Modeling ionograms with deep neural networks: Applications to nowcasting

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Scientific problem

- Initially, we developed this work 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[1].

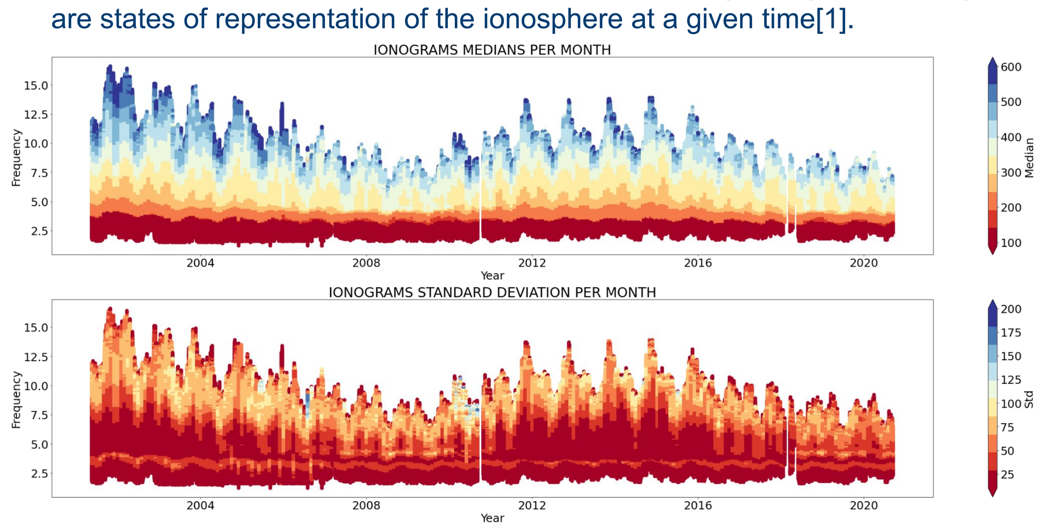


Figure 1. Ionograms medians and standard deviation per month from 8am - 11am ionograms.

- We assume that there is a functional unknown relation between some geophysical parameters and virtual heights from ionograms. Even though this unknown function could in principle be extremely complicated, we assume that the versatility of deep neural networks (DNN) could be a good candidate to capture its behavior. Therefore, we propose to train a DNN with Jicamarca Radio Observatory's digisonde data to reconstruct this unknown function, which would give us ionogram forecasting capabilities.

Why do we need to predict foF2?

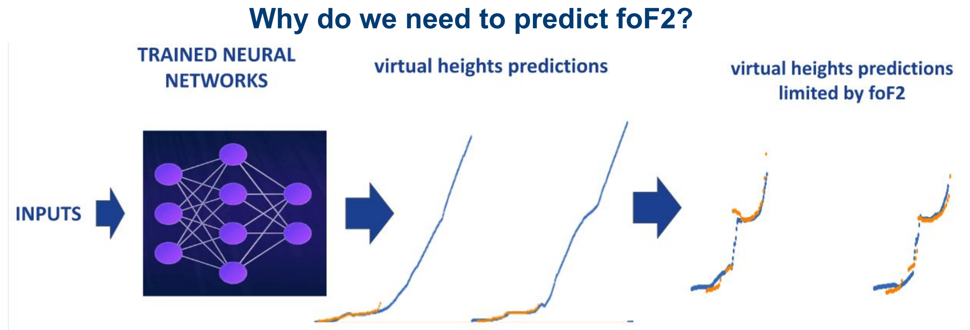


Figure 2. Ionograms predictions limited by foF2.

- Given that regression DNN will estimate a virtual height for every possible frequency, a separate estimate of fof2 has to be provided.
- Several approaches have been used to estimate foF2 by training neural networks with foF2 and geophysical data and, as presented in [2]. Nevertheless, to our knowledge, this is the first time that ionograms have been included in the model.

Datasets

- We trained and tested our model using eight different datasets. We considered four different seasons with different levels of f10.7, and hours from 8 am to 5 pm (local time). Within each season, we trained our model using 1 and 3 months of data to compare the effect of the different data sizes.
- We filtered Digisonde ionograms used to train the model using ARTIST flags' c-level flag. The c-level flag indicates and qualifies some ARTIST scaled results[3]. 11 means high quality and 55 low quality. We took ionograms labeled with 11.

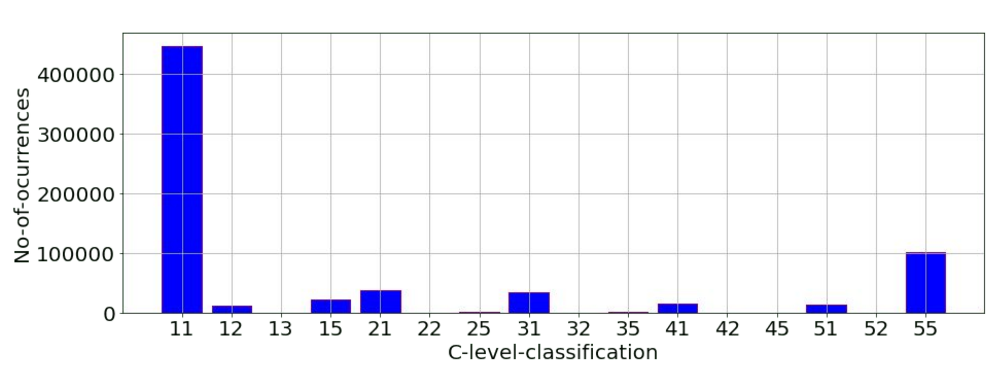


Figure 3. Bar chart to show the quantity of 20 years of Jicamarca digisonde data labeled with different c-levels categories.

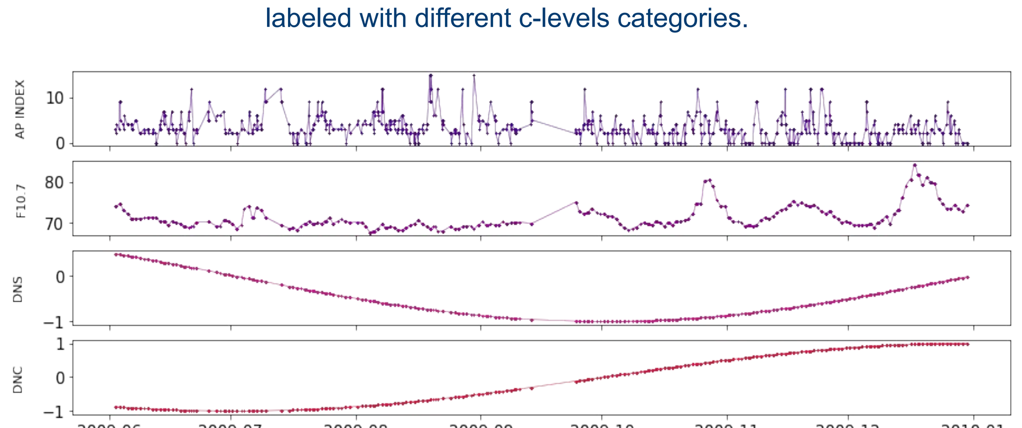


Figure 4. Input parameters time series for some dates.

- Day of year values were converted into 2 quadrature components to avoid discontinuities as proposed in [4].
- 72% of data in each dataset was used to train the model, 24% was considered for the validation set and 4% to test the data. This 4% represents 1 day of ionograms data.

Models and Hyperparameter tuning

- Two supervised models are presented. Both models use a regression neural network for virtual heights forecasting. Model one uses a regression NN with foF2 data and Model 2 is a binary classification one that unliked other machine learning methods or approaches includes virtual heights and frequencies that are not foF2 in the training data.

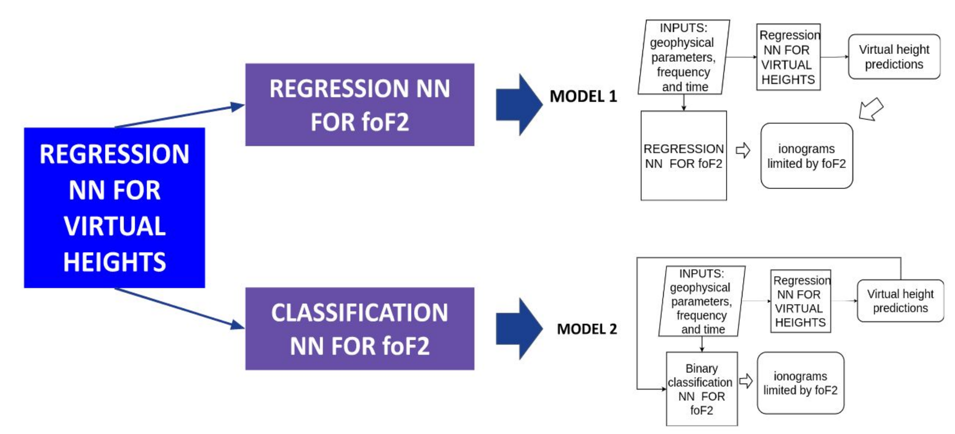


Figure 5. The two proposed models.

- The learning rate and numbers of nodes by layers were chosen with OPTUNA, an open-source hyperparameter optimization framework[5].
- Relu and sigmoid activation functions were used.

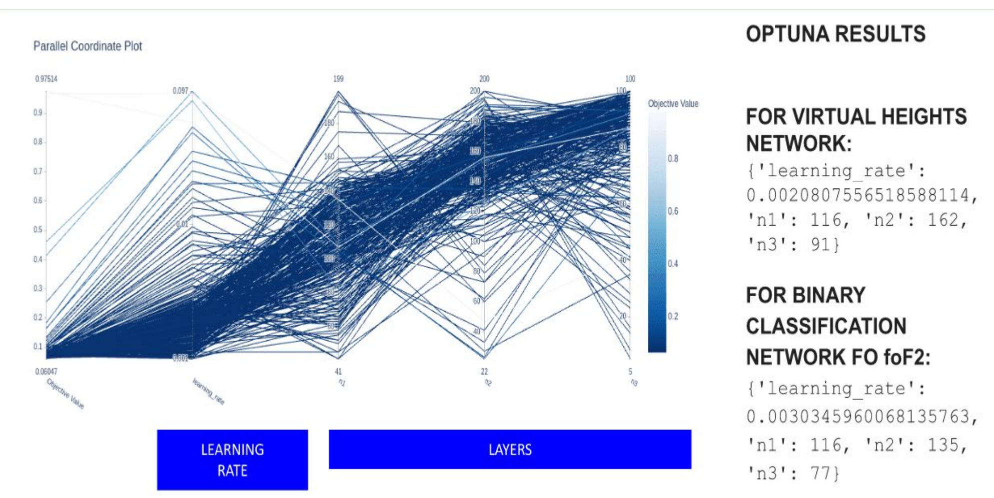


Figure 6. Optuna parallel plot and some results obtained with OPTUNA.

- Different hyper-parameters were obtained for each dataset.
- Validation set was given to OPTUNA to find the best hyper-parameters.

Results and comparisons

- Four activity seasons were evaluated for testing the model: a solstice of a solar minimum, one equinox of solar minimum, one solstice of solar maximum, and one equinox of solar maximum. We present results and comparisons for the solstice of the solar minimum.

Results for solstice of solar minimum

Ionogram comparisons

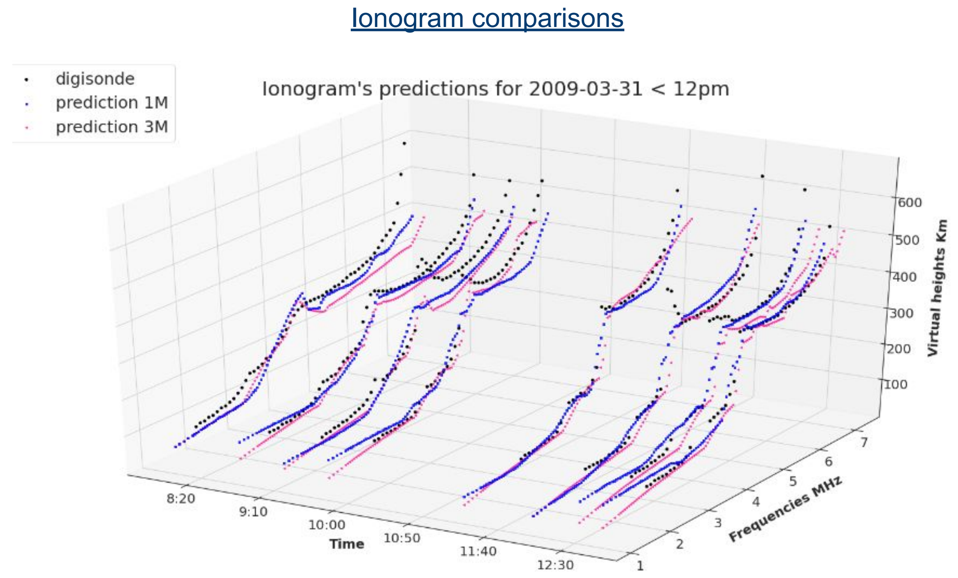


Figure 7. Comparisons of morning ionograms predictions using one month and three months of data to train the model.

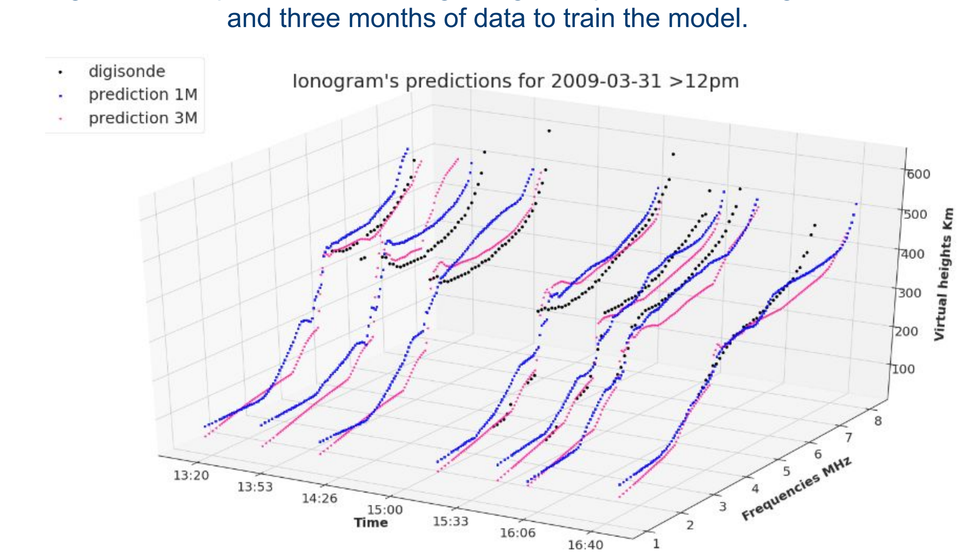


Figure 8. Comparisons of afternoon ionograms predictions using one month and three months of data to train the model.

Results and comparisons

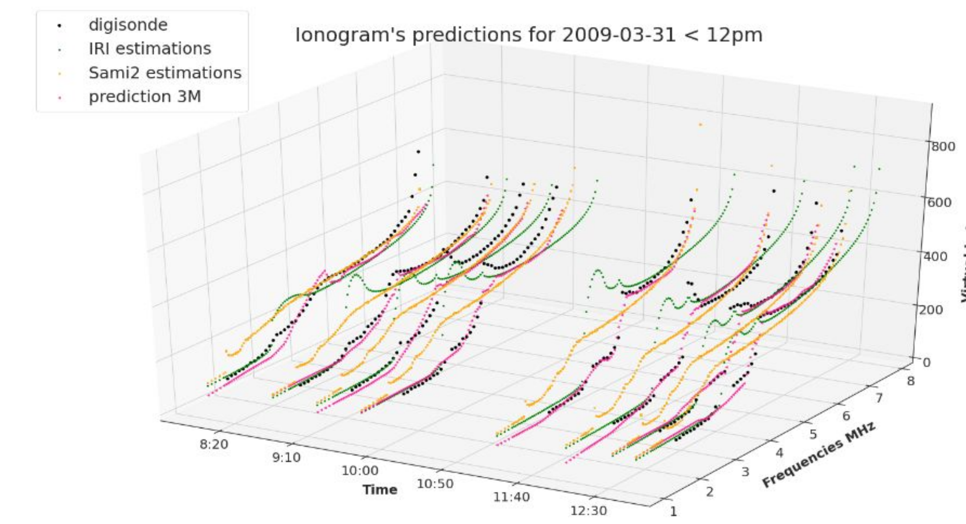


Figure 9. Comparisons of morning ionograms predictions to digisonde values, IRI and SAMI2 predictions.

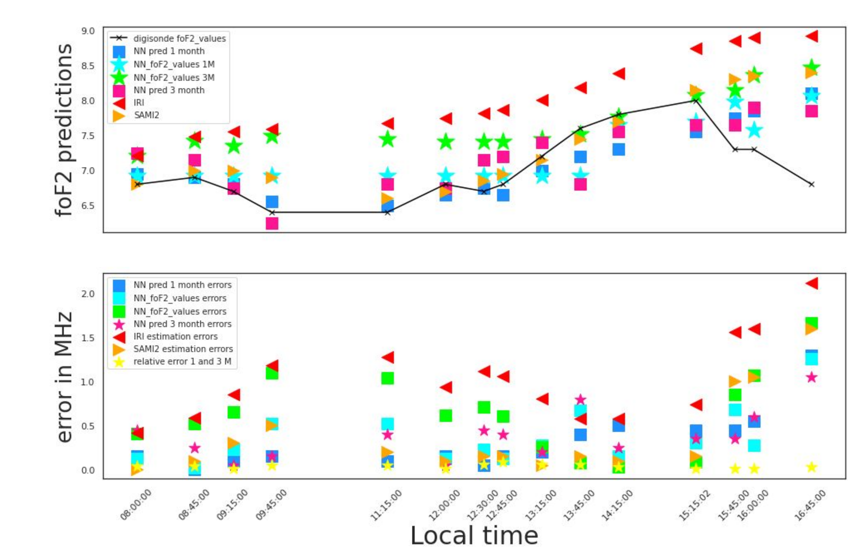
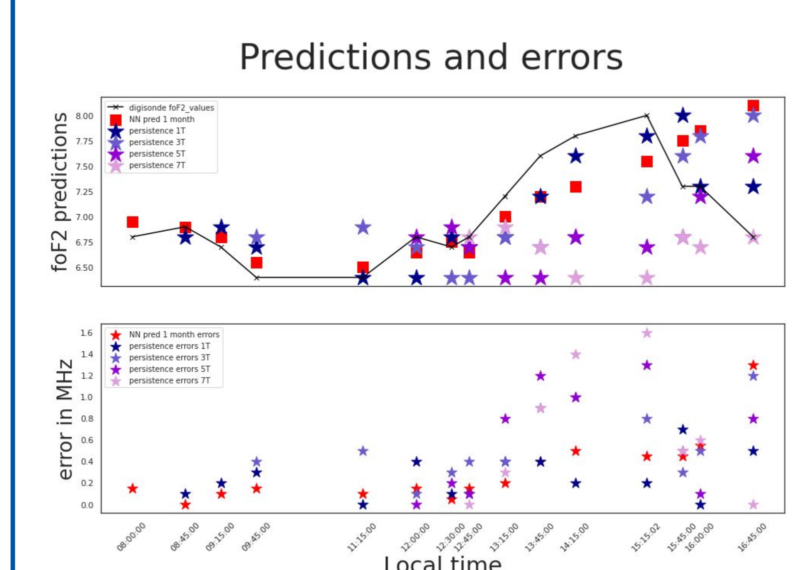


Figure 10. foF2 predictions and errors of our models and their comparisons to digisonde values, IRI and SAMI2.



- The persistence model uses the value at the previous time step (t-1) to predict the expected outcome at the next time step (t+1).

Figure 11. foF2 predictions and errors of our models and their comparisons to persistence models.

Figure 12. Metrics table to compare performance of the evaluated models to forecast ionograms to IRI and SAMI2 using model 2(uses binary classification NN for foF2).

Evaluation of neural network models to estimate ionograms (RMSE Km)				
Metrics	Model 2 (1 month of data)	Model 2 (3 months of data)	IRI ESTIMATIONS	SAMI2 ESTIMATIONS
Solstice of a Solar Minimum (December 2009)	43.47	51.69	87.23	81.15
Equinox of a solar minimum (March 2009)	25.64	30.37	82.86	70.07
Solstice of a solar maximum (June 2014)	53.04	40.20	54.45	91.68
Equinox of a solar maximum (March 2013)	32.46	31.15	67.0	49.23

Figure 13. Metrics table to compare performance of the evaluated models to forecast foF2 to IRI and SAMI2 using model 2(uses binary classification NN for foF2).

Evaluation of neural network models to estimate foF2 (RMSE-MHz)				
Metrics	Model 2 (1 month of data)	Model 2 (3 months of data)	IRI ESTIMATIONS	SAMI2 ESTIMATIONS
Solstice of a Solar Minimum (December 2009)	0.44	0.47	1.12	0.59
Equinox of a solar minimum (March 2009)	0.58	0.51	1	0.75
Solstice of a solar maximum (June 2014)	0.62	0.82	0.67	1.47
Equinox of a solar maximum (March 2013)	1.81	1.53	1.25	0.70

Figure 14. Metrics table to compare the two methods proposed to estimate foF2.

Evaluation of neural network models to estimate foF2					
Season	Metrics	Binary classification network (1 month of data)	Binary classification network (3 months of data)	Regression network of only foF2 (1 month of data)	Regression network of only foF2 (3 months of data)
Solstice of a Solar Minimum (December 2009)	F1	0.97	0.97	does not apply	does not apply
	RMSE	0.44	0.47	0.48	0.78
Equinox of a solar minimum (March 2009)	F1	0.9566	0.9665	does not apply	does not apply
	RMSE	0.58	0.51	0.75	0.48
Solstice of a solar maximum (June 2014)	F1	0.967	0.95	does not apply	does not apply
	RMSE	0.62	0.82	0.66	0.38
Equinox of a solar maximum (March 2013)	F1	0.89	0.9	does not apply	does not apply
	RMSE	1.81	1.53	0.78	0.96

Nowcasting approach

- This neural network outputs differences between ionograms. These will be added to the persistence in order to get new ionogram predictions.

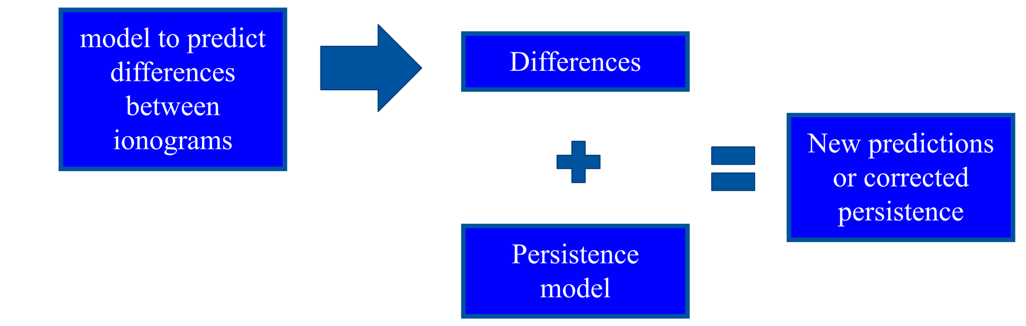


Figure 15. Differences neural network approach

- This nowcasting approach predicts ionograms for the next one or two hours. Here are some preliminary results:

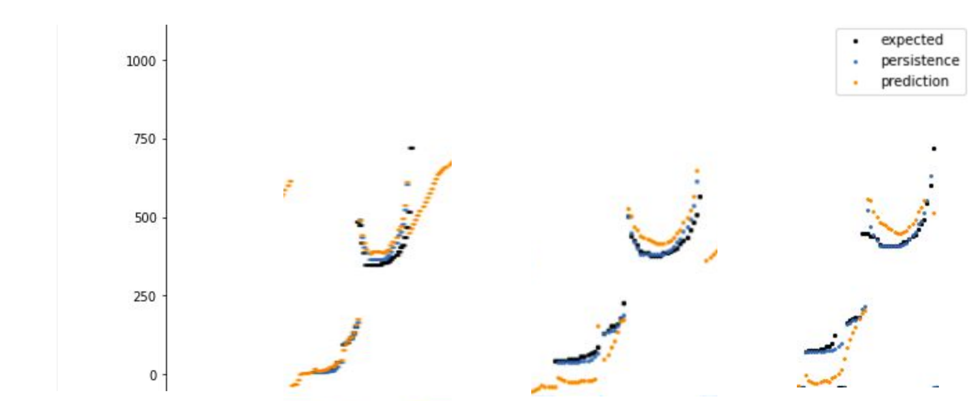


Figure 16. Sequence of predictions produced by the proposed algorithm. Each ionogram prediction is the addition of the previous prediction and the differences produced by the model.

Conclusions and future work

Our preliminary results show:

- Neural networks model trained with 1 and 3 months of data can capture geophysical parameters and virtual heights variations to show virtual heights results better than IRI and SAMI2 estimations.
- 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 is slightly better than using a regression neural network for foF2 during the solar minimum.
- Morning estimated ionograms are better than afternoon ionograms.
- After making tests on small datasets, we can observe through the good estimations that using deep learning or Machine learning approaches with non-complex models can have potential applications to make ionosonde parameters forecasting using ionosondes with few data or recently installed ionosondes.
- We will continue exploring the nowcasting approach.
- Future work will be oriented toward electron densities forecasting.

References

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