Methods to improve magnitude accuracy for machine learning predictions of ground magnetic field perturbations

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MAGICIAN Machine Learning Algorithms for Geomagnetically Induced Currents in Alaska and New Hampshire

Introduction

- Geomagnetically induced currents (GICs) that occur during geomagnetically active intervals can drive power outages
- The ability to forecast GIC occurrence is needed to provide warnings to power companies
- Ground magnetic field perturbations (dB/dt) are used as a proxy for GICs
- Solar wind and interplanetary magnetic field (IMF) data from OMNIWeb are used as input and SuperMag data are used as output to train neural networks to predict dB/dt
- Neural network models have some capabilities of predicting timing of dB/dt variations, but the magnitude is almost always lower than real values
- We explore several methods to improve the magnitude of the dB/dt predictions

Methodology

- We trained several fully connected, feed-forward, artificial neural networks for six SuperMag stations and compared the results for eight storms
- The first comparison uses "All" data and "Storm"-time-only data. Because geomagnetically active intervals are relatively rare, training on all data includes a lot of quiet time with only small perturbations to the ground magnetic field, which is likely to result in a model that predicts smaller perturbations.
- The second comparison uses several different loss functions for training. The loss function is used to compare the predicted value to the real value, and training continues until the loss function yields acceptable results. Mean square error (MSE) is commonly used for a loss function, but this tends to penalize models that predict extreme values, resulting in smaller predicted perturbations. We show comparisons for two loss functions from Ziegler and McGranaghan (2021):
  - Dynamic range :

$$Loss = |y_{true} - y_{pred}| + 0.1|(\max(y_{true}) - \min(y_{true})) - (\max(y_{pred}) - \min(y_{pred}))|$$

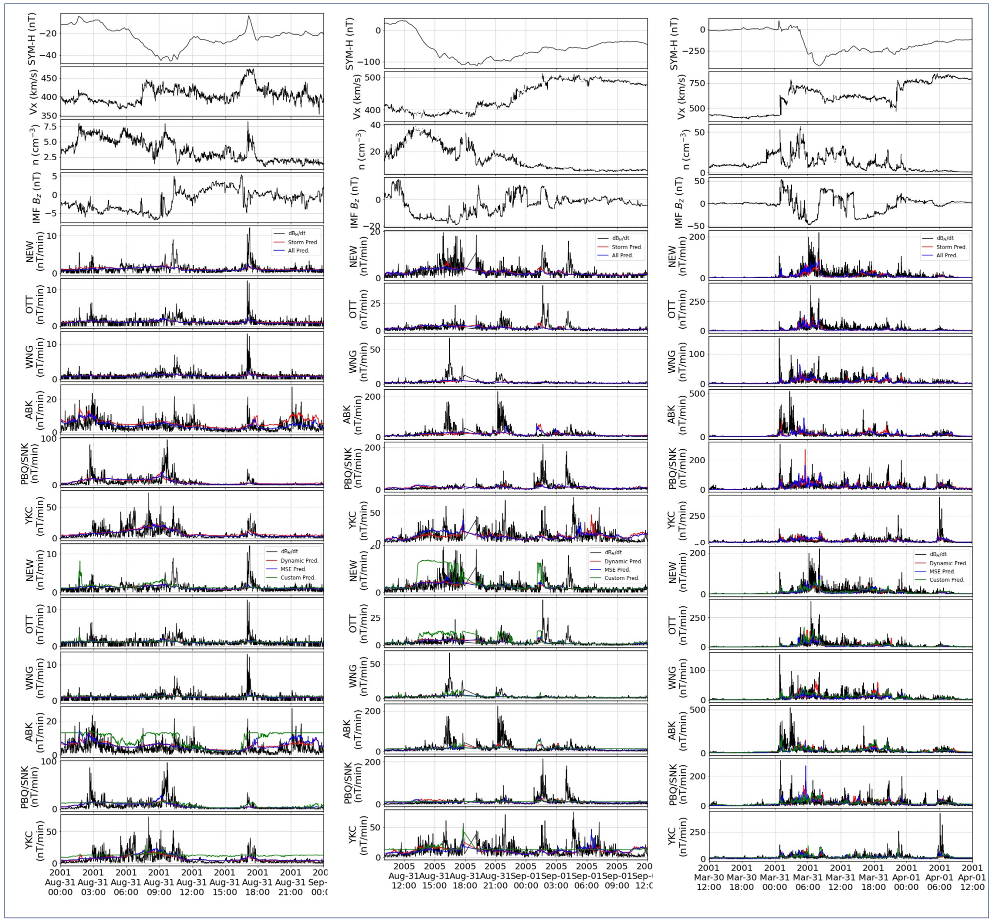
  - Custom tail:

$$Loss = (y_{true} - y_{pred})^2(1 + a)$$

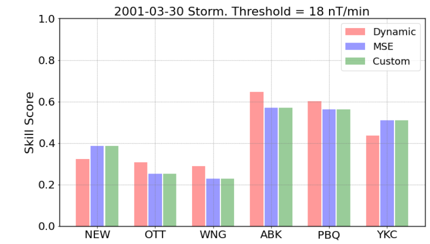
$$\text{where } a = \begin{cases} p \text{ if } y_{true} > T \text{ and } y_{pred} < T \\ 0 \text{ otherwise} \end{cases}$$

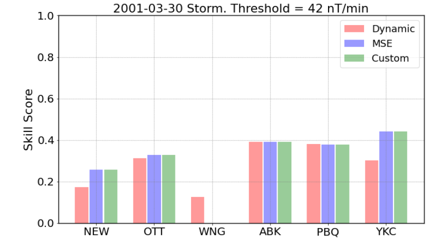
p is a penalty and T is a threshold

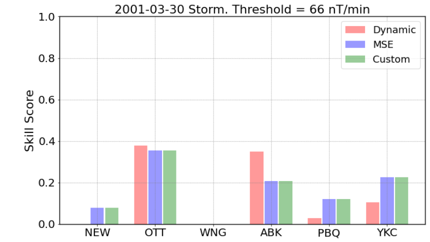
Storm Prediction Comparisons



Heidke Skill Scores-Loss Functions







The data are averaged over 20-minute windows, and the Heidke Skill Score is calculated based on the crossing of several thresholds within the window. Shown here are the results for the 2001-03-30 storm for three thresholds comparing the different loss functions.

Discussion

- In the comparison of All vs. Storm-time data for training, neither model has predictions with consistently larger magnitude. Training is faster with less data so we have deemed it reasonable to continue training only with Storm-time data.
- In the loss function comparison, the Custom loss function has some intervals of overprediction. The HSSs are comparable for the 2001-03-30 storm. In future work we will adjust the parameters of the Custom loss function and look for improved performance.

Acknowledgements and References

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SuperMAG data were obtained from https://supermag.jhuapl.edu Gjerloev, J. W. (2012). The SuperMAG data processing technique. Journal of Geophysical Research: Space Physics, 117(9), 1–19. https://doi.org/10.1029/2012JA017683

OMNIWeb data were obtained from https://omniweb.gsfc.nasa.gov

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The dynamic range loss function (https://github.com/rmcgranaghan/HEARTBEAT/blob/master/PrecipNet_April_2021/CrossValidationAnalysis/Explore_ML_DB_validationExploration-CVanalysis.ipynb) and custom tail loss function (https://github.com/rmcgranaghan/precipNet/blob/master/custom_tail_loss.ipynb) are available on github and described in J. Ziegler and R. M. McGranaghan, "Harnessing expressive capacity of Machine Learning modeling to represent complex coupling of Earth's auroral space weather regimes," 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), 2021, pp. 1189-1196, doi: 10.1109/ICMLA52953.2021.00193.