Modeling ionograms with deep neural networks: Applications to foF2 forecasting

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Abstract

The ionosphere state parameters are of fundamental importance not only for radio communication but also for space weather. As most of the space phenomena, the dynamics are governed by nonlinear processes that make forecasts a challenging endeavor. We now have available enormous datasets and ubiquitous experimental sources that can help us finding the intricate regularities in these phenomena.
In this work, we will focus on the forecasting of some parameters of the steady-state low latitude ionosphere. We used ionograms from Jicamarca Radio Observatory digisonde to train two neural networks. We produced forecasts of ionospheric parameters such as virtual heights and foF2 taking into consideration ionogram characteristics. These estimations were compared to the corresponding values obtained from the digisonde, the persistence model, and foF2 values obtained from the International reference ionosphere.

1.Scientific problem and background

- Initially, this work was developed as part of our main research project which aims to estimate electron densities while forecasting ionograms. Ionograms are states of representation of the ionosphere at a given time and whose defined traces can be identified through the use of neural networks[1]. However, we noticed that we were applying a novel method to predict ionograms and foF2, which results will be shown in this poster.
- There were several approaches to estimate foF2 by using foF2 time series data, geophysical data, and neural networks as presented in [2]. However these methods did not use ionograms to make foF2 predictions.
- In this work, not only foF2, geophysical parameters and time are used to find this important value for ionogram predictions. But also, frequencies that are not foF2 and their virtual heights are used to let a multi-layer perceptron neural network classify and help us to find foF2.

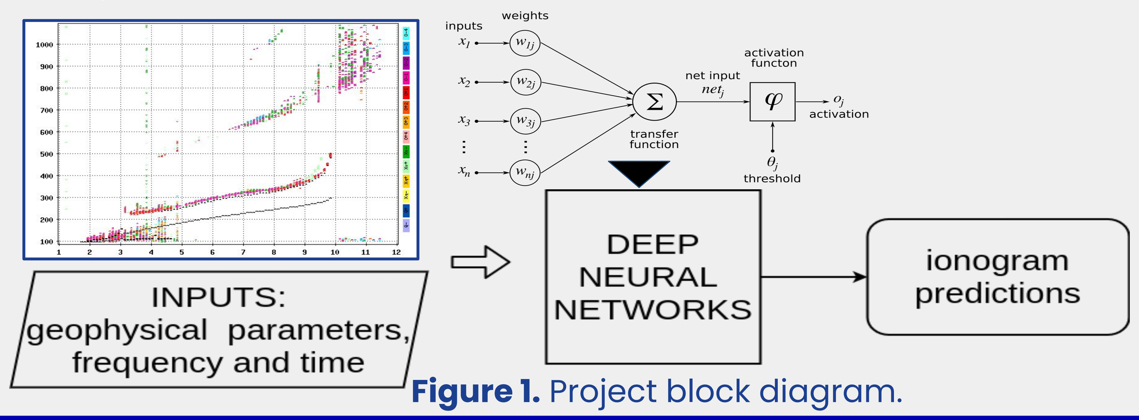
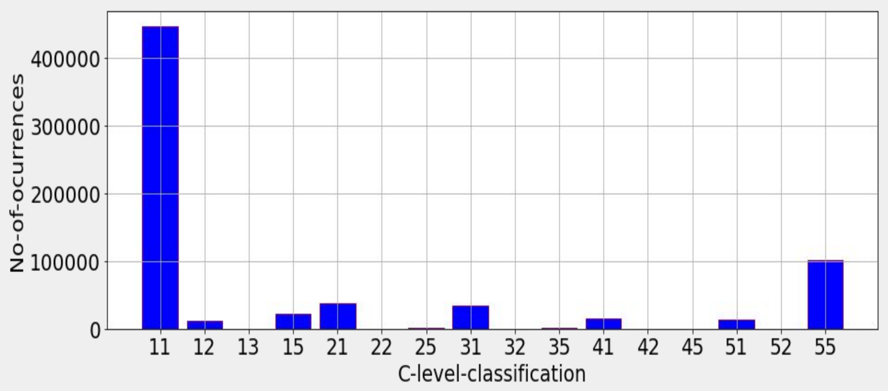


Figure 1. Project block diagram.

2. Datasets

- Digisonde ionograms used to train the model were filtered by the c-level flag provided by ARTIST flags-. c-level flag indicates and qualifies some of the ARTIST scaled results[3]. 11 indicates high quality and 55 low quality. Ionograms labeled with 11 were taken.
- 3 years and five months (2012 - May 2015) from 10 am to 5:00 pm LT hours were considered to train the model.

Figure 2. Bar chart to show the quantity of 20 years of Jicamarca digisonde data labeled with different c-levels categories



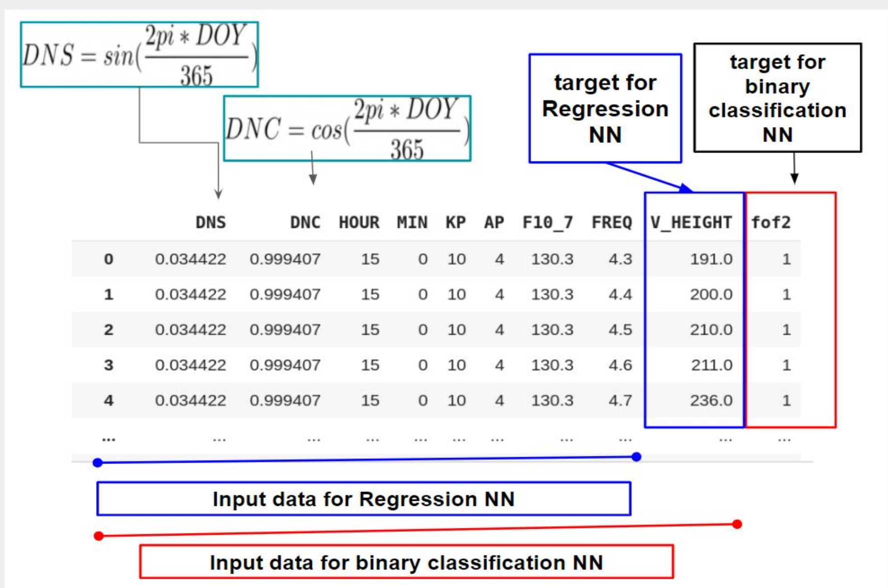


Figure 3. Complete dataset to train the 2 neural networks. Day of year values were converted into 2 quadrature components to avoid discontinuities as proposed in [4].

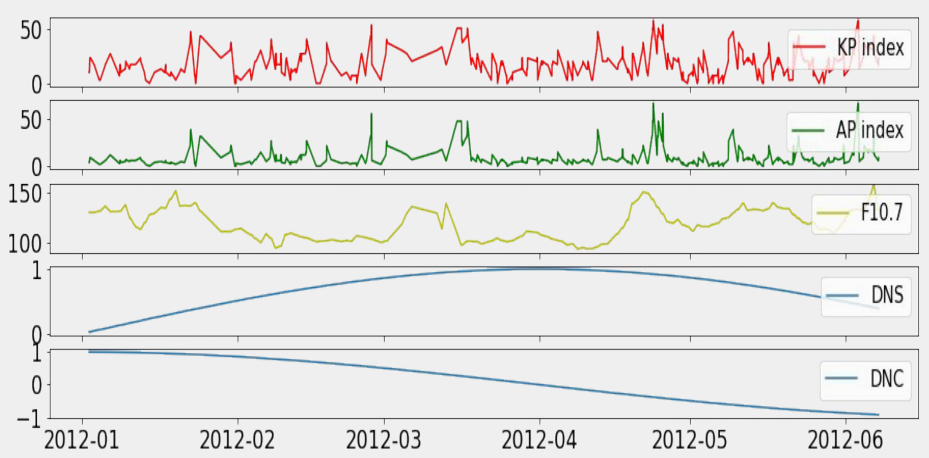


Figure 4. Input parameters time series for some dates. Geophysical parameters were obtained from Omniweb.

3. Model architecture

We chose neural networks architecture based on experience and multiple tests.

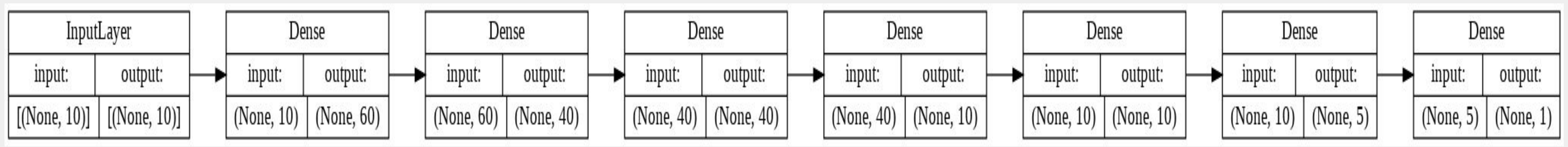


Figure 6. Graph of regression NN architecture to predict and capture ionograms shape. Relu activations functions were used.

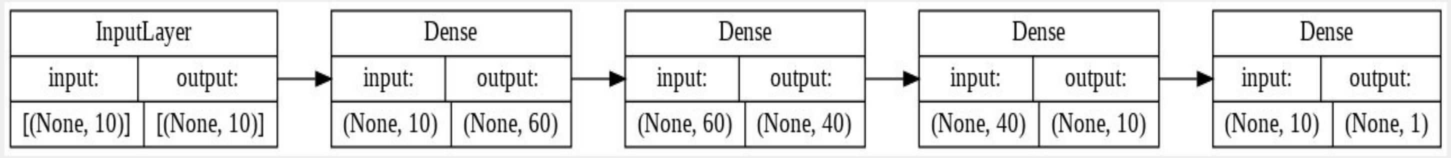


Figure 7. Graph of binary classification NN architecture to find which frequencies of the given are not foF2 and are before foF2. Thereby we used this information to identify which are foF2. Relu and sigmoid activation functions were used.

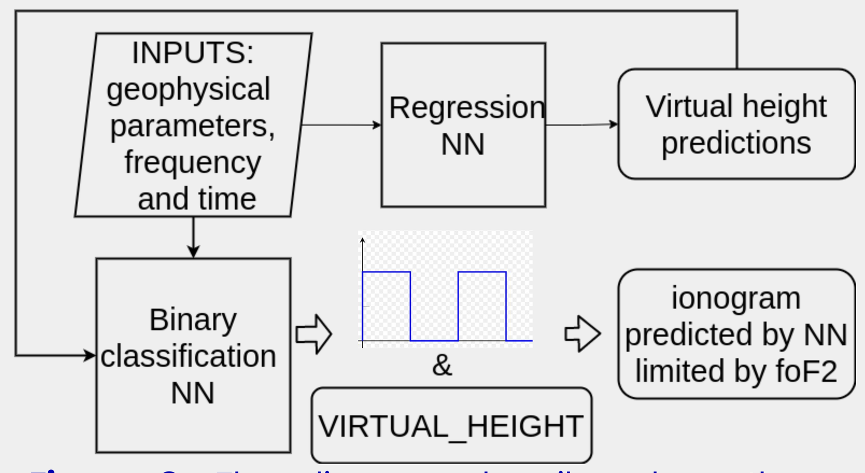


Figure 8. The diagram describes how the two-deep neural network models work to predict foF2 and ionograms after been trained.

4. Samples predictions and comparisons

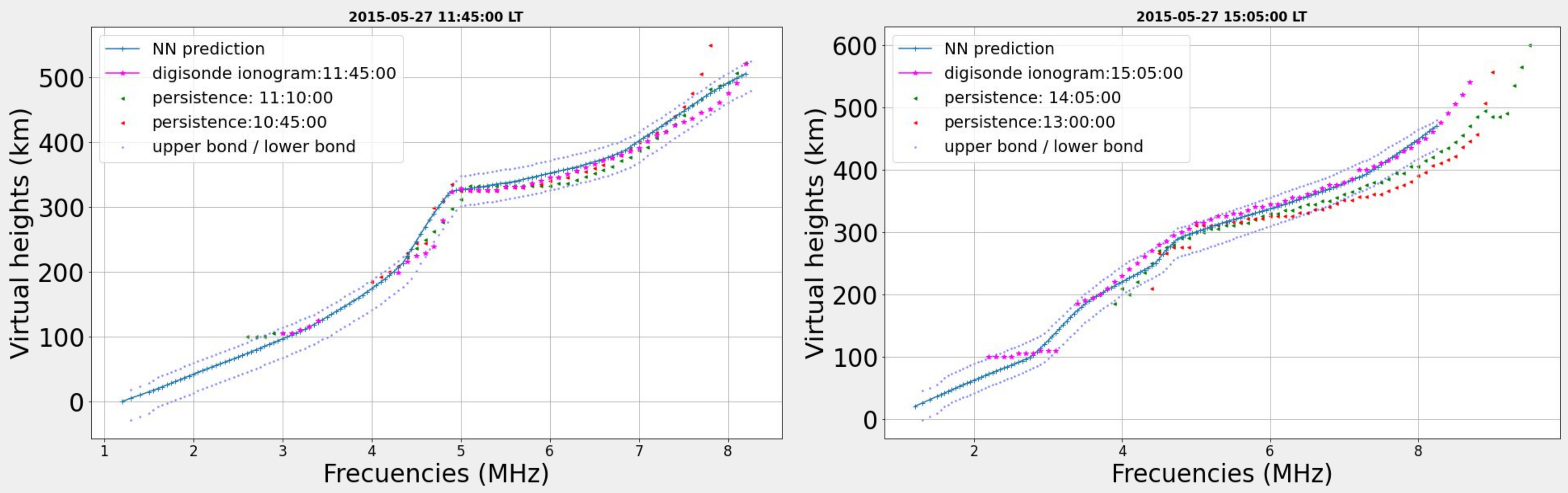


Figure 9 and 10. Ionogram prediction, its prediction interval, digisonde ionogram, and persistence models.

Traces for lower and highest frequencies were extrapolated by the neural network. However, extrapolated virtual heights for the highest frequencies were reduced by the binary classification neural network that helps us to identify which frequencies are Fof2. To make tests we did not consider days of storms(21-23 June of 2015)

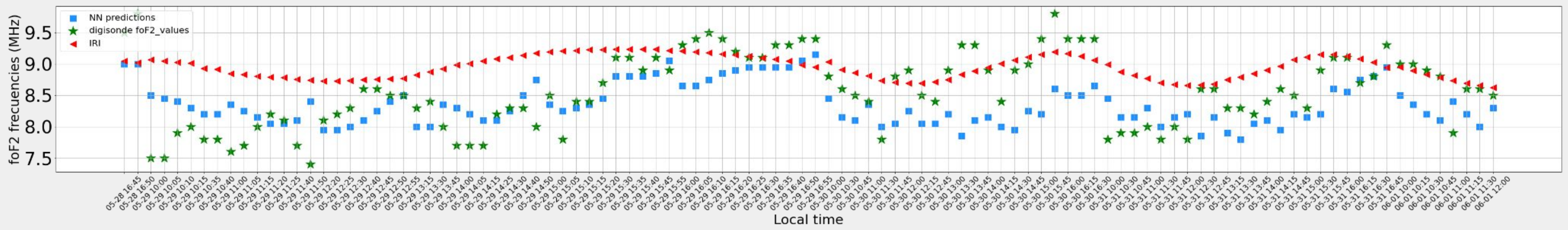


Figure 11. foF2 predictions of the NN, foF2 IRI estimations and foF2 digisonde values for 104 ionograms.

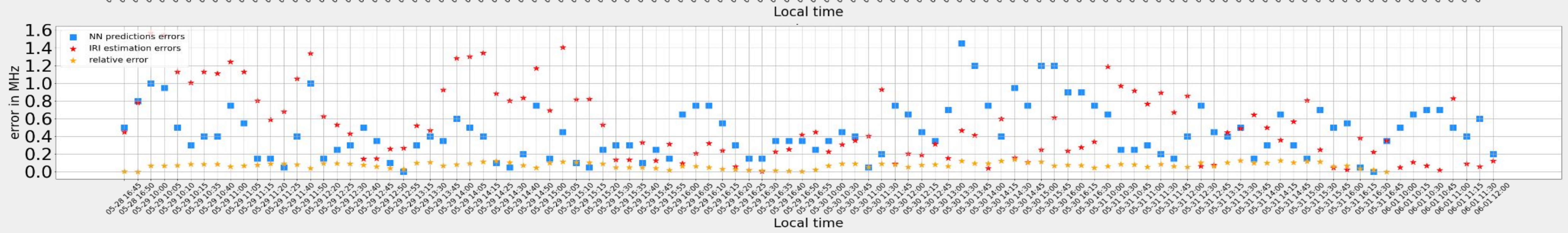


Figure 12. foF2 relative errors calculated with IRI model and the foF2 NN model predictions.

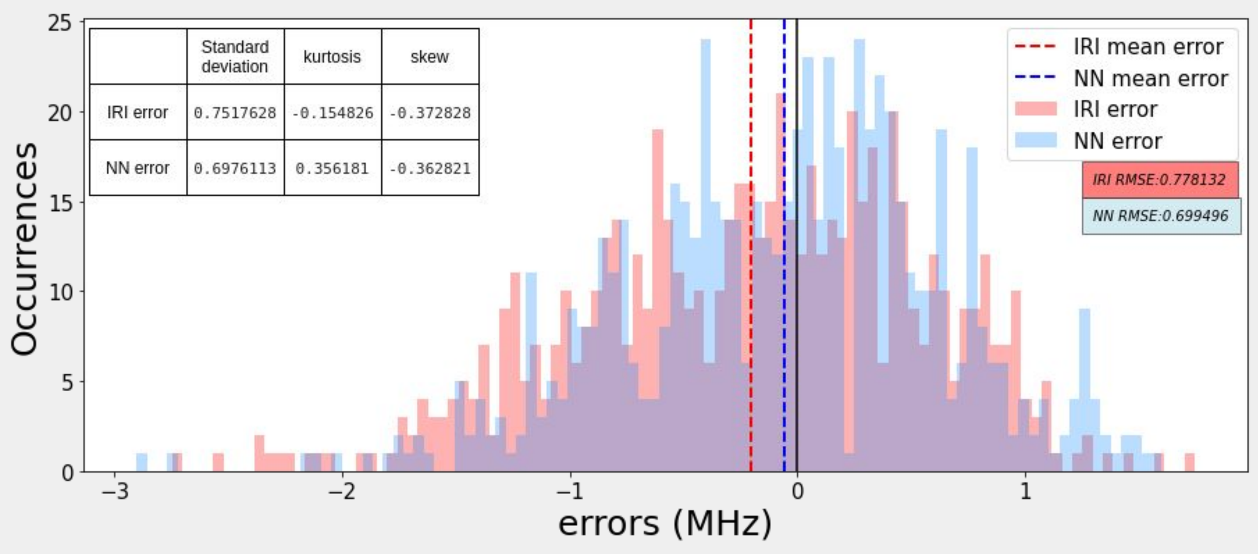


Figure 13. Histogram to show IRI and NN model error distribution and, error statistics.

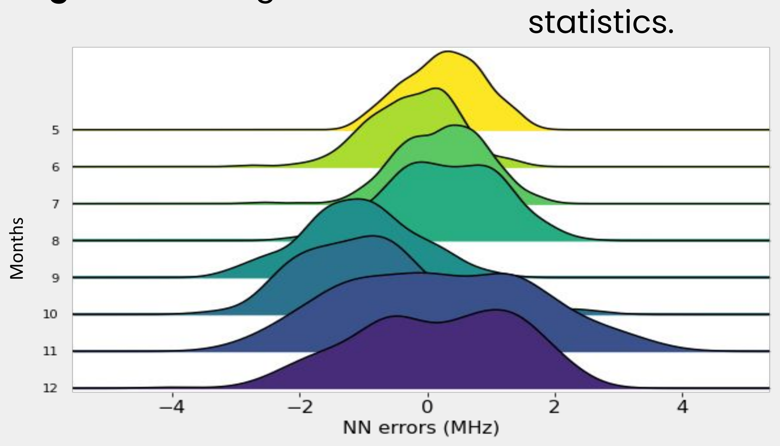


Figure 14. Density plot to show Neural network prediction errors around months from some days of May to December.

5. Conclusions

- Neural networks model can capture, geophysical parameters and virtual heights variations to show foF2 results slightly better than IRI estimations.
- Ionogram estimations that adjust to the ionogram's common shape were predicted for eight months.
- By using not only frequencies that are foF2 but also frequencies that are not and virtual heights to estimate foF2, we can observe that this approach looks like a promising application for small datasets made with a neural network that is not based on memory, which implies it is a less complex approach. However, more training with more data must be made to make affirmations.

6. Future works

- There are available 20 years of ionogram data at Jicamarca digisonde. Thus, more training will be realized and all hours will be include.
- To evaluate this performance new SAMI2 comparison will be made.
- After accurate ionogram predictions have been made, future work will be oriented toward electron densities forecasting.

7. Acknowledgments

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8. References

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