Space weather forecasting

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- Solar activity - the driver of space weather
- Forecast methods
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Solar activity, space weather and climate

**The positive NAO index phase**
- The positive NAO index phase shows a stronger than usual subtropical high pressure cell and a deep and intense Icelandic low.
- The increased pressure difference results in more and stronger winter storms crossing the Atlantic Ocean on a more northerly track.
- This results in warmer and wetter winters in Europe and to cold and dry winters in Britain, Canada and Greenland.
- The eastern US experiences mild and wet winter conditions.

**The negative NAO index phase**
- The negative NAO index phase shows a weaker subtropical high and weak Icelandic low.
- The reduced pressure gradient results in fewer and weaker winter storms moving on a more westerly path.
- They bring milder air into the Mediterranean and mild weather to northern Europe.
- The US east coast experiences more cold air outbreaks and hence snowier winter conditions.
- Greenland, however, will have milder winter temperatures.

During the Little Ice Age, London’s Thames River froze in winter, something that no longer happens. This 19th century engraving depicts the annual Frost Fair held on the ice-bound river, this one during the winter of 1814-15.

MDI/SOHO reveals the interior and explains surface activity

MDI shows how the dynamo changes (1.3y)

Sunspots are footpoints of emerging magnetic flux tubes

MDI shows how magnetic elements form sunspots
Wavelet power spectra reveals solar activity periodicities

WSO solar mean field May 16, 1975 - March 13, 2001

Wavelet power spectra shows 13.5, days 27 days, 154 days, 1.3 years periodicities

The solar magnetic field further expand and CMEs occur
Wavelet power spectra of MDI magnetic mean field

Upper panel shows for 53 CME events. Lower panel shows for times without CMEs.

Forecast Methods

- First principles (MHD models)
  
  (MHD models of the whole Sun-Earth Connection are good at explaining and good for education, but not so good at forecasting.)

- Linear and nonlinear filters (MA, ARMA, NARMA)
  
  \[ AL(t + \Delta t) = \sum_{j=0}^{t} H(j\Delta t) \cdot VB_{j}(t - j\Delta t) \]
  
  \[ D_{j}(t + \Delta t) = \sum_{i=0}^{t-1} a_{i} \cdot D_{j}(t - i\Delta t) + \sum_{j=0}^{t-1} b_{j} \cdot VB_{j}(t - j\Delta t) \]

  MA filter applied as linear filter of AL. The impulse response function H of the magnetospheric system is convolved with a sequence of solar wind inputs.

  Dst is predicted with an ARMA filter.

  (Problems: Linearity, nonstationary systems, high dimensions)

- Knowledge-Based Neural Models (KBNM) i.e.
  
  Knowledge (Diff eqs of physics, dynamical system analysis, filters, ...
The basic element of every ANN is an artificial neuron or simply a neuron (which is an abstract model of a biological neuron (nerve cell)).

The neuron receives signals (information) from other nerve cells thru the dendrites. The axons take information away from the neuron. The output of the neuron is $y = f(\sum w_i x_i)$, with $x$ as input vector. The value $y$ is the state of the neuron. If $f = \text{sgn}$ then the state of the neuron is $(+1, -1)$.

A time-delay network is essentially a nonlinear generalization of linear moving-average (MA) filter.

Multi-layer error-back-propagation (MLBP)

- $a_i^\mu = g_i(\sum W_{ij} g_j(\sum w_{jk} z_k^\mu))$

Back-propagation learning: $\Delta W_{ij}(t+1) = -\eta \frac{\partial E}{\partial W_{ij}} + \alpha \Delta W_{ij}(t)$

Error measure: $E = \frac{1}{L} \sum_{t=1}^{L} (a_i^\mu - d_i^\mu)^2$

A time-delay network is essentially a nonlinear generalization of linear moving-average (MA) filter.
Neural networks

Self Organized Map (SOM)

\[ a_{ij}^t = \begin{cases} 1 & \text{if } i = j^* \\ 0 & \text{if } i \neq j^* \end{cases} \]

\[ h_i^t = \sum_j w_{ij} x_j \] for all \( i \)

Kohonen learning:

\[ \Delta w_{ij} = \eta \Delta t \left( x_i^t - w_{ij} \right) \]

Neighborhood function:

\[ A(i,j^*) = e^{-\frac{(j-j^*)^2}{2\sigma^2}} \]

Radial Basis Function Network

\[ y_i = \exp\left[ -\frac{(x_j - u_j^T)^2}{2\sigma^2} \right], \quad y = \sum_i y_i \]

Download Lund Dst model in Java and Matlab (www.lund.irf.se/dst/models)

The ARMA filter is obtained by adding auto-regressive terms to a MA filter. The partial recurrent network (Elman) becomes identical to a linear ARMA filter if it is assigned linear activations functions.

\[ \frac{dD_{st}^*}{dt} = Q - \lambda D_{st}^* \]

The normalization transforms \( B_n \in [-30, +30] \) nT, \( n \in [0, 120] \) cm⁻³, \( V \in [200, 1000] \) km/s, and \( D_{st} \in [-250, +50] \) nT to the \([-1, +1]\) interval.

The output from the network is described by the following equations

\[ x_i(t+1) = \tanh\left( \sum_{j=1}^{n_2} w_{ij}(t) u_j(t) + \sum_{j=1}^{n_2} w_{ij}^{(2)} x_j(t) + b_i^{(1)} \right) \] (9)

\[ y(t+1) = \sum_{i=1}^{n_2} w_{ij}^{(2)} x_i(t+1) + b^{(2)} \] (10)
Test Dst forecasts

Knowledge-Based Neural Models

The basis of using neural networks as mathematical models is "mapping". Given a dynamic system, a neural network can model it on the basis of a set of examples encoding the input/output behavior of the system. It can learn the mathematical function underlying the system operation (i.e. generalize not just fit a curve), if the network is designed (architecture, weights) and trained properly (learning algorithm).

Both architecture and weights can be determined from differential equations which describe the causal relations between the physical variables (solution of diff eq is approximized by a RBF). The network (KBN) is then trained with observations.

The architecture (number of input and hidden nodes) can also be determined from dynamic system analysis (reconstruction of state space from time series gives dimension).

Neural networks can discover laws from regularities in data (Newton’s law e.g.). If one construct a hierarchy of neural networks where networks at each level can learn knowledge at some level of abstraction, even more advanced laws can be discovered.
Workshops on ”Artificial Intelligence Applications in Solar-Terrestrial Physics” were held in Lund 1993 and 1997.

Applications

- Forecasting solar wind velocity
- Forecasting Geomagnetic activity
- Tables summarizing forecasts based on KBNM
Forecasts of solar wind velocity from daily solar WSO magnetograms

**Input**

A time-series \( f_s(t - 4), \ldots, f_s(t) \) of the expansion factor

\[
f_s(t) = \left( \frac{R_{ps}}{R_{ss}} \right)^2 \frac{B_{ps}}{B_{ss}}.
\]

**Output**

Daily solar wind velocity \( V(t + 2) \)

With the use of MDI data (short-term solar activity) we will try to forecast hourly \( V \)

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**Forecasting global Dst and AE indices**

Forecasts of Dst index

Two hours ahead from only solar wind data based on an Elman recurrent neural network.

Forecasts of AE index one hour ahead from only solar wind data based on a Time Delay Network.
A hybrid (MLP, RBF) neural network was applied to data from Sodankylä Geomagnetic Observatory. It was shown that 73% of the ΔX variance is predicted from solar and solar wind data as input.

Number of context nodes gives the dimension of magnetospheric dynamic system. Weights give decay time τ.

### Applications

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Real-time forecasts and warnings based on KBN

Solar input data

Solar observations with SOHO make warnings 1-3 days ahead possible.

Solar wind observations with ACE make accurate forecasts 1-3 hours ahead possible.

Satellite anomalies of July 14-16, 2000 event

The proton event caused problems for ACE, SOHO, Ørsted, Japanese X-ray satellite, star trackers on board commercial satellites.

Proton flux (pfu) > 10 MeV, 24000 pfu (July 15, 12.30 UT). Third largest!


Today IRF-Lund has real-time neural networks forecasts of satellite anomalies one day in advance (ESA project SAAPS). The work has been in collaboration with Swedish satellite operators (ESRANGE).
Radiation risks and aviation

The radiation exposure is doubled every 2.2 km.

Solar flares can increase the radiation by 20-30 times.

Pilots get cancer more often than average.

New EU law: Pregnant (aircrew) should not be exposed to more than 1 (1-6) millisievert/year.

The intensive solar flare of April 2, 2001, which caused major communication problems also made Continental Airlines to change their route between Hong Kong and New York.

IRF-Lund collaborates with the Swedish Radiation Protection Institute and Medical University in Stockholm to develop forecasts of radiation doses for Aviation Industry.

Power systems and pipeline systems are affected at times of geomagnetic storms

This severe electrojet caused the failure of Quebec's power system March 13-14, 1989.

One of the generators of OKG's (Sydkraft's) nuclear plants was heated due to the geomagnetically induced current in March 13-14 1989.

We in Lund have collaborated with the Swedish power industry during more than twenty years. Today we have real-time neural network forecasts of local GICs, based on ACE solar wind and warnings based on SOHO (LASCO and MDI) data.
Proton events give positive NAO within days!

A User: Power system operators

The NAO response on increased solar wind $E$, one month later! That makes forecasts one month ahead possible.

11 års, 1.3 variations are seen both in solar wind and NAO.
Near and farside solar activity from MDI/SOHO observations
Latest information on arrival of halo CME at L1

Latest info on forecasts of satellite anomalies (SAAPS)
Latest information on forecasts of Kp, Dst, AE and GIC

Forecast Centers (ISES/RWC)
Forecasts of aurora as SMS, voice messages or WAP service

Where to learn more?