Prediction of Geomagnetic Auroral Electrojet Indices with Long Short-Term Memory (LSTM) Recurrent Neural Network

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Introduction

- Space weather phenomena occur from the Sun to the Earth with damaging impacts on the ground-based and space-borne technological infrastructure. The geomagnetic auroral electrojet indices *AU*, *AL*, and *AE* have been widely used for monitoring space weather and geomagnetic activities during space storms and substorms. The time series of solar wind monitored by upstream satellite and ground-based auroral electrojet indices form the input-output system characterizing the dynamic coupling among solar wind, Earth's magnetosphere and ionosphere.
- The data-driven predictions of auroral electrojet indices during geomagnetic storms and substorms face the challenges of capturing the ionospheric electrojet currents growth driven by multiple solar wind parameter drivers onto a coupled complex solar wind-magnetosphere-ionosphere system with finite and variable memory.
- In this study, a recurrent neural network (RNN)-based Long Short-Term Memory (LSTM) model has been built to predict the time series of AE index with multi-variate solar wind inputs. Both 5-min and hourly long-term time series data obtained from NASA OMNI database were used to drive the LSTM model. The coupled time series data are divided into training and testing datasets. Using the Root-Mean-Square-Error (RMSE) between the predicted and actual AE index for the testing sets as the performance measurement metrics, various evaluations such as the impacts of the memory length of the coupled system, the variation of prediction time, and different combinations of solar wind input parameters (magnetic field, velocity and density) were implemented.
- The performance of the LSTM model in predicting AE index during major geomagnetic storm events are analyzed. The challenges of applying LSTM to predict long term 5-min and hourly AE index are also discussed.

Solar Wind-Magnetosphere Interaction, LSTM Model and Dataset

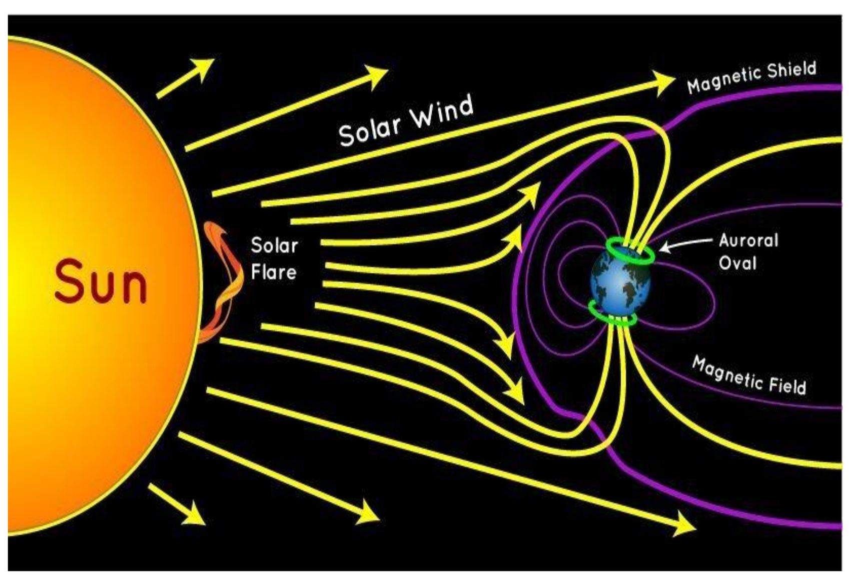


Illustration of solar wind from the Sun impacting on Earth's magnetosphere and creating aurora borealis during geomagnetic storms. (https://www.pbsnc.org/blogs/science/auroras-and-coronal-mass-ejections/)

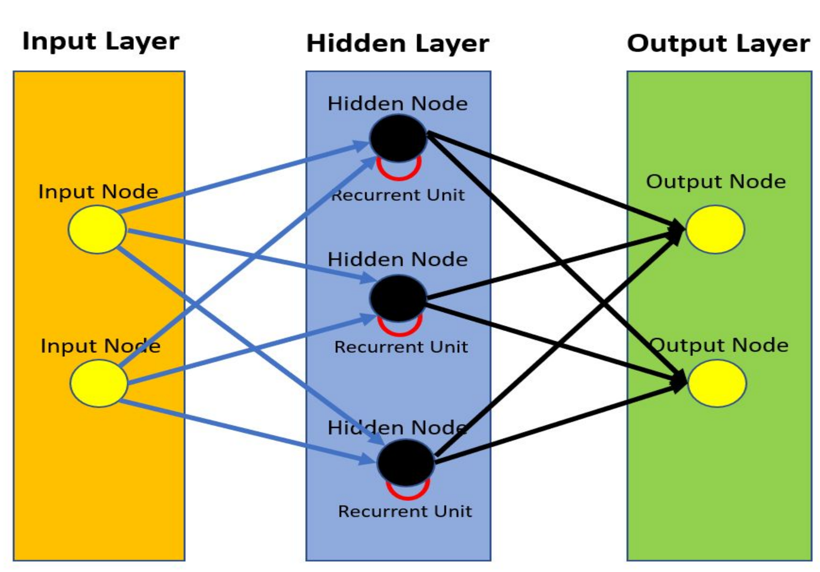


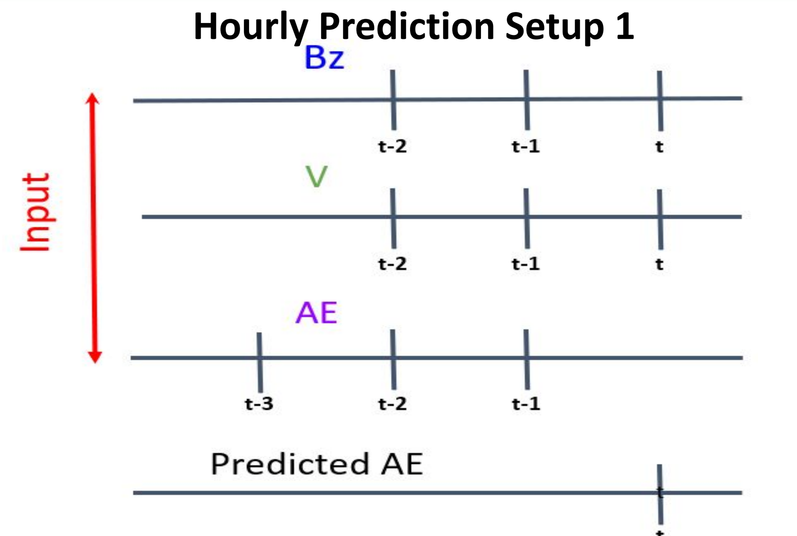
Illustration of Long-Short Term Memory Recurrent Neural Network (https://towardsdatascience.com/lstm-recurrent-neural-networks-how-to-teach-a-network-to-remember-the-past-55e54c2ff22e)

- The RNN-based LSTM machine learning algorithm is well suited to classify, process and make predictions for time series of coupled solar wind-auroral electrojet index system by dynamically preserving important information from earlier parts of the coupled time series and carrying it forward.
- LSTM Implementation: Multi-variate LSTM developed with Python Deep Learning TensorFlow/Keras Library.
- Datasets: Solar wind IMF Bz magnetic field, velocity, density and geomagnetic AE indices obtained from NASA OMNI webpage https://omniweb.gsfc.nasa.gov/ (both low resolution (hourly) and high resolution (5-min) data).

Hourly AE Prediction with LSTM

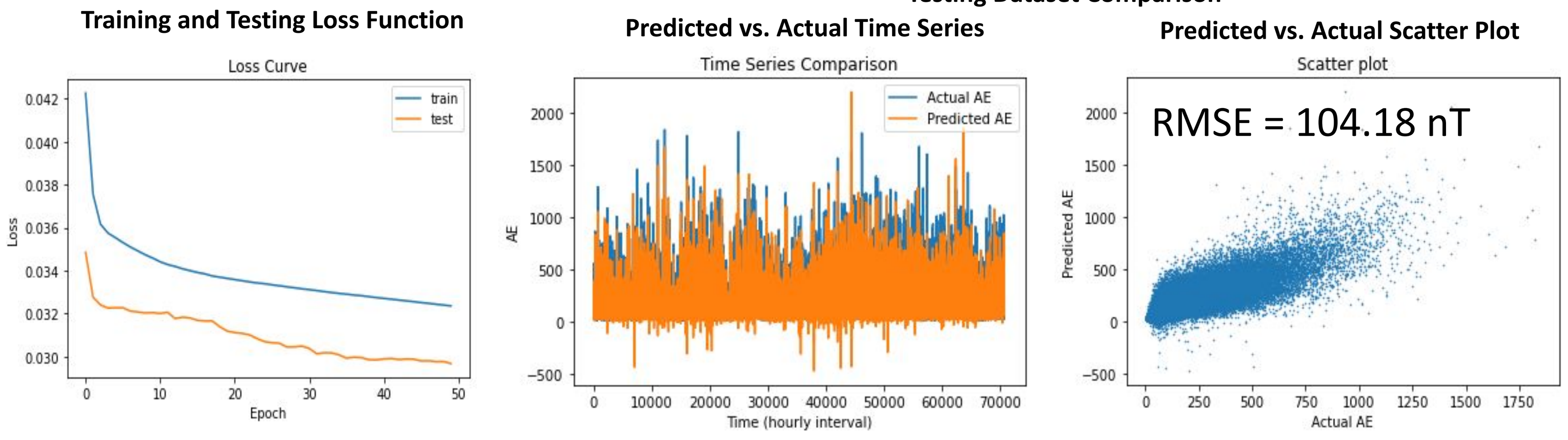
- Input: Time series of 1990 to 2018 hourly solar wind IMF Bz and velocity and geomagnetic AE index with data gap removal
- Output: Hourly AE Index
- Training dataset: ⅔ of data (~16 years)
- Testing dataset: ⅓ of data (~8 years)
- LSTM set up: 50 neurons in input layer, 1 hidden layer, 50 epochs
- Performance metrics: Root-Mean-Square-Error (RMSE)

Hourly Prediction Setup 1



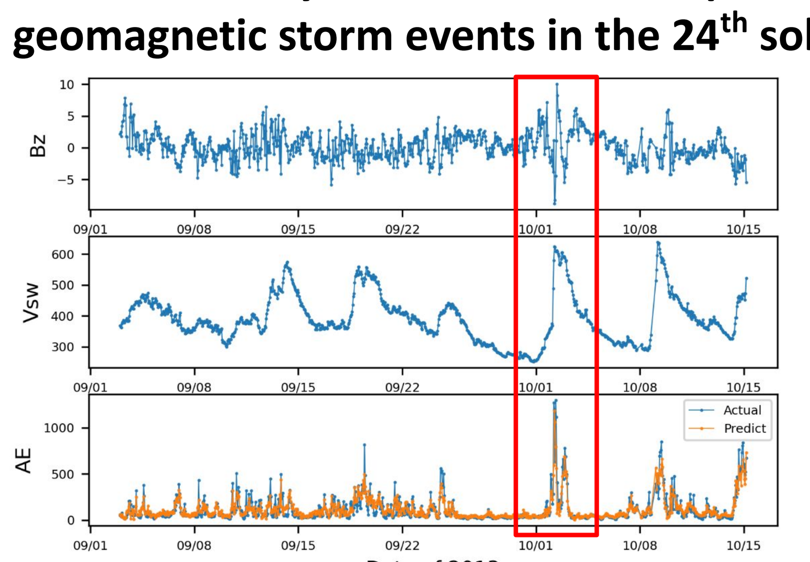
LSTM Hourly Prediction Setup 1: Use solar wind IMF Bz and V at t, t-1, and t-2 and AE at t-1, t-2, and t-3 (Memory = 3 hour) to predict AE(t)

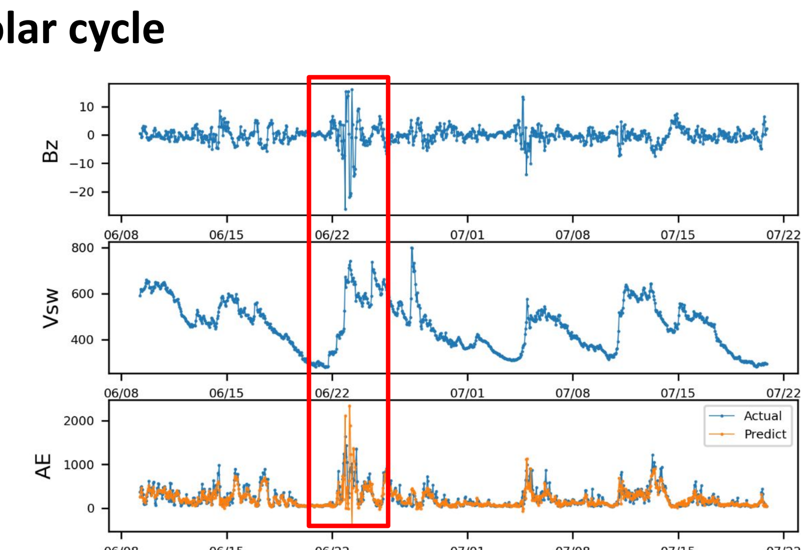
Training and Testing Loss Function | **Testing Dataset Comparison** — **Predicted vs. Actual Time Series** | **Predicted vs. Actual Scatter Plot**

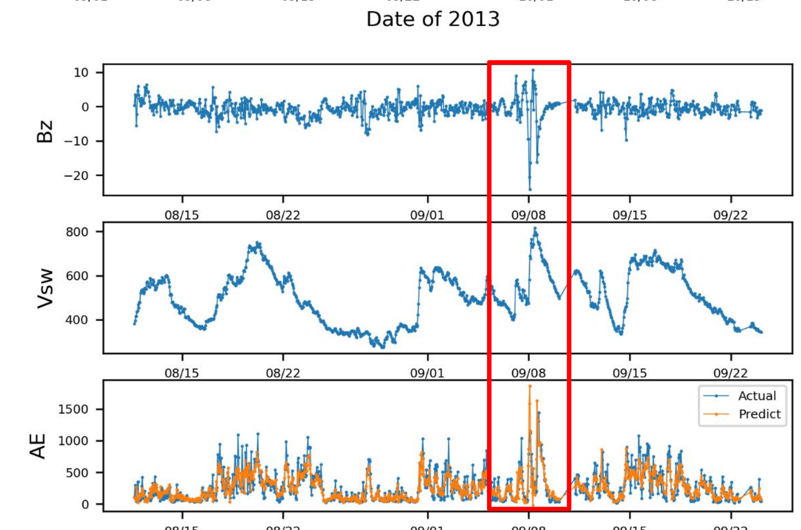


- RMSE between predicted and actual hourly AE index for the entire (~ 8 years) testing dataset is 104.18 nT.

Selected hourly AE time series comparison containing G-4 Severe (Kp =8) geomagnetic storm events in the 24th solar cycle



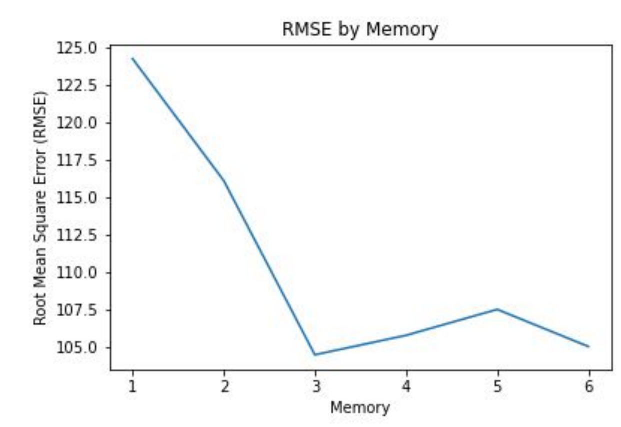




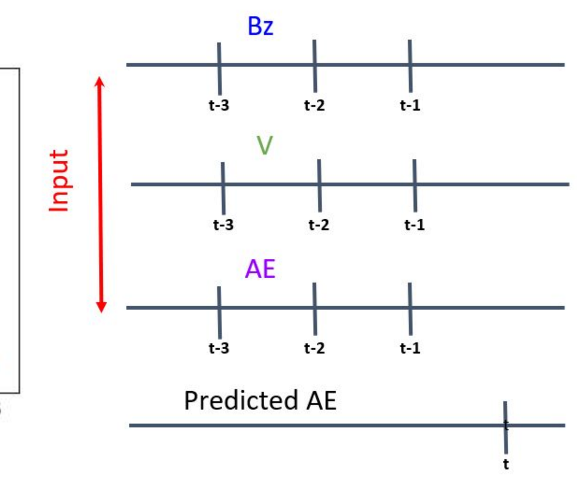
- Prediction case studies contain the G1-G4 (minor, moderate, strong and severe) levels of geomagnetic storms.
- In particular, these cases include the most severe (G-4) geomagnetic storms: 2013-10-02, 2015-06-22 and 2017-09-07 to 2017-09-08 G-4 with peak Kp index ≥ 8 (According to https://www.spaceweatherlive.com/en/auroral-activity/top-50-geomagnetic-storms)
- The LSTM-based hourly AE index prediction with model Setup #1 can well capture AE index variations during different (G1-G4) levels of geomagnetic storms. Particularly, the prediction captures the rapid and large increase of AE index during severe geomagnetic storms when the large amplitude solar wind velocity and IMF Bz fluctuation act on the Earth's magnetosphere.
- This confirms that solar wind velocity and IMF Bz variations directly drive auroral electrojet activity during geomagnetic storms.

Variation of LSTM model setup on hourly AE index prediction performance

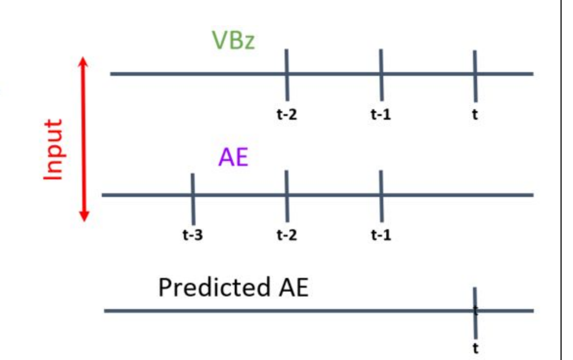
Impact of Memory Length (1-6 hours) on Hourly AE Prediction



Hourly Setup 2: RMSE = 135.68



Hourly Setup 3: Combining solar wind velocity (V) and IMF Bz inputs into one coupled VBz (=IMF Ey) as the input and RMSE = 110.48

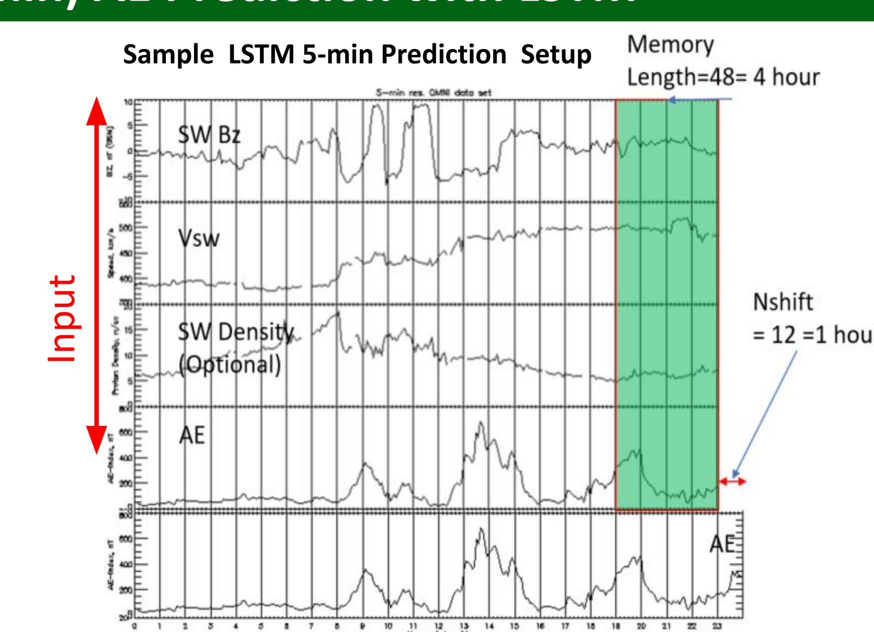


- Keeping Setup 1 and varying memory length (keeping relative time difference between solar wind IMF Bz, V and AE): the memory length = 3 hours has the most optimal performance with the lowest RMSE, 104.18. The 3-hour memory is indicative for strong geomagnetic storms.
- Comparing prediction performance between Setup 1 and 2: the IMF Bz and solar wind V values within the same hour can affect the AE index. The aurora electrojet index can be affected by solar wind within the same hour which is consistent with the time scale of the development of geomagnetic substorms.
- Comparing prediction performance between Setup 1 and 3: the separation of solar wind velocity and IMF Bz as independent inputs has better performance in prediction as compared to the prediction with one combined VBz as input.

High time-resolution (5-min) AE Prediction with LSTM

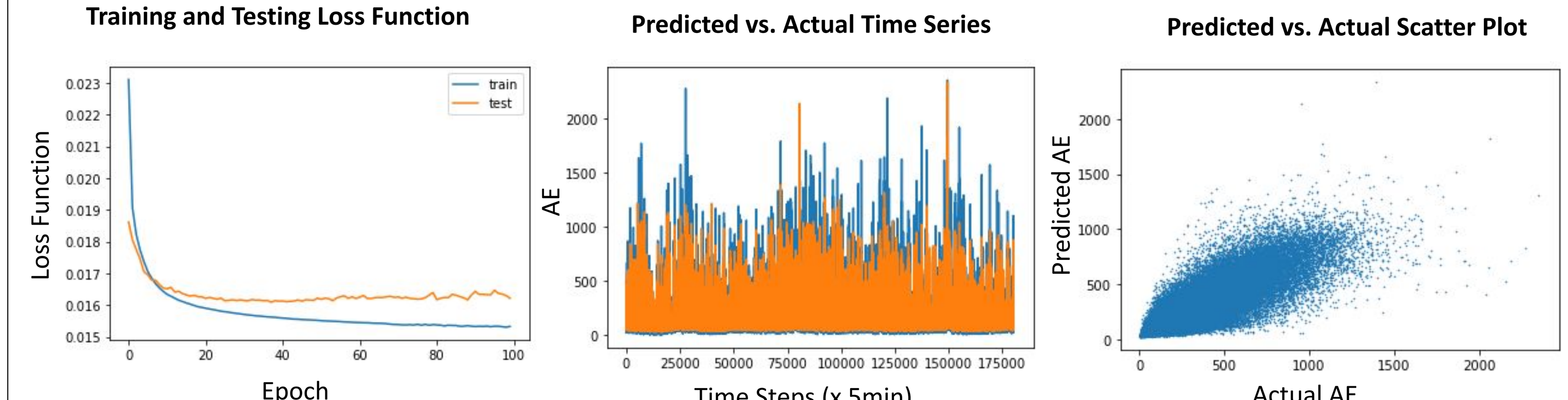
- Input: Time series of 2005 to 2018 5-min solar wind IMF Bz, velocity, and density (optional for sensitivity testing), and geomagnetic AE index
- Output: 5-minute AE Index
- Training dataset: ⅔ of data (~9 years)
- Testing dataset: ⅓ of data (~4.5 years)
- LSTM set up: 100 neurons in input layer, 1 hidden layer, 100 epochs
- Tuning parameters: number of input variables, memory length, shift (ahead-prediction time)
- Performance metrics: Root-Mean-Square-Error (RMSE)

Sample LSTM 5-min Prediction Setup

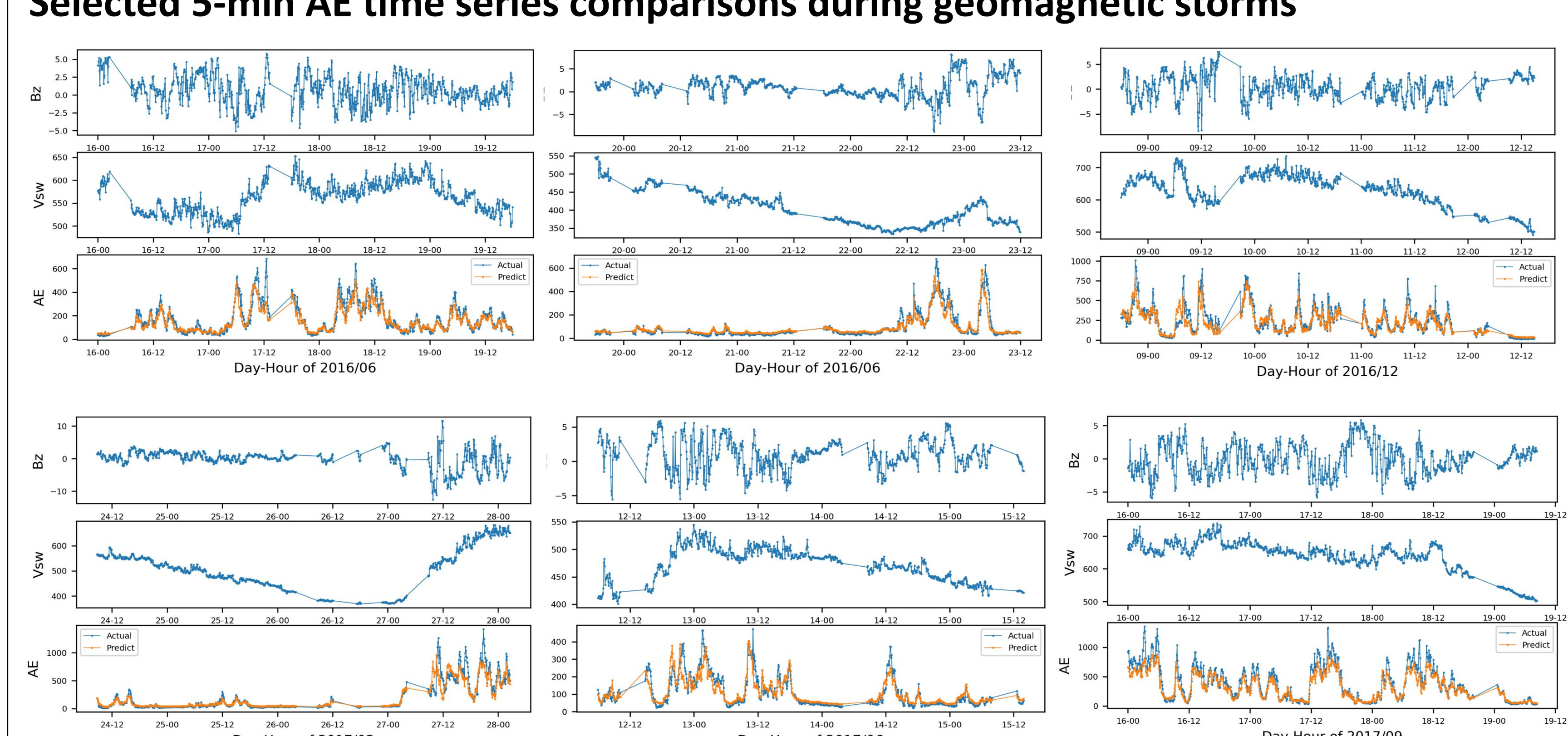


LSTM 5-min Prediction Setup 1: Input (V, Bz, AE), Nshift = 6 (30 min), Memory= 48 (4 hour), RMSE = 97.0

Training and Testing Loss Function | **Testing Dataset Comparison** — **Predicted vs. Actual Time Series** | **Predicted vs. Actual Scatter Plot**



Selected 5-min AE time series comparisons during geomagnetic storms



Variation of LSTM model setup on 5-min AE index prediction performance

Setup	1	2	3	4	5	6
Input Variables	3 (Solar wind V, Bz, and AE)	3 (Solar wind V, Bz, and AE)	4 (Solar wind V, Bz, Density and AE)	3 (Solar wind V, Bz, and AE)	3 (Solar wind V, Bz, and AE)	2 (Solar wind VBz, and AE)
Nshift	6 (30 min)	6 (30 min)	6 (30 min)	12 (1 hour)	12 (1 hour)	12 (1 hour)
Memory Length	48 (4 hour)	36 (3 hour)	36 (3 hour)	24 (2 hour)	48 (4 hour)	48 (4 hour)
RMSE	97.0	100.73	100.38	129.59	122.04	125.25

- These selected geomagnetic storm event comparisons show that the LSTM model can predict the high time-resolution (5-min) AE index variations during various levels of geomagnetic storms;
- Current LSTM model setup shows relative lower amplitude of predicted 5-min AE index during strong/severe geomagnetic storms, which needs further improvements.
- **Variation of LSTM model setups** show that a shorter prediction time has better prediction performance; a 3 to 4 hour system memory length is optimal for AE index prediction; The solar wind density variations have relatively weaker impacts on AE index variations during geomagnetic storms; Decoupling solar velocity and IMF Bz as drivers shows slightly better performance.

Summary

- This study developed a multi-variate LSTM model and showed that the LSTM-based model can predict both hourly and high time-resolution (5-min) AE index variations during various levels of geomagnetic storms.
- The performance comparison of different LSTM model setups can aid in understanding the dominant driving solar wind parameters, the delay in the ionospheric response, and the finite system memory effects in the dynamical coupling between solar wind drivers and auroral electrojet activities.
- This study confirms that solar wind velocity and IMF Bz variations are the dominant drivers of auroral electrojet activity during geomagnetic storms.
- Further studies will focus on understanding the relatively low amplitude of predicted 5-min AE indices during strong/severe geomagnetic storms and improving 5-min AE prediction to combat data gaps due to the use of long memory in the model setup.