A neural network based method for input parameter selection

Stefan Lotz [1,2], **Jacques Beukes** [2,3], **Marelie Davel** [2,3]
[1]SANSA Space Science Directorate, Hermanus, South Africa
[2]Multilingual Speech Technologies (MuST), North-West University, South Africa
[3]Centre for Artificial Intelligence Research (CAIR), South Africa

Introduction

- NNs yield predictions, without aiding understanding of input–output relationship
- Fully connected networks mix signal from all inputs as information flows through the network
- Input parameter selection usually done by the user, outside NN training framework

- Can we configure a NN to allow for separation of inputs in to subsets?
- Can we use this to find a ranking of input parameters in terms of importance?

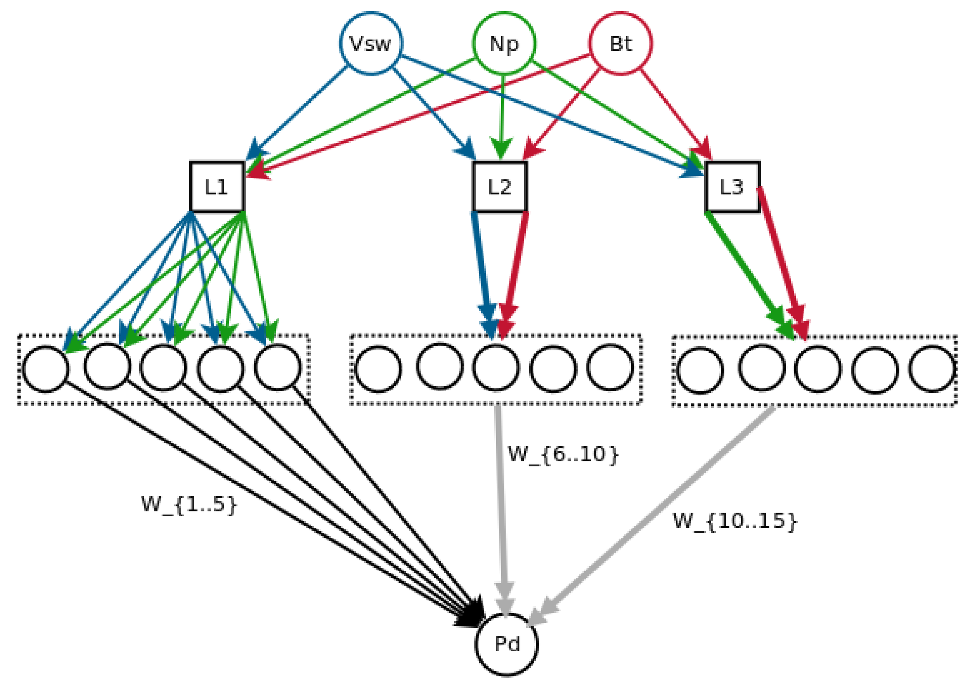
→ We present a first try: pair-wise inputs through λ-layers

A pair-wise input NN

Toy problem: Predict

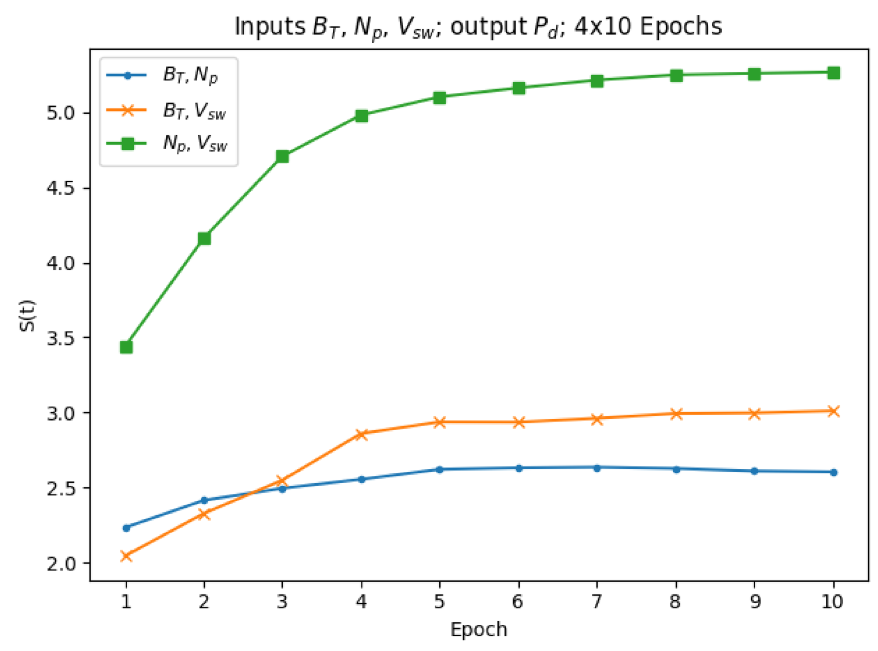
$$P_d \sim N_p V_{sw}^2$$

from V_{sw}, N_p, total IMF B_T



Track sum of normalised weights $W_i^*(t)$ at every training epoch for the pairs of inputs

$[V_{sw}, N_p]$ dominates as expected



Predict SYM-H with storm phase information

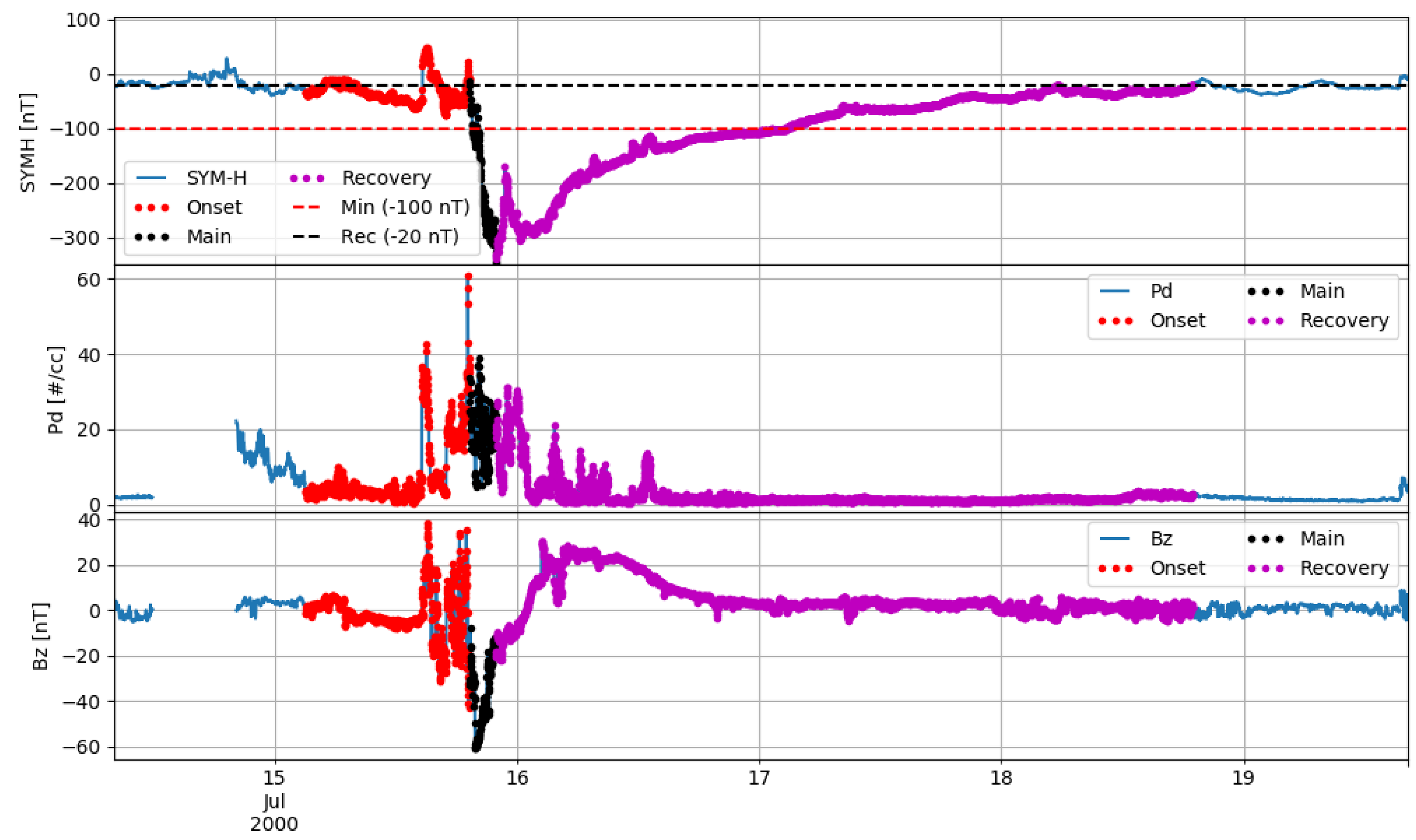
- Dst / SYM-H prediction from solar wind input has been fairly successful [e.g. 1]
- Storm phase information could be important source of information during training

→ We develop simple FFNN model to predict SYM-H from solar wind parameters, with and without phase information

Data Set

- Interval 2000 – 2018, Inputs: OMNI 1-min, Output: SYM-H
- SYM-H < -100nT must be crossed, recovery at -20nT
- 97 storms identified, $N = 396{,}164$ minutes of data (error-free)
  - Training (TRN): 67 Storms, $N = 282{,}517$ (71.3%)
  - Validation (VAL): 15 Storms, $N = 57{,}634$ (14.1%)
  - Out of sample test (TST): 15 Storms, $N = 56{,}013$ (14.5%)
- No mixture of events → Independent TRN/VAL/TST sets
- Storm phases encoded with `100 - Onset | 010 - Main | 001 - Recovery`

Storm and Phase identification in SYM-H



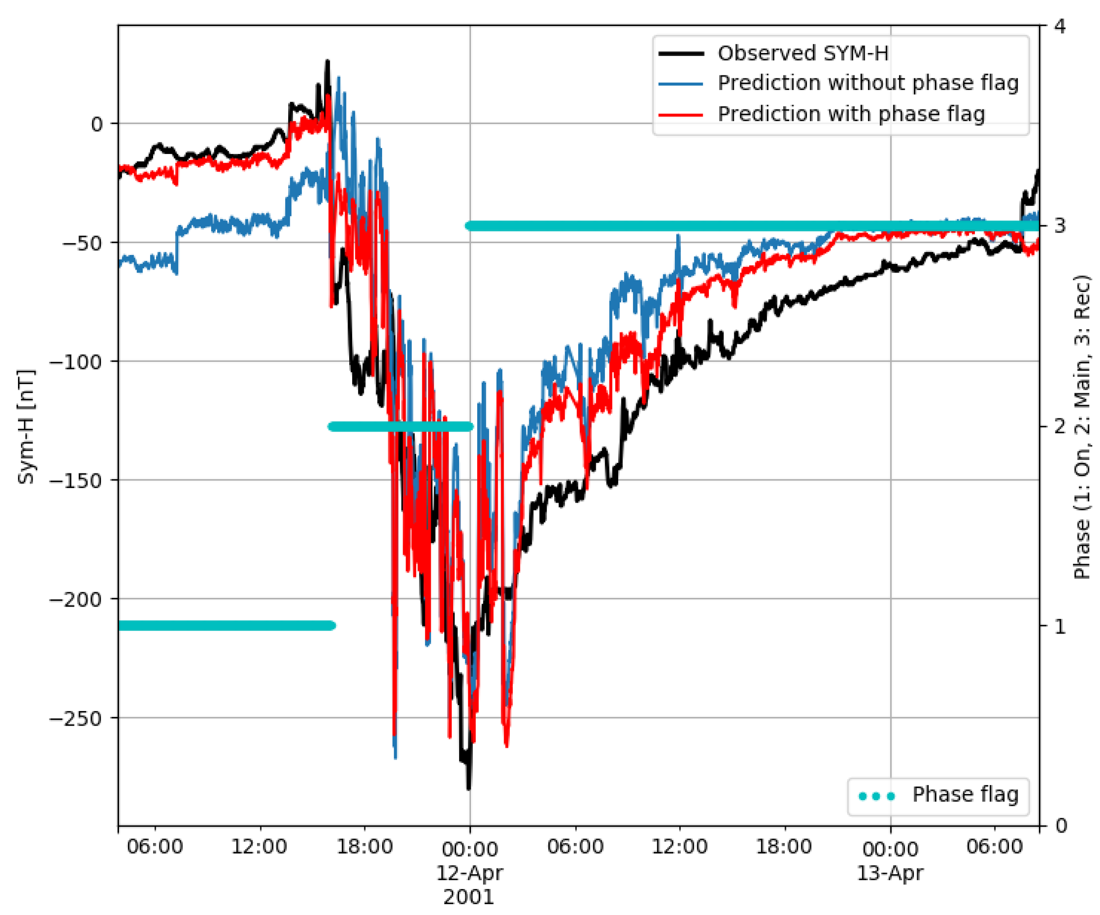
Geomagnetic storm intervals selected from SYM-H [See 2].

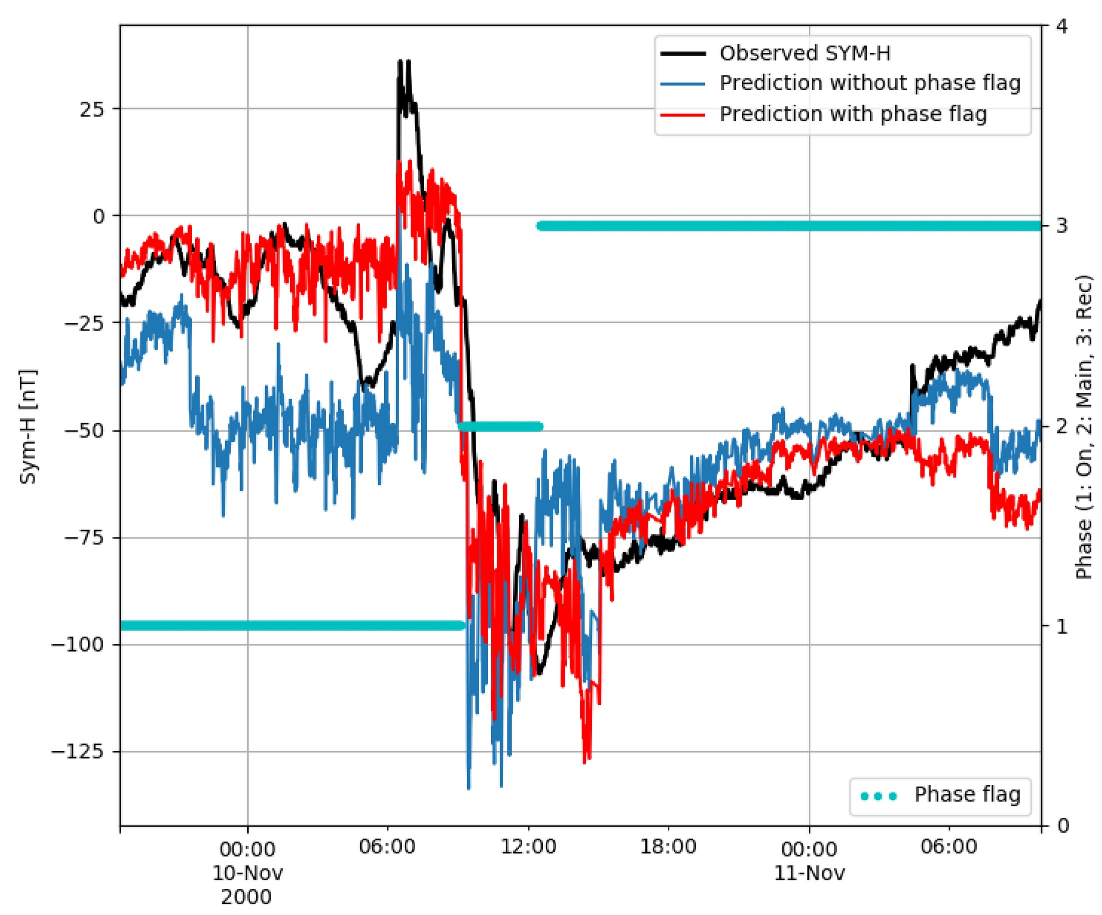
FFNN Model **No phase**

- Inputs (at t and $t-180$)
  V_{sw}, N_p, P_d, E_m, B_T, B_x, B_y, B_z
- 16:50:1 FFNN
  `relu` activations
  `adam` optimiser
  `batch_size = 64`
- **Performance (R) on TST 0.78**

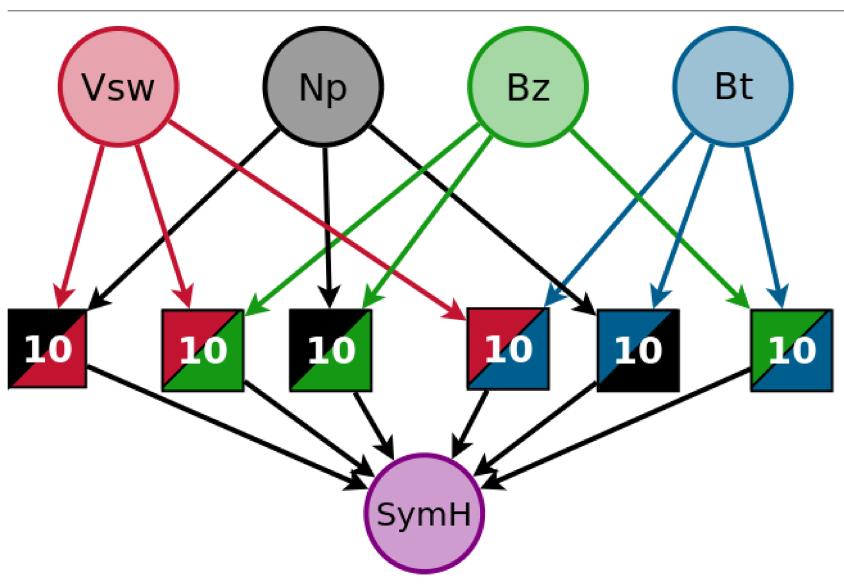
FFNN Model **With phase**

- Inputs (at t and $t-180$)
  V_{sw}, N_p, P_d, E_m, B_T, B_x, B_y, B_z
  Phase one-hot encoding:
  `100-Onset | 010-Main | 001-Recovery`
- 22:50:1 FFNN
  `relu` activations
  `adam` optimiser
  `batch_size = 64`
- **Performance (R) on TST 0.85**



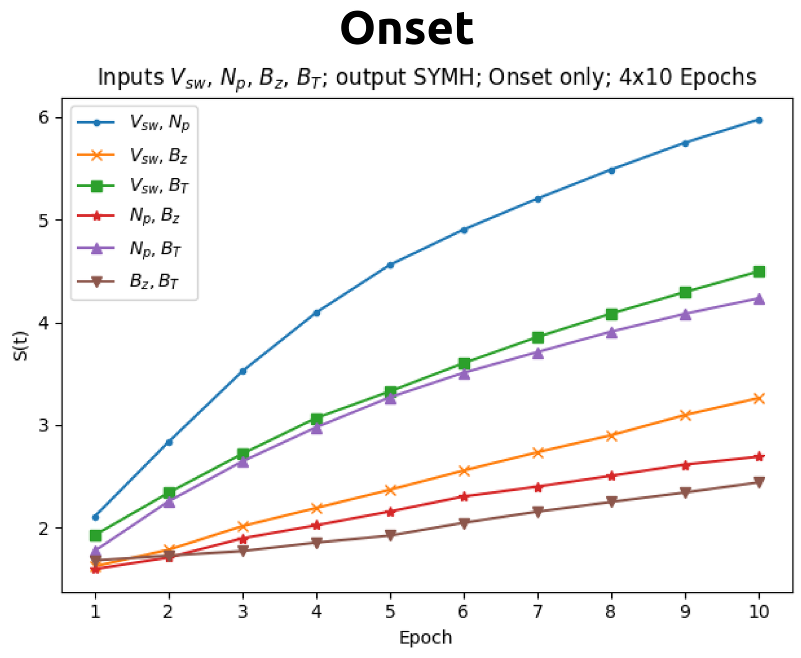


Parameter Selection per Storm Phase



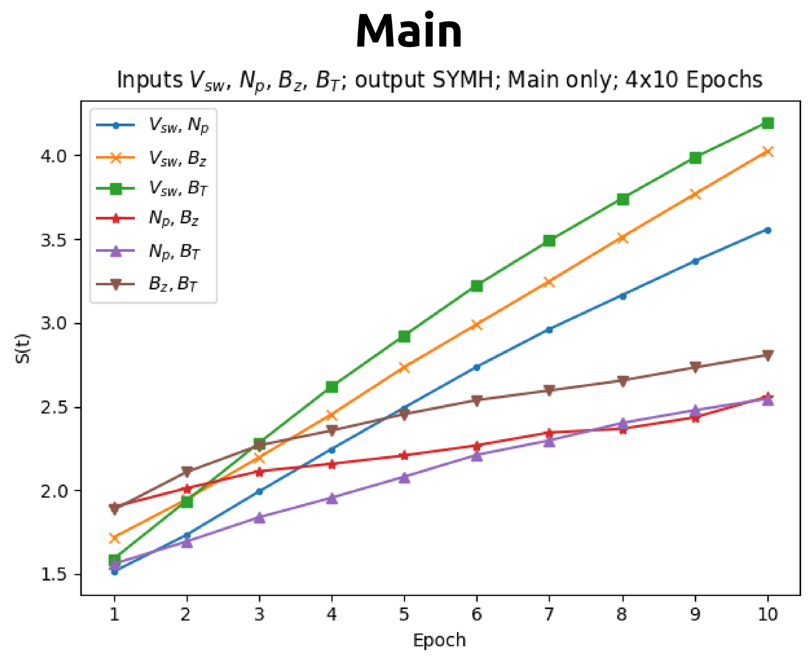
- 4:60:1 FFNN with pairwise λ-configuration
- Use reverse rank to score each input
- Conclusion: V_{sw} is always influential, N_p not important during main phase, but IMF B_T, B_z is

Onset



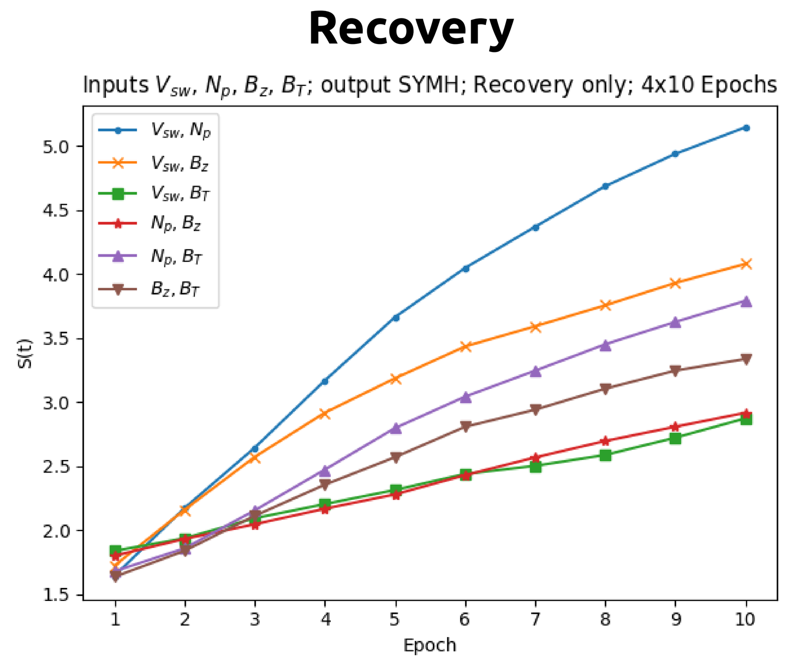
#	Par	Ranks	Scores	Tot Score
1.	V_{sw}	1,2,4	6,5,3	14
2.	N_p	1,3,5	6,4,2	12
3.	B_T	2,3,6	5,4,1	10
4.	B_z	4,5,6	3,2,1	6

Main



#	Par	Ranks	Scores	Tot Score
1.	V_{sw}	1,2,3	6,5,4	15
2.	B_T	1,4,6	6,3,1	10
2.	B_z	2,4,5	5,3,2	10
4.	N_p	3,5,6	4,2,1	7

Recovery



#	Par	Ranks	Scores	Tot Score
1.	V_{sw}	1,2,6	6,5,1	12
2.	N_p	1,3,5	6,4,2	12
3.	B_z	2,4,5	5,3,2	10
4.	B_T	3,4,6	4,3,1	8

References

[1] M. A. Gruet, M. Chandorkar, A. Sicard, E. Camporeale. *Multiple hours ahead forecast of the Dst index using a combination of Long Short-Term Memory neural network and Gaussian Process.* Space Weather (2018), doi: 10.1029/2018SW001898.

[2] S. I. Lotz and D. W. Danskin. *Extreme value analysis of induced geoelectric field in South Africa.* In: Space Weather 15 (2017), doi: 10.1002/2017SW001662.