Neural network reconstruction of in-situ solar wind parameters

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Abstract

The properties of the solar wind change with different solar source regions and in addition most solar wind properties are affected by transport effects. Relevant transport effects are expansion, collisions, stream interaction regions and wave particle interaction. On the one hand, the charge state composition of the solar wind is particularly well suited to identify the solar source region, since in good approximation the charge state composition remains unchanged after the solar wind leaves the hot corona. On the other hand, proton plasma properties and the magnetic field strength are better suited to identify solar wind plasma that is affected by transport effects, for instance stream interaction regions. Nevertheless, proton plasma properties also change with the solar source region. Here, we evaluate this redundancy with the help of neural networks. Either the solar wind proton speed, proton density, proton temperature, magnetic field strength or the O7+/O6+ ratio are reconstructed by a feed-forward neural network, while the (other) proton plasma properties are used as input parameters. The results show that it is easier to reconstruct the proton speed or proton temperature from the other transport-affected proton plasma properties than predicting the purely source-dependent O7+/O6+ ratio, the magnetic field strength or the proton density from the respective other solar wind properties. Nevertheless, the neural network prediction also succeeded to recover the O7+/O6+ from solar wind parameters that are all transport-affected, however less accurate than in the case of the proton speed or proton temperature.

Motivation

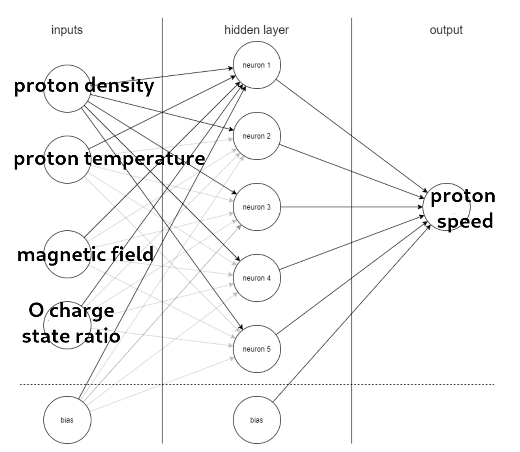
- Can the redundancy in the solar wind data be exploited to circumvent difficult measurements?
- Can the solar source of the solar wind be recovered from only transport effected parameters?

Data selection

We apply our method to ten years of observations from the Advanced Composition Explorer (ACE). The solar wind proton plasma parameters are taken from the Solar Wind Electron, Proton, and Alpha Monitor (ACE/SWEPAM) ([6]) and magnetic field observations from the magnetometer ACE/MAG ([8]).
The ionic composition is derived from the Solar Wind Ion Composition spectrometer (SWICS, [2] Pulse Height Analysis (PHA) words as described in [1]. We use the native 12-minute time resolution of ACE/SWICS which results in at most 43800 data points in non-leap years and 43920 in leap years.
To characterize the solar wind type, we employ the four-type solar wind categorization scheme from [9]. To exclude interplanetary coronal mass ejections (ICMEs) we use two ICME lists, the [4, 3] list and the [7] list, instead of the ejecta category.

Experimental setup

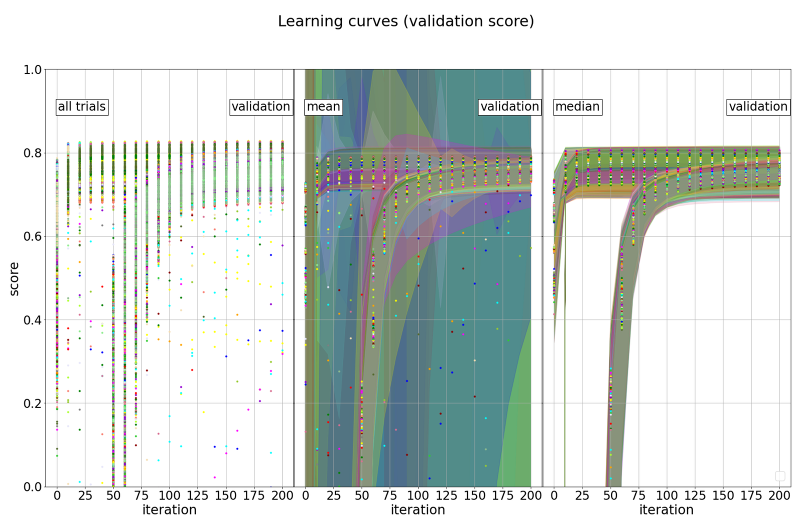
We consider five solar wind parameters, proton density n_{p}, proton temperature T_{p}, proton speed v_{p}, magnetic field strength B, and O^{7+} to O^{6+} charge state ratio $n_{O^{7+}}/n_{O^{6+}}$, take four of them as input to a feed forward neural network (NN) with one hidden layer and a bias neuron and aim to reconstruct the fifth parameter as the output of the NN. The data set is divided into training, validation and test data sets, wherein each batch of data has the length of 27.24 days to increase the probability that a comparable sample of solar wind conditions is represented in test and training data, i.e. to ensure the assumption that both data sets are independently identically distributed). For the model selection, the training and validation data sets are used in a 5-fold cross-validation.



We used the `MLPRegressor` from the python scikit-learn package. As training algorithm *adam* [5] was employed. With sufficient numbers of iterations (≥ 200), we found only non-significant dependence on the number of neurons in the hidden layer. This indicates, that the modelled relation between the respective solar wind parameters are not complicated. Therefore, in the following, we show only results for 10 neurons.
For model selection, the R^2 **score** was used, for comparison on different data sets and between different reconstructions, the **mean absolute percentage error (MAPE)** was employed.

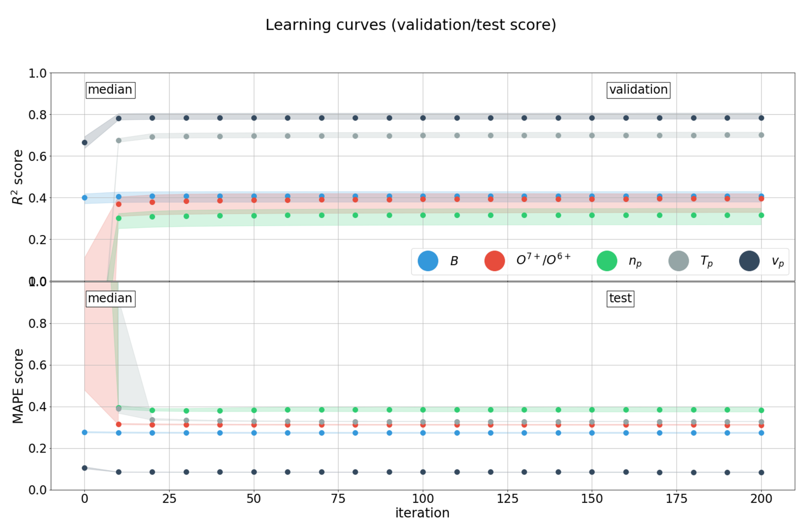
setup	# trials	100
	# iterations	200
	# neurons	$10 \in [10, 20, 50, 100]$
hyper-parameters	initial learning rate λ	$[0.01, 0.001, 0.0001]$
	L2 penalty α	$[0.001, 0.0001, 0.00001]$
	Exponential decay rate for estimates of first moment vector β_1	$[0.75, 0.8, , 0.85, 0.9, 0.95, 0.99]$
	Exponential decay rate for estimates of second moment vector β_2	$[0.8, 0.85, 0.9, 0.95, 0.99, 0.999]$
	Value for numerical stability ϵ	$[10^{-6}, 10^{-7}, 10^{-8}, 10^{-9}, 10^{-10}]$
Reconstruction	v_{p}	Input $[n_{\mathrm{p}}, T_{\mathrm{p}}, B, n_{O^{7+}}/n_{O^{6+}}]$
Reconstruction	n_{p}	Input $[T_{\mathrm{p}}, v_{\mathrm{p}}, B, n_{O^{7+}}/n_{O^{6+}}]$
Reconstruction	T_{p}	Input $[n_{\mathrm{p}}, v_{\mathrm{p}}, B, n_{O^{7+}}/n_{O^{6+}}]$
Reconstruction	B	Input $[n_{\mathrm{p}}, T_{\mathrm{p}}, v_{\mathrm{p}}, n_{O^{7+}}/n_{O^{6+}}]$
Reconstruction	$n_{O^{7+}}/n_{O^{6+}}$	Input $[n_{\mathrm{p}}, T_{\mathrm{p}}, v_{\mathrm{p}}, B]$

Model selection



Learning curves for all hyper-parameter combinations used for the reconstruction of the solar wind speed.

- The optimal NN hyper-parameters depend on the reconstructed solar wind parameter.
- Many hyper-parameter settings lead similar reconstructions.

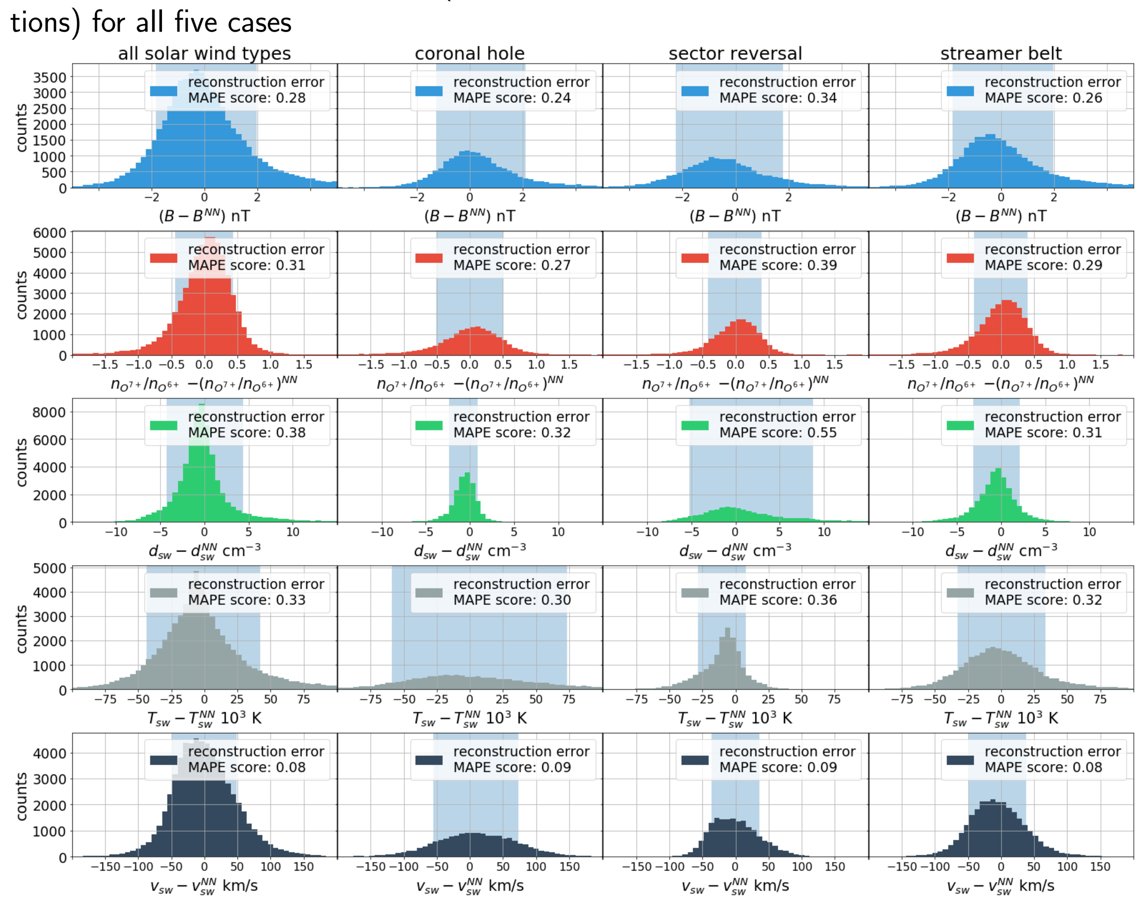


Learning curves for validation and test data sets for all five reconstruction cases

- Reconstruction easiest for v_{p}. B, $n_{O^{7+}}/n_{O^{6+}}$, T, and n_{p} all show similar MAPE.

Neural network reconstructions

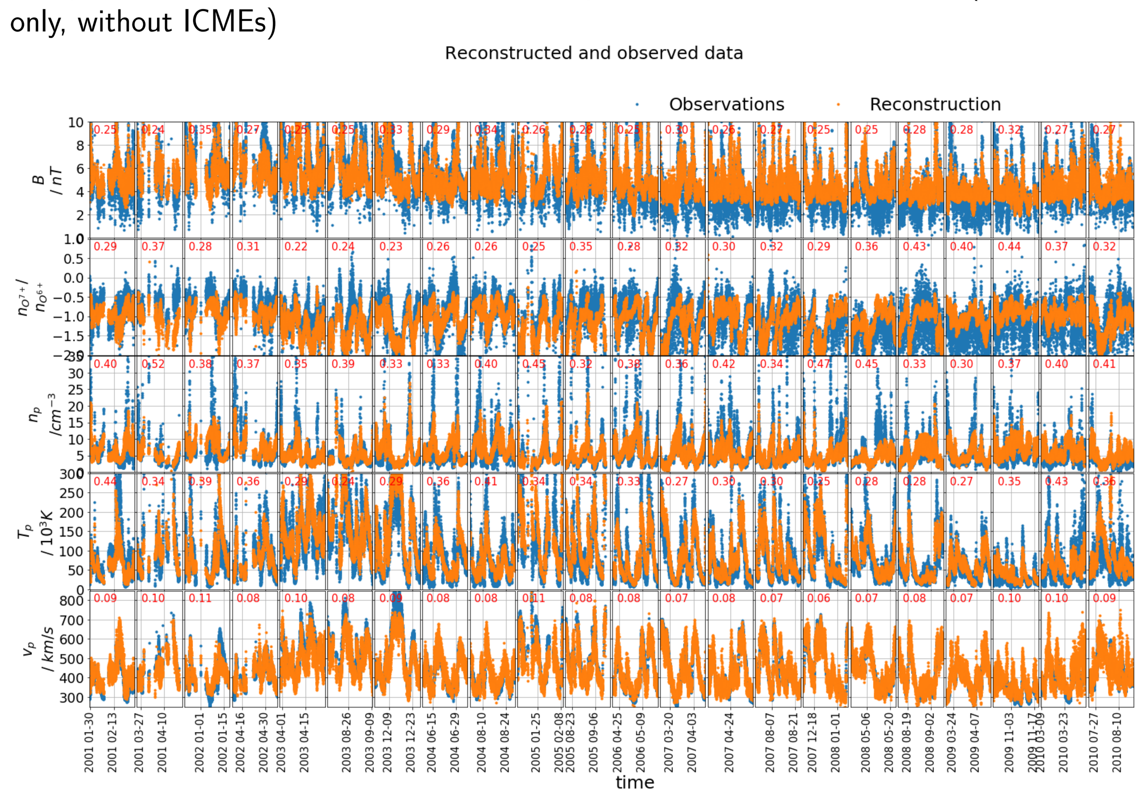
Histogram of reconstruction error (differences between observed data and NN reconstructions) for all five cases



- Reconstruction error depends on solar wind type. Smallest errors occur for coronal hole wind (and streamer belt plasma), largest errors for sector reversal plasma (i.e. stream interaction regions).
- $n_{O^{7+}}/n_{O^{6+}}$ underestimated, B, n_{p}, T_{p}, v_{p} overestimated.
- In coronal hole wind, the distribution of reconstruction errors is more symmetric.

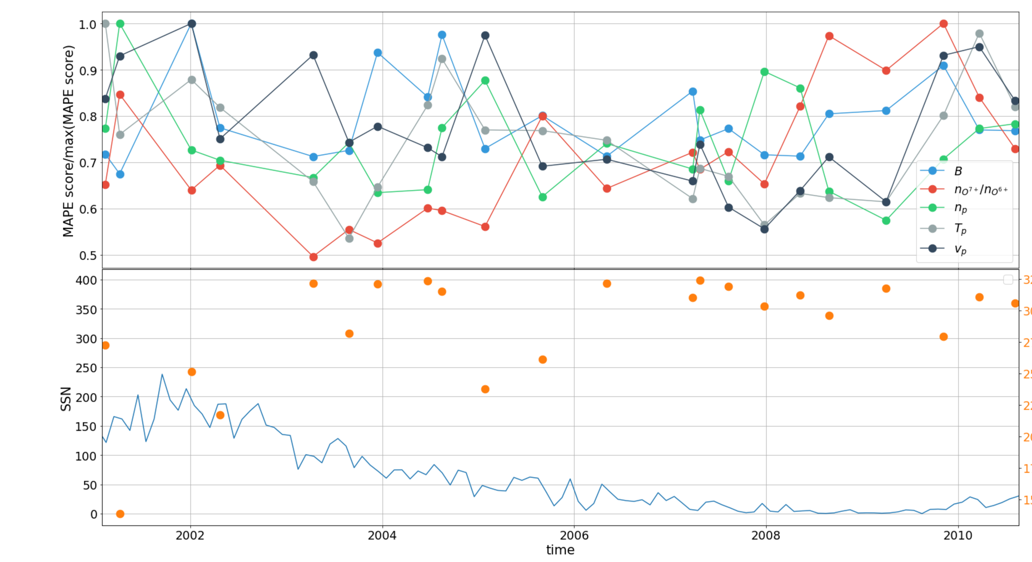
Solar cycle dependence?

Comparison of NN reconstructed solar wind parameters with observations (on test data only, without ICMEs)



- Reconstructions tends to miss extreme values, best for most frequent intermediate values.
- systematic lower threshold on B
- Scores on individual test data sets (of length 27.25 days) are variable.

Scores on test data sets over time and for all five reconstruction cases

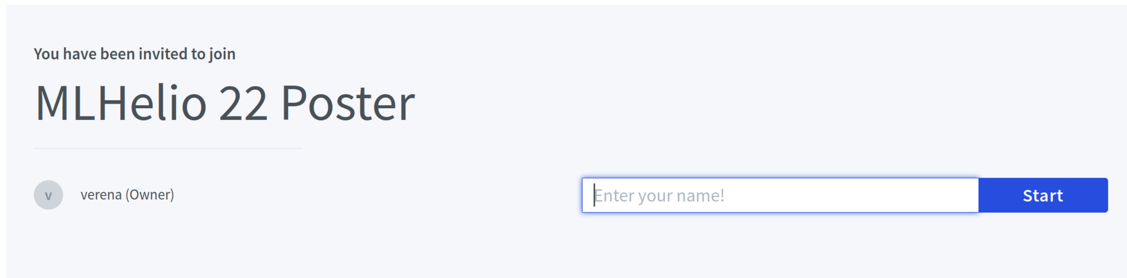


- Effect of solar cycle is not much larger compared to differences between individual test data periods.
- Nevertheless: for v_{p} and T_{p} reconstruction is easier during solar activity minimum, for n_{p} and B no trend is visible, for $n_{O^{7+}}/n_{O^{6+}}$ reconstruction is easier during solar activity maximum (higher fluxes)

Conclusions

- v_{p}, T_{p}, B, n_{p}, and $n_{O^{7+}}/n_{O^{6+}}$ can be reconstructed from the respective other solar wind parameters. The reconstruction is best for v_{p}, i.e. this parameter is most redundant. But also for T_{p} as the most difficult proton parameter to determine instrumentally, a neural network reconstruction can provide a useful alternative/baseline.
- $n_{O^{7+}}/n_{O^{6+}}$ can be reconstructed with similar accuracy than B, T_{p} and n_{p}. This supports the idea that the solar source region can be identified based on transport-effected solar wind parameters, but the identification can be expected to be less accurate.
- The relative error (MAPE) depends on the solar wind type and is usually best for coronal hole wind and worst for sector reversal plasma. In addition, in slow solar wind $n_{O^{7+}}/n_{O^{6+}}$ is more frequently underestimated, whereas as B, n_{p}, T_{p}, v_{p} are more frequently overestimated.
- Reconstruction quality differs for individual test intervals. Proton speed and proton temperature are easier to reconstruct under more stable conditions, whereas the O charge state ratio shows the opposite behavior.

For questions or comments please email me heidrich@physik.uni-kiel.de, or join me for video chat at https://blau.psjt.org/b/ver-mxr-jvy-jaa.



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