

Probabilistic Regional Forecasting of Geomagnetically Induced Currents (GICs) using a Refined Machine Learning-Based Classifier

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Introduction

Geomagnetically induced currents (GICs) are currents induced by rapid variations in the near-Earth magnetic field. These currents pose a serious threat to power grids since they can saturate transformers and cause widespread blackouts by destabilizing system operations.

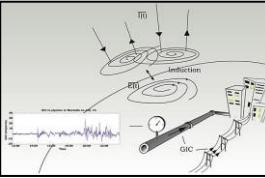


Fig. 1: The basic principle for the generation of GICs following Maxwell's equations.

Our main objective is to consolidate industry requirements and present scientific capabilities by developing a machine-learning based classifier model for multi-hour, regional GIC risk forecasting. In this study, we provide a preliminary analysis of high-resolution ground magnetic field datasets from key magnetometer stations across New Zealand and polar-to-mid latitude regions. These stations were selected due to their publicly available observations on GIC measurements, and their sensitivity to geomagnetic events as discussed in previous GIC correlation studies in these regions [Rodger et al. (2017), Smith et al. (2024)]. We demonstrate a strong coupling between solar wind patterns and ground perturbations.

Datasets & Methodology

We assembled a 2015-2024 database with 1-s cadence from 3 magnetometer stations – Scott Base, Antarctica (SBA), Eyrewell, New Zealand (EYR) and Macquarie Island, Australia (MCQ).

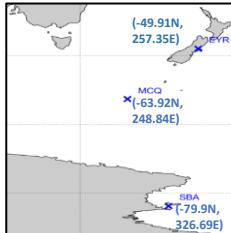


Fig. 2: Global view showing the locations of the 3 stations used in this study. Locations have been marked by corrected geomagnetic coordinates (IGRF-13 2020.5).

As a starting-point, we choose to analyze a recent storm event on 1 specific day – the 2024 Mother's Day solar storm or the Gannon storm.

Mother's Day Storm Analysis

The Mother's Day geomagnetic storm in 2024 was classified as a G5-class storm ($K_p = 9$, $DST = -412$ nT).

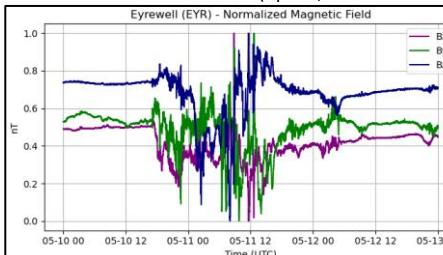


Fig. 3: Normalized magnetic field components showing magnetic field responses during both storm and quiet periods from raw data at EYR. From Maxwell's equations,

$$\nabla \times \vec{B} = \mu \vec{J} + \epsilon \mu \frac{\partial \vec{E}}{\partial t}; \nabla \times \vec{E} = -\frac{\partial \vec{B}}{\partial t}; \vec{J} = \sigma \vec{E}$$

As a proxy for \vec{E} , dB/dt can be computed using the definition as per Camporeale et al. (2020):

$$\frac{dB}{dt} = \max_{\Delta t} \left(\frac{dB_x}{dt} \right)^2 + \left(\frac{dB_y}{dt} \right)^2$$

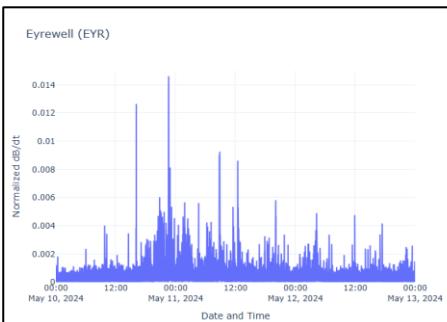


Fig. 4: Line plot showing normalized dB/dt over a rolling period of 10 mins during both quiet periods and storm periods at EYR.

We define thresholds specific for each location by following the approach adopted in Camporeale et al. (2020).

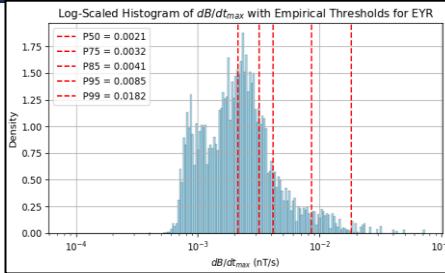


Fig. 5: Log-scaled histogram of maximum 1-s dB/dt values (dB/dt_{max}) at Eyrewell (EYR) over multiple thresholds. Empirical thresholds are an important feature for our model, thus computed at the 50th, 75th, 85th, 95th, and 99th percentiles of normalized aggregated dB/dt .

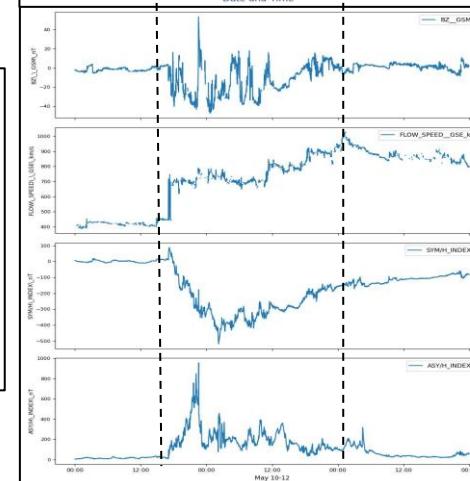
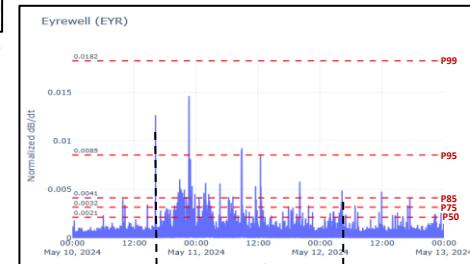


Fig. 6: Solar wind speed increased steadily, indicating storm onset on May 10, reaching 750-950 km/s.

Fig. 6 demonstrates how sudden changes in solar wind data precede or coincide with peak dB/dt values at EYR.

Conclusion & Next Steps

This study highlights the relationships between dB/dt perturbations and disturbances in solar wind conditions. The initial data analysis will be used as input features to a ML-based probabilistic classifier which would estimate the probability that dB/dt values might exceed the defined station-specific thresholds. We will use the GOES X-ray flux data as geomagnetic storm periods. Empirical thresholds are an important feature for our model, thus computing at the 50th, 75th, 85th, 95th, and 99th percentiles of normalized aggregated dB/dt . We will measure the performance of the model using evaluation metrics: Probability of Detection and False Detection, True Skill Statistic, and Receiver Operating Characteristic curves.

Acknowledgements

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References

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