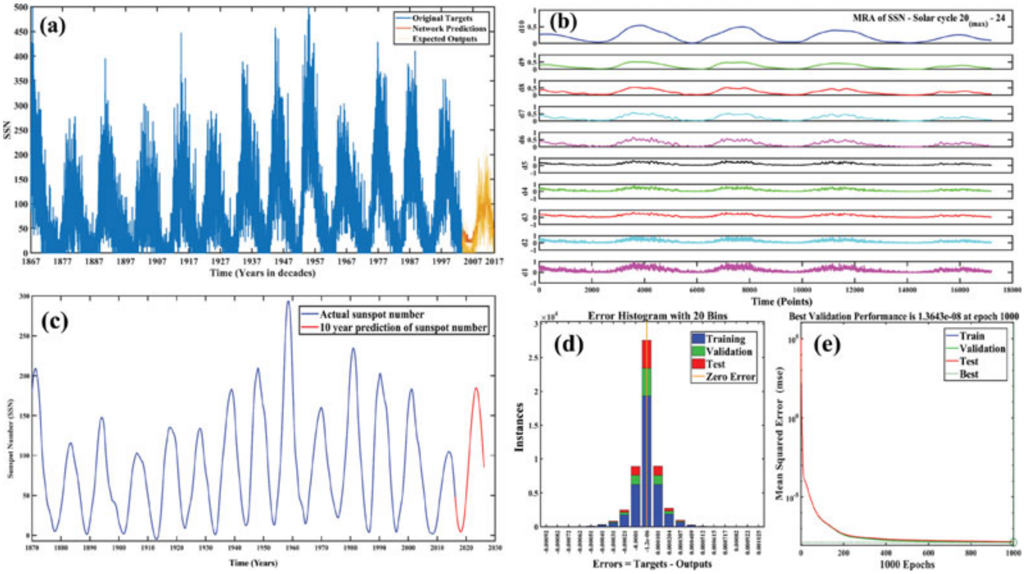

Figure 1. (a) The NARX prediction for the period 2007-2017 (b) A sample of multiresolution analysis of SSN shown during the period of maximum phase of solar cycle 20 to solar cycle 24. Here d1-d10 denote the approximate modes at levels 1-10. (c) The NAR prediction during the period 2016 - 2026. (d) Error histogram (e) The MSE analysis of NAR prediction.

3. Results and Conclusion

The NARX network based prediction of SSN during the period of 2007-2017 is shown in figure 1(a). The exogenous input is the 10-point delayed SSN data. The yellow dotted line shows the expected outputs while red line shows the network predictions. As we can see, the network predictions follow the expected outputs. Now, for the prediction of unknown future values of SSN, NARX is used in NAR mode (without the exogenous input). The input given is the tenth level approximate mode decomposed from SSN using the multiresolution analysis during the period 1870-2016. From figure 1(c), it is clear that the NAR network predicts the evolution during the period of 2016-2026 where red line indicates predicted values. Our work shows that the next solar cycle (solar cycle 25) will be having a SSN magnitude comparable to the previous solar cycle (solar cycle 23). Hence we can expect more solar activity during the next solar cycle (solar cycle 25) than the present solar cycle (solar cycle 24) even though heliospheric polar field values of present cycle are not showing a promising picture (Muñoz-Jaramillo *et al.* 2013). In spite of contradictory information theoretical results (Kakad *et al.* 2017), the possibility of occurrence of another deep minimum is also not evident at the end of solar cycle 24 from NAR results.

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