Prediction of the magnetic index am based on the development and the performance comparisons of static and dynamic neural networks

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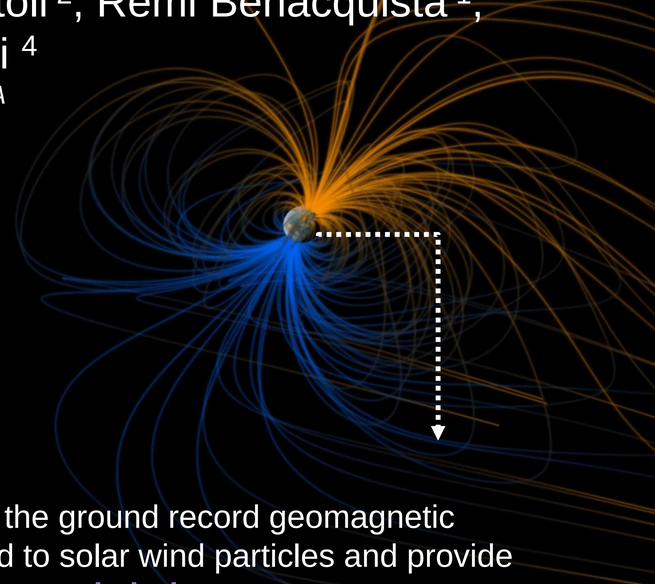


Solar wind parameters are provided by :

- OMNI database provided by NASA SPDF [1]: located at the bowshock of the magnetopause
- Advanced Composition Explorer satellite database [2]: located at the Lagrangian point L1 :

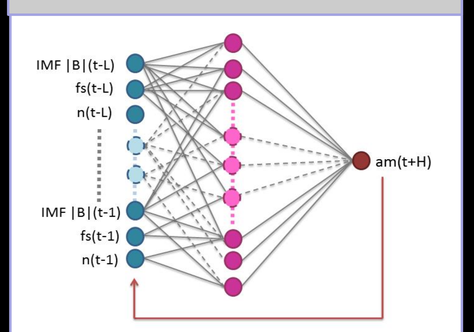
Magnetometers on the ground record geomagnetic disturbances associated to solar wind particles and provide **geomagnetic indexes.**

Neural Networks are used to make predictions of the geomagnetic index based on solar wind parameters. It helps to anticipe the impact of solar events on the Earth's geomagnetic environment.

The geomagnetic index is the ***am*** index. [3]. This is a global 3 hour index, defined in nT, representing the global input of energy linked to the solar wind in the magnetosphere.

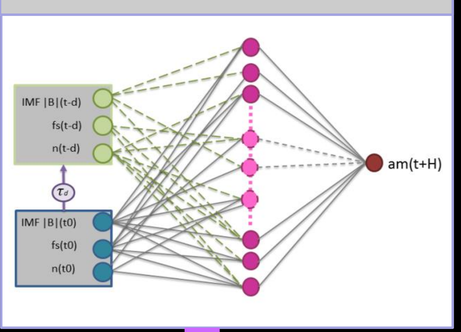
Candidates of Neural Networks (NN) using Matlab

MultiLayer Perceptron **MLP**



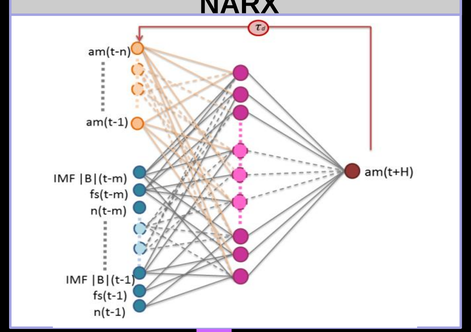
Static – The dynamic comes from the history of solar wind parameters used as an input and the use of the nowcast index computed by the NN

Time Delay neural network **TDNN**



Dynamic – Contains a temporal window called the window of specialization, recording informations of the past

Non linear autoregressive with exogenous inputs network **NARX**



Dynamic – Contains an embedded memory fed by solar wind parameters and the output of the network with a delayed connection

Training time ~ seconds ~ minutes ~ tens of minutes

Development using the Neural Network toolbox of Matlab 2016.

To evaluate performances of prediction of NN, statistical parameters are used. They are based on a contingency table. .
→ **Predicted values are classified according to observed values**

	Observed : TRUE	Observed : FALSE
Predicted : TRUE	True positive (hits)	False positive (false alarms)
Predicted : FALSE	False negative (misses)	True negative (correct negatives)

Contingency table

Probability Of Detection

$$POD = \frac{true\ positive}{true\ positive + false\ negative}$$

0 < POD <1

Which fraction of the observed « true » events were correctly forecasted ?

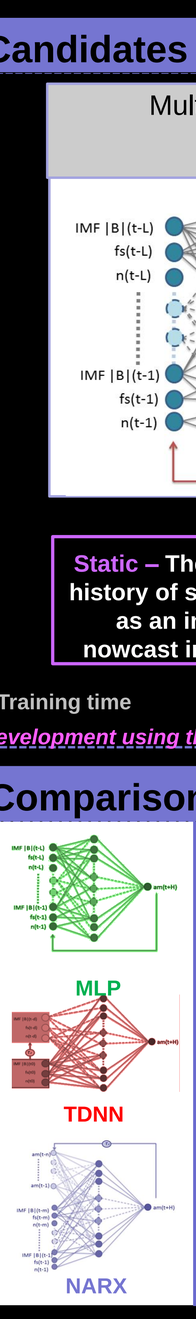
False Alarm Ratio:

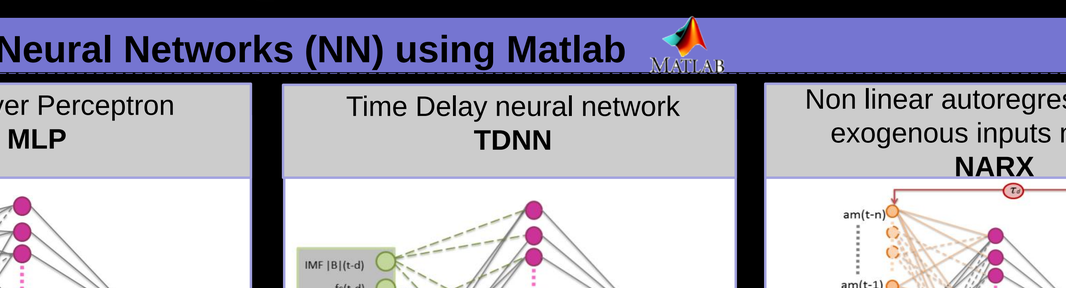
$$FAR = = \frac{false\ positive}{true\ positive + false\ positive}$$

0< FAR<1

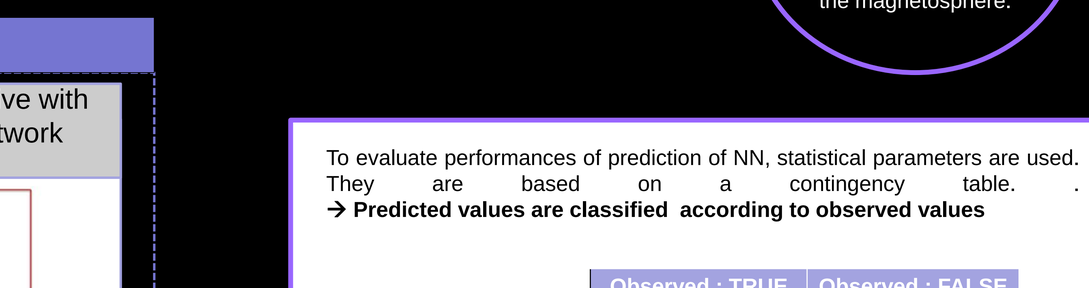
Which fraction of the predicted « true » events actually did not occur?

Comparison of performances of NN using OMNI database … … and ACE database





Performances of each NN in terms of POD and FAR, using OMNI database



Performances of each NN in terms of POD and FAR, using ACE database

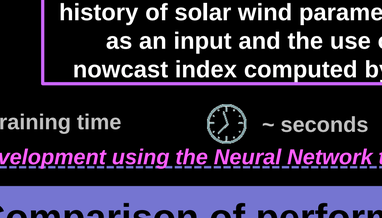
NARX is the NN which offers the best performances at all level of activity with a POD>0,98 and a FAR <0,05, with OMNI and ACE databases.

TDNN and **MLP** have similar performances with both databases → make a choice between **MLP** which takes into account as an input the geomagnetic index but which takes less time to compute than the **TDNN** which is based only on solar wind parameters.

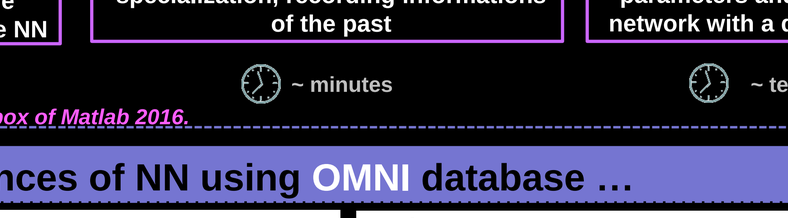
Performances decrease when using the ACE database because when there is an important solar activity, detectors are saturated → missing data in the database. Scientists working at NASA on the OMNI database try to handle those missing data so the OMNI training database contains more informations than the ACE database to train NN.

Long Short Term Memory recurrent Network using Python

Long Short Term Memory network **LSTM**



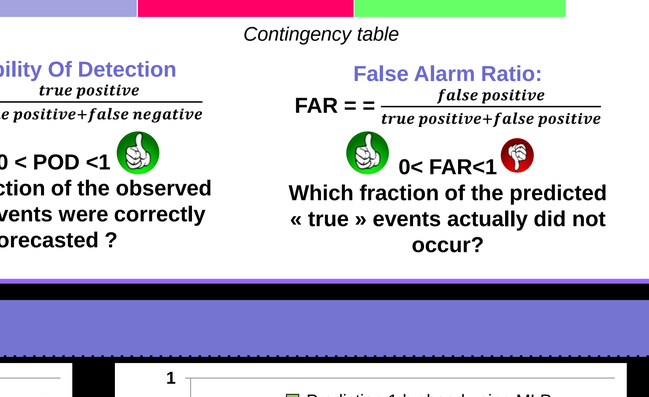
Dynamic – LSTM is based on Elmann recurrent network
They have the abiity to connect by themselves informations from the past to the moment. They are also able to learn long term dependencies.
→ Like the **TDNN**, based only on solar wind parameters
Development using Theano and Lasagne libraries.



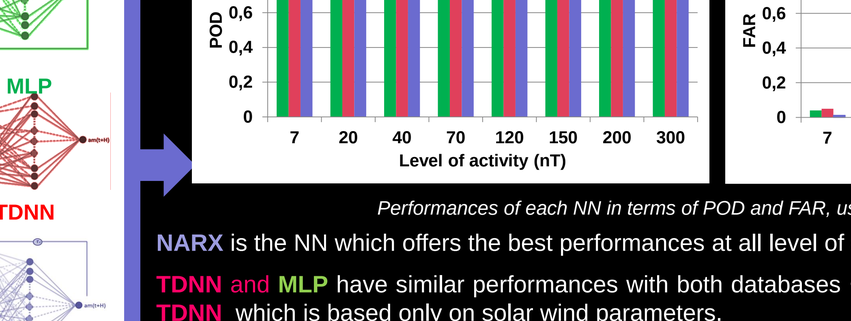
Standard RNN : repetition module has a simple structure (only one tanh layer)

LSTM RNN : repetition module has 4 layers interacting with each other

- To evaluate performances of this network we use this table to classify predicted data regarding observed data, for each level of activity.
- The colour code is based on the value of the Probability of Detection.
- Thanks to this table we can observe the accurracy of the network , and how it overestimates and underestimates.



Performances on the important event of July 2004



LSTM NN offers great performances to predict this important solar event. The 3 peaks of activity are overestimated as we can observe on the plot showing the activity on the left and on the table on the rignt

References and Acknowledgements

*[1] The solar wind plasma data of **OMNI** were obtained from the National Space Science Data Center (NSSDC) of National Aeronautics and Space Administration (NASA) https://omniweb.gsfc.nasa.gov/ow.html*

*[2] The solar wind plasma data of **ACE** were obtained from the Caltech websites site http://www.srl.caltech.edu/ACE/ASC/level2/index.html*

*[3] **Website ISGI Unistra**, http://isgi.unistra.fr/ . Geomagnetic indices are calculated and made available by ISGI Collaborating Institutes from data collected at magnetic observatories. We thank the involved national institutes, the INTERMAGNET network and ISGI*

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