Empirical Physics Informed Neural Networks for Magnetopause Tracking

*Po-Han, Hou | Jih-Hong, Shue

*Contact Information: Department of Space Science and Engineering, National Central University | *Email: kozak20010716@gmail.com

Abstract

The ultimate goal of studying the magnetopause position is to accurately determine its location. Both traditional numerical computation methods and the currently popular machine learning approaches have shown promising results. In this study, we propose a Empirical Physics-Informed Neural Networks (Emp-PINNs) that combines physics-based numerical computation with vanilla machine learning. This new generation of PINNs overcomes the limitations of previous methods restricted to solving ordinary and partial differential equations by incorporating conventional empirical models to aid the convergence and enhance the generalization capability of the neural network. Compared to Shue et al. [1998], our model achieves a reduction of approximately 30% in root mean square error.

The methodology presented in this study is not only applicable to space research but can also be referenced in studies across various fields, particularly those involving empirical models.

Introduction

◆ Magnetopause

- The boundary where the solar wind dynamic pressure is balanced by the magnetic pressure of Earth's magnetosphere.
- Major controlled by IMF Bz & Dp

◆ Current Practices

- Numerical Method
  - 👍 Generalization
  - 👍 Based on Physics Theorem
  - ⚠ Precision
  - Roelof and Sibeck [1993]
  - Shue et al.[1997 / 1998]
  - Chao et al.[2002]
  - ...
- Machine Learning
  - 👍 High precision in fitting process
  - ⚠ Generalization
  - ⚠ Black Box
  - Wang et al. [2008]
  - Ghisalberti et al. [2022]
  - Li et al. [2023]
  - ...

Currently, there is a lack of models that can simultaneously address the aforementioned issues. Therefore, we propose a new generation of Physics Informed Neural Networks (PINNs) named Emp-PINNs.

Dataset

- There are a total of 34,998 magnetopause in-situ crossing data points. (THEMIS(28634), Geo-Tail(5764), ISEE, IMP 8, etc.)
- Applying the OMNI dataset recorded every five minutes, identify the corresponding time stamps and calculate the 5-minute averages.

Methodology

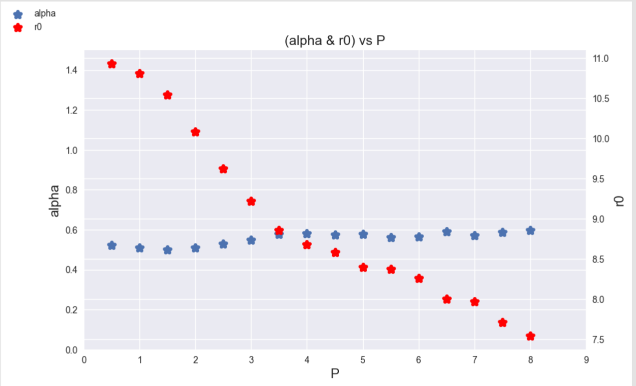
We inherit the function form proposed by Shue et al. [1997] and re-evaluate the relationship between Bz and Dp with respect to r_0 and α. Additionally, we propose an alternative parameter-based numerical model.

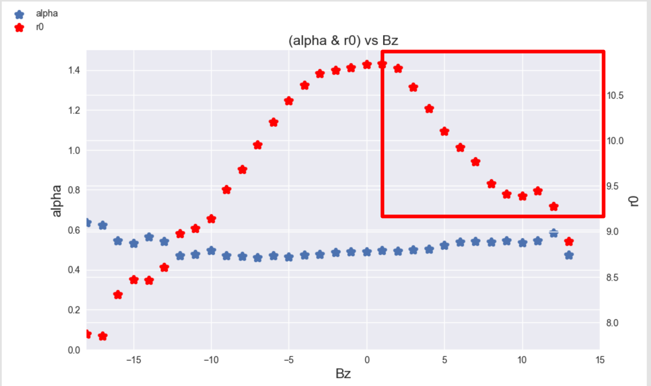
$$r = r_0\left(\frac{2}{1+\cos\theta}\right)^{\alpha}$$, Shue et al. [1997]

◆ Proposed Numerical Model

$$r_0 = (9.332 + 1.308 \cdot \tanh(0.213(Bz + 11.191) - 0.568 \cdot \tanh(0.479(Bz - 7.188))(Dp)^{\left(-\frac{1}{6.22}\right)}$$

$$\alpha = \left(0.493 - 3.5 * 10^{-4} * Bz\right)(Dp)^{\left(\frac{1}{11.92}\right)}$$



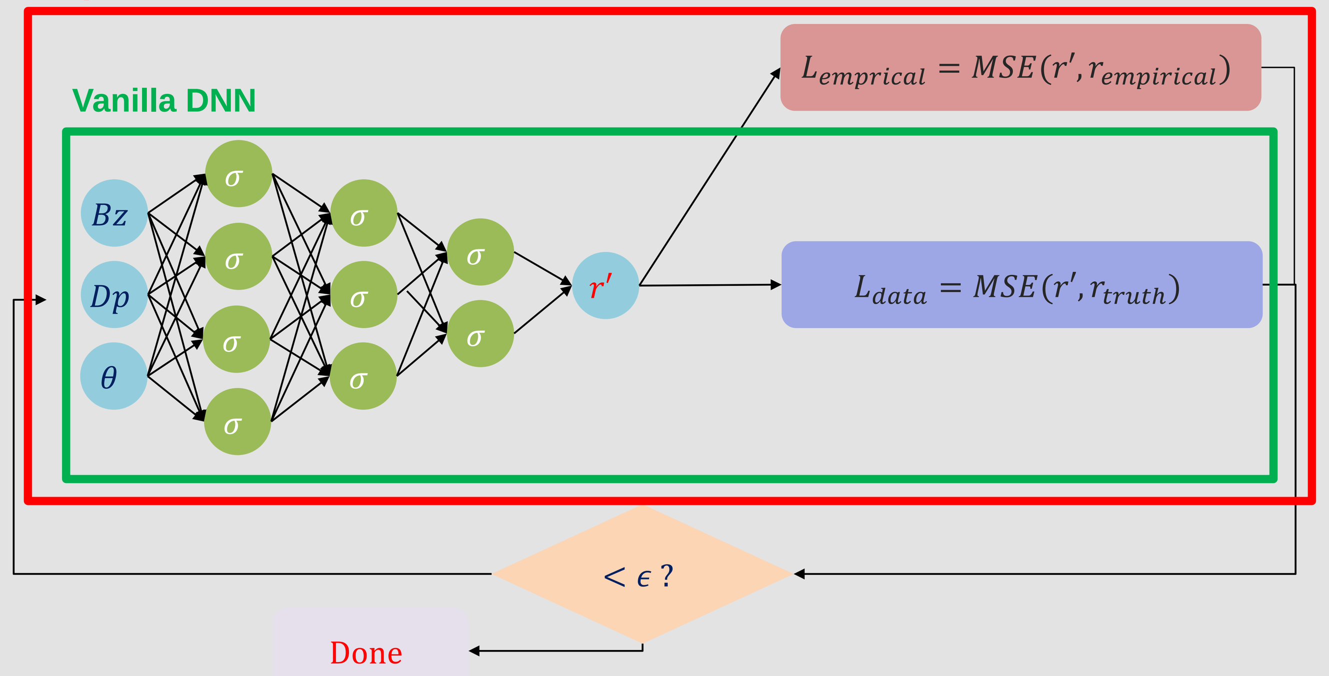


(Dušik et al. [2010])
(Li, Sun and Chen, 2023)

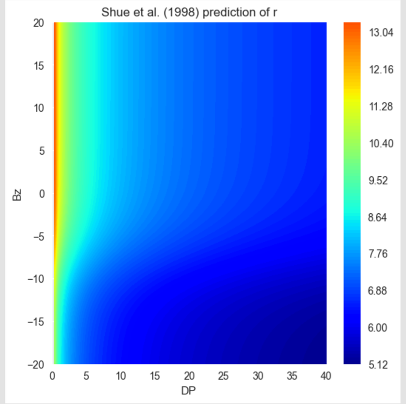
◆ Proposed Algorithm

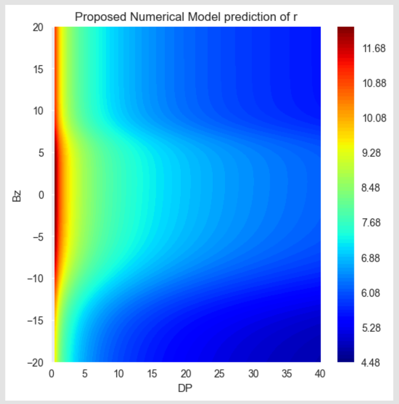
- The inspiration for the model proposed in this study originates from the use of Physics Informed Neural Networks (PINNs) for solving high-resolution spatio-temporal simulations, where partial differential equations (PDEs) and other physical equations guide the model to achieve zero-shot generalization. However, previous literature does not mention the use of algebraic equations for guiding the model. Therefore, we propose incorporating the results obtained from physically meaningful algebraic models to guide the neural network. This novel approach is referred to as Empirical-PINNs, abbreviated as Emp-PINNs

Functional Flow Block Diagram of Emp-PINNs

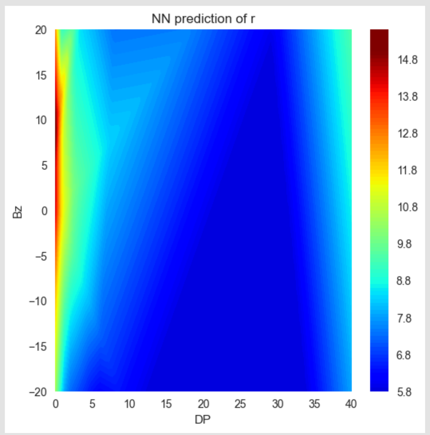


Results

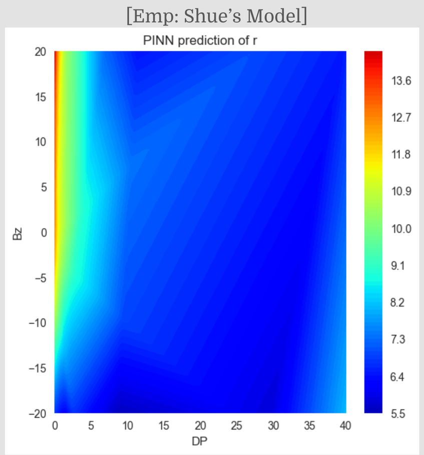




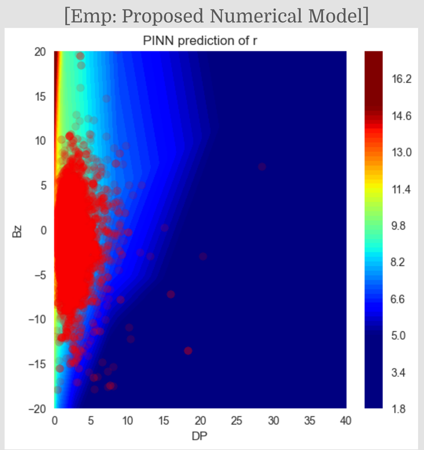
Model	RMSE (All)	RMSE(Shue's dataset)
Shue et al.[1998]	1.22321 Re	1.34754 Re
Proposed Numerical Model	1.19232 Re	1.33783 Re
MCMC	1.19587 Re	1.32348 Re



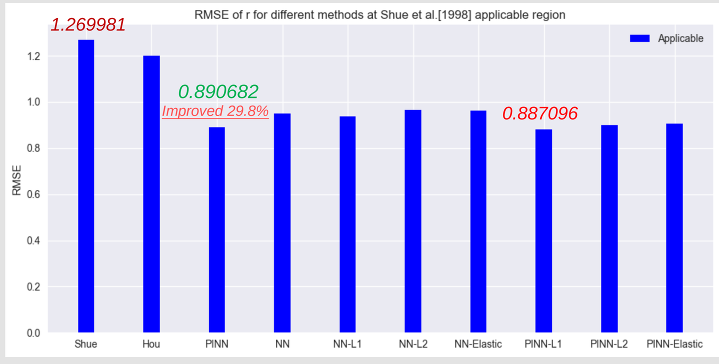
[Emp: Shue's Model]

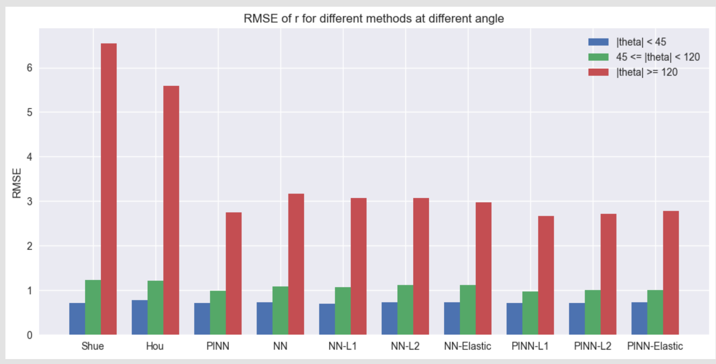


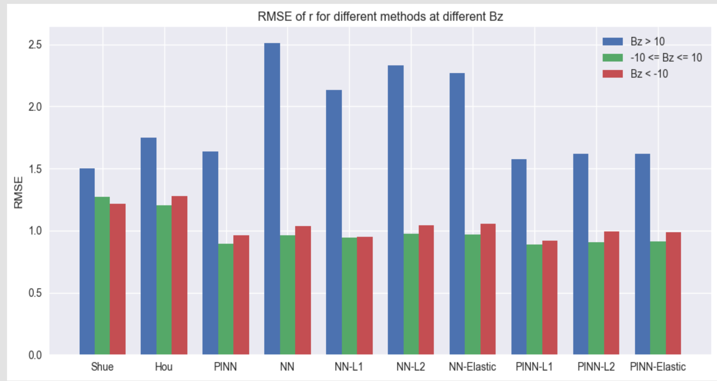
[Emp: Proposed Numerical Model]

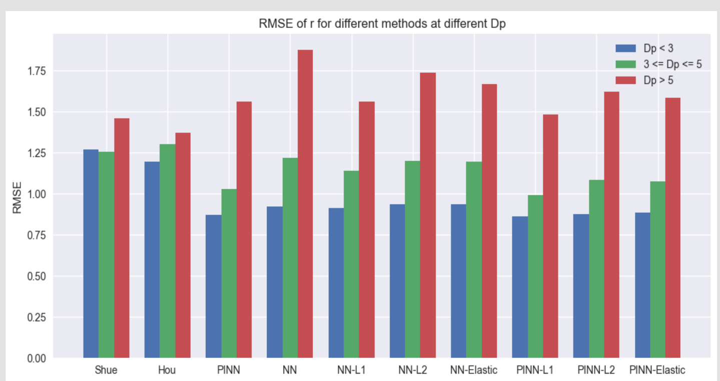


Model	RMSE (Total)	RMSE (20% Testing)	RMSE (80% Testing)
Shue et al.[1998]	1.22321 Re	1.19368 Re	1.26587 Re
Neural Networks	0.88437 Re	0.94781 Re	1.10475 Re
Emp-PINNs - Shue et al.[1998]	0.90103 Re	0.92539 Re	0.96703 Re
Emp-PINNs - Proposed Model	0.92375 Re	0.89304 Re	0.91483 Re









Conclusion

- We re-evaluate the relationship between parameters (Bz, Dp) and r_0 and α, and propose alternative types of numerical models.
- The proposed algorithm (Emp-PINNs) resolves the issues of numerical methods' inherent lack of precision and the poor generalization capabilities of machine learning.
- Emp-PINNs is an algorithm that constrains vanilla neural networks to converge on predictions and enhances generalization by excluding intervening outliers.
- Emp – PINNs is capable of handling multivariate input and multivariate output. However, in this study, we only focus on discussing the prediction of magnetopause locations in the space domain, considering multivariate inputs and a single output.
- The proposed Emp-PINNs introduced in this study allows the incorporation of algebraic equations for model training, expanding the capabilities of traditional PINNs, which primarily focus on solving ordinary and partial differential equations (ODEs and PDEs).
- Emp-PINNs greatly improve the model's performance in predicting the location of the Magnetopause, achieving a remarkably improvement of 29.8 %.
- L1 (Lasso), L2 (Ridge), and Elastic regularization techniques show a significant improvement in predicting the variable *r* when Bz varies..
- Emp-PINNs significantly improves the precision within the applicable scope of Shue et al. [1998].

References

- Shue, J.-H. *et al.* (1997) 'A new functional form to study the solar wind control of the magnetopause size and shape', *Journal of Geophysical Research: Space Physics*, 102(A5), pp. 9497–9511. Available at: https://doi.org/10.1029/97JA00196.
- J.-H. Shue *et al.* (1998) 'Magnetopause location under extreme solar wind conditions', *Journal of Geophysical Research: Space Physics*, 103(A8), pp. 17691–17700. Available at: https://doi.org/10.1029/98JA01103.
- Dusik, S., et al. (2010). THEMIS observations of magnetosheath-like plasma in the near-Earth magnetotail. Journal of Geophysical Research: Space Physics, 115(A12), A12223. https://doi.org/10.1029/2010JA015681
- Raissi, M., Perdikaris, P. and Karniadakis, G.E. (2019) 'Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations', *Journal of Computational Physics*, 378, pp. 686–707. Available at: https://doi.org/10.1016/j.jcp.2018.10.045.
- Li, S., Sun, Y.-Y. and Chen, C.-H. (2023) 'An Interpretable Machine Learning Procedure Which Unravels Hidden Interplanetary Drivers of the Low Latitude Dayside Magnetopause', *Space Weather*, 21(3), p. e2022SW003391. Available at: https://doi.org/10.1029/2022SW003391
- *The Stata Blog » Introduction to Bayesian statistics, part 2: MCMC and the Metropolis–Hastings algorithm* (2016). Available at: https://blog.stata.com/2016/11/15/introduction-to-bayesian-statistics-part-2-mcmc-and-the-metropolis-hastings-algorithm/ (Accessed: 16 May 2023).

Acknowledgements

I would like to express my heartfelt appreciation to Dr. Chun-Yu Lin, Associate Researcher at NCHC – NARLabs, for providing invaluable insights into the concept of Physics Informed Neural Networks and for engaging in fruitful discussions. Additionally, I would like to extend my gratitude to Mr. Yu-Wei Chen and Mr. Pai-Shen Wang, Researchers at the Space Environment Laboratory – NCU, for their contribution in reinforcing the understanding of magnetopause.