Composite model for predicting sym-H index

Yong Ji, Chao Shen*, Lan Ma

Harbin Institute of Technology, Shenzhen, 518055, China

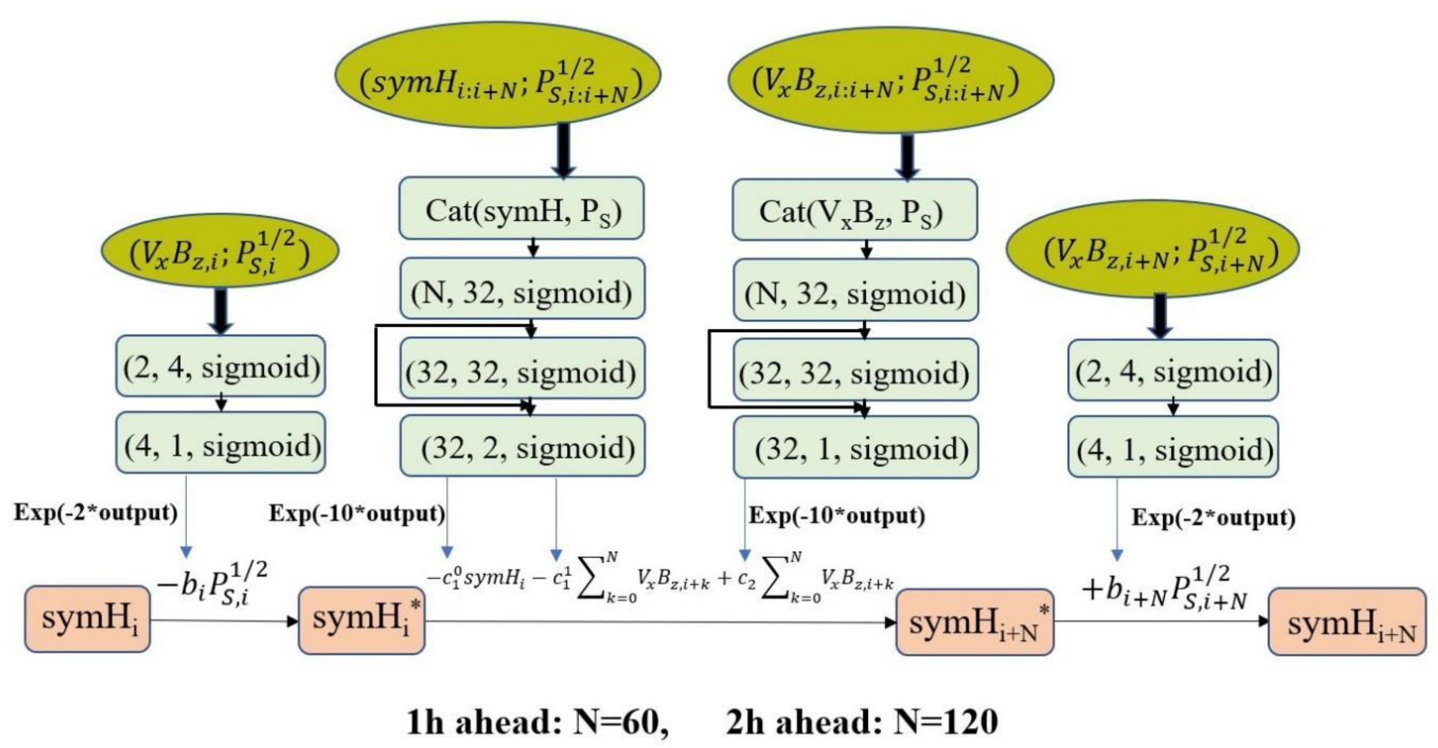
Abstract

This study presents a composite model to predict sym-H index based on solar wind parameters by combing the empirical magnetospheric dynamical equation and the neural network. The formula of sym-H equation learns from the well-known empirical relationship between interplanetary conditions and Dst put forward by Burton et al. [J. Geophys. Res., 80, 4204-4214(1975)]. In particular, the coefficients in the empirical equation are determined by using neural network which is good at approaching the function between the coefficients and the solar wind parameters. The composite model is trained using the solar wind density, velocity, the Interplanetary Magnetic Field (IMF) and the related storm index for both the storm periods and the quiet time in the last two solar cycles. It turns out that the forecast of sym-H in 1h and 2h ahead during storm time is reliable and the precision is even better than the latest models solely based on deep neural networks.

Introduction

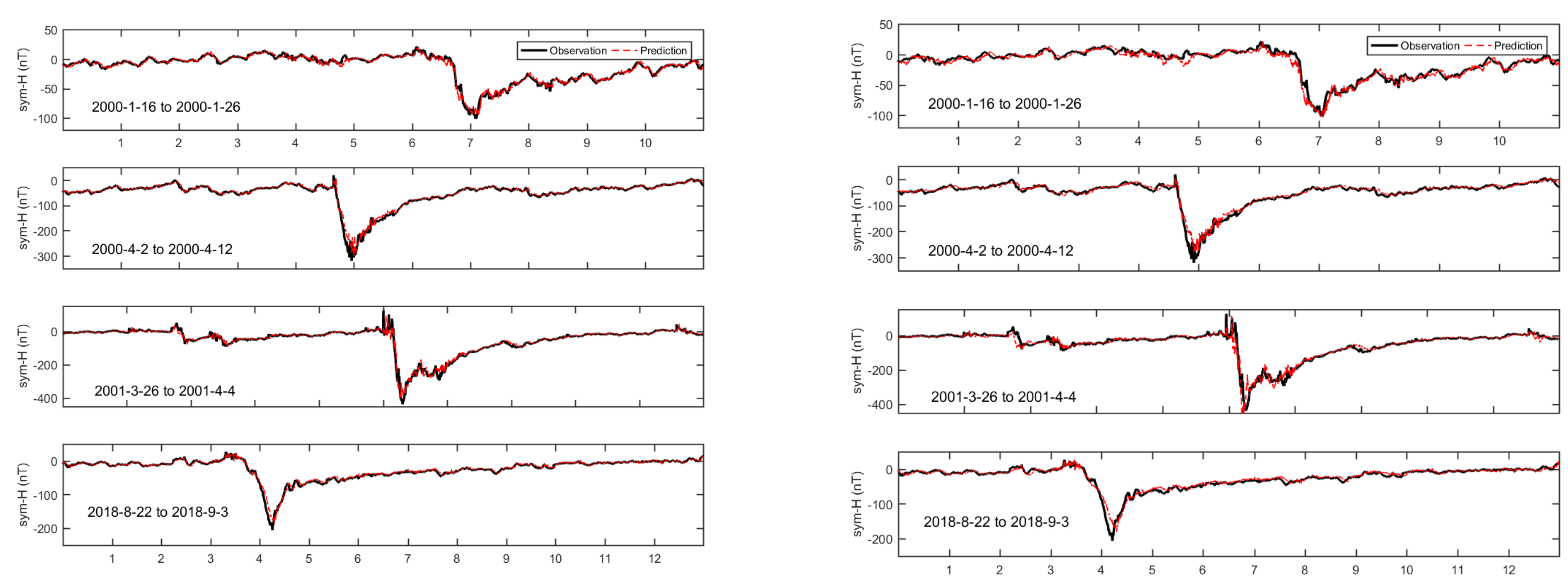
Disturbance of geomagnetic field caused by solar wind can be quantified by sym-H index which can be used to predict space weather disasters[1]. In view of the balance of energy in the inner magnetosphere, empirical relation between solar wind parameters and geomagnetic indices had been constructed[2] and developed[3,4]. Recently, neural networks such as CNN and RNN had been applied to construct model for predicting sym-H[5, 6]. However, empirical model cannot capture the complex interaction between the solar wind and magnetopshere, and neural network is unexplainable. In this study, we aim to put forward a scheme which can combine the advantages of the empirical model and the neural network. Based on the energy balance of ring current, we deduce the time variation of sym-H as the sum of energy injection and the loss. The functions between solar wind parameters, sym-H and the energy injection as well as loss are realized by neural networks.

Method & Data



Left figure shows the sketch of the composite model. The objective is to predict sym-H at time i+N, where N=60 for one hour or N=120 for two hour. First subtracting the component contributed by magnetopause current. Second considering the contributions by the energy injection and loss. Third adding the contribution by magnetopause. The coefficient b and c1,2 used to calculate contributions from magnetopause current, energy injection and loss are fitting by neural networks. Data selection in this study is same with ref.[6]

Results



No.	Storm Time	RMSE(nT)		
		Ref. [5]	Ref.[6]	Our Model
1	2000 1-16 to 1-26	5.6	5.200, 7.288	3.715, 5.497
2	2000 4-2 to 4-12	10.7	8.584, 12.436	8.328, 10.110
3	2001 3-26 to 4-4	16.3	13.340, 18.481	12.504, 19.811
4	2018 8-22 to 9-3	5.9	5.669, 8.273	5.520, 7.383

Figures show the comparison between observed sym-H(black line) and predicted sym-H(red line) belong to four storms with different intensity. The left panels are one hour ahead and the right two hour ahead. Table shows the root-mean-square error(RMSE). For comparing with the predictions by pure neural network, the errors predicted by reference [5] and [6] are also extracted and shown in table. Siciliano et al. only show 1 hour prediction errors. Collado-Villaverde et al. and our model show 1 hour and 2 hour prediction errors. It is obvious that RMSE of our model are about 1nT better than the latest neutral networks model

Conclusion

The algorithm introduced in this study to predict sym-H based on solar wind condition shows high precision. The RMSE for 1 hour and 2 hour prediction are better than results given by CNN or RNN network[5,6]. The cornerstone of the algorithm is using the energy balance mechanism in inner magnetosphere to deduce temporal variation of sym-H. It is meaningful for understanding the relation between the solar wind conditions, the ring current particle injection and motions, as well as the ring current particle loss processes.

References

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