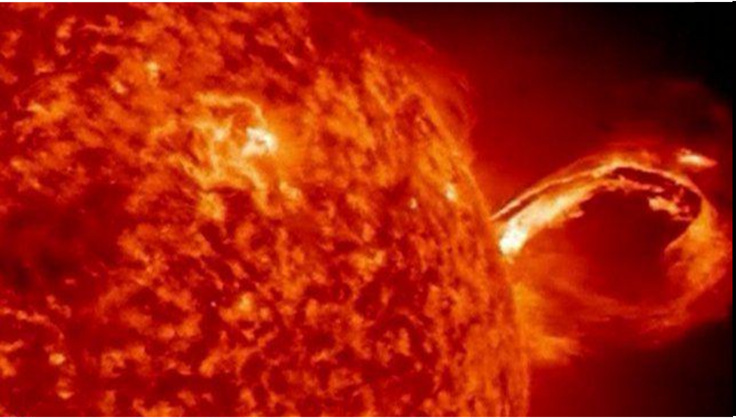

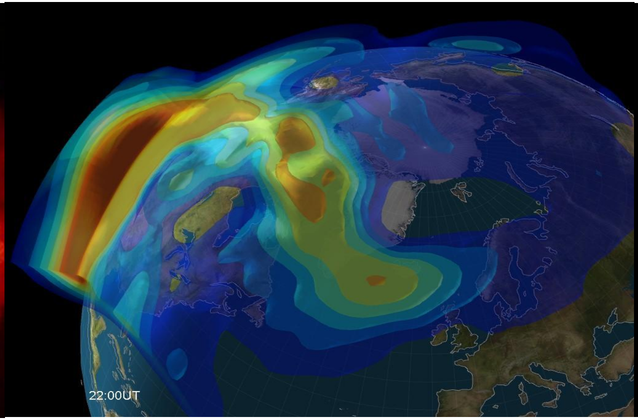

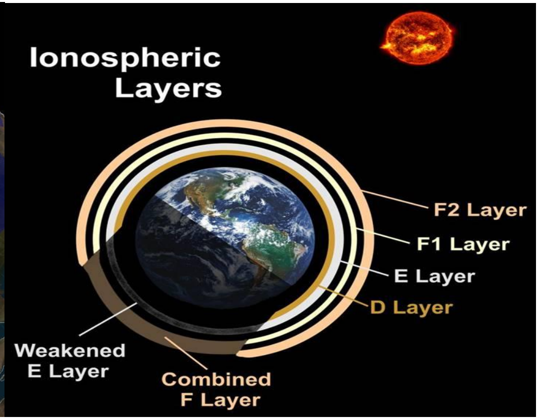

Global VTEC Modeling with Neural Networks

Karolina Kume [1,2], Prof. Dr. Yuri Shprits [1,2,3], Artem Smirnov [1,2], Dr. Irina Zhelavskaya [1], Dr. Ruggero Vasile [1], Dr. Stefano Bianco [1]

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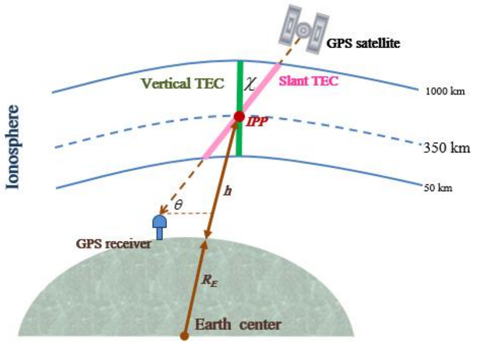
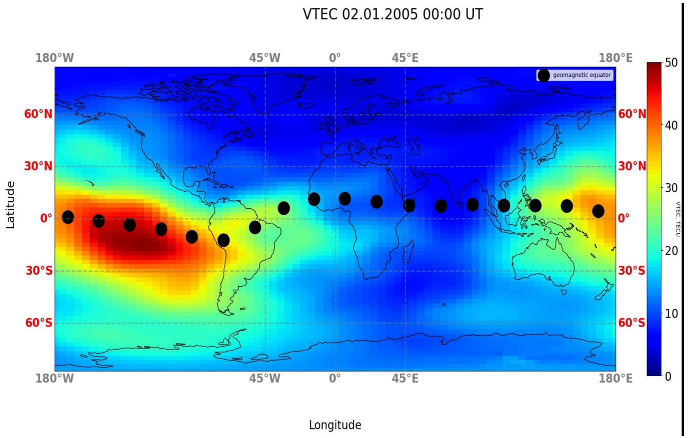
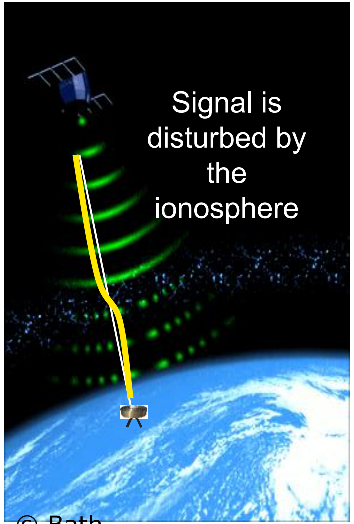


source: Thai GNSS and Space Weather
http://iono-gnss.kmitl.ac.th/?page_id=243





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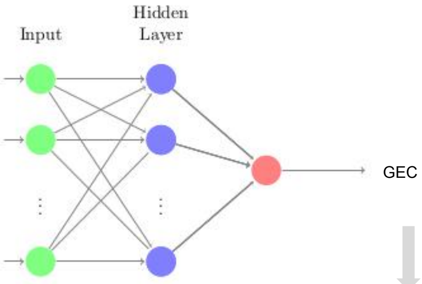
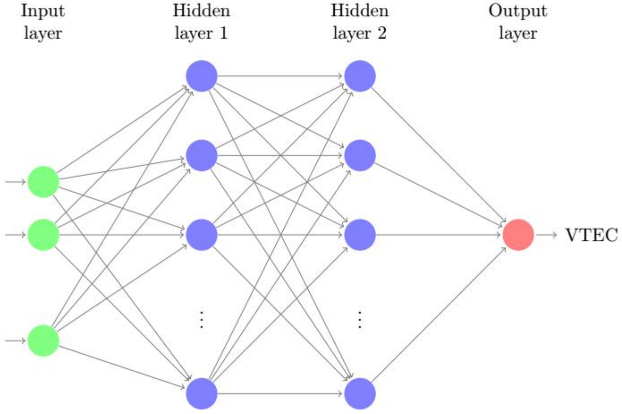
- Objective of the study: develop machine learning model of Vertical Total Electron Content (VTEC)
- VTEC: electron columnar number density
- Extracted by GNSS measurements from the IGS network
- Measured indirectly based on the GPS signal transmission delay

- solar irradiation
- solar wind
- geomagnetic disturbances
- time and DOY

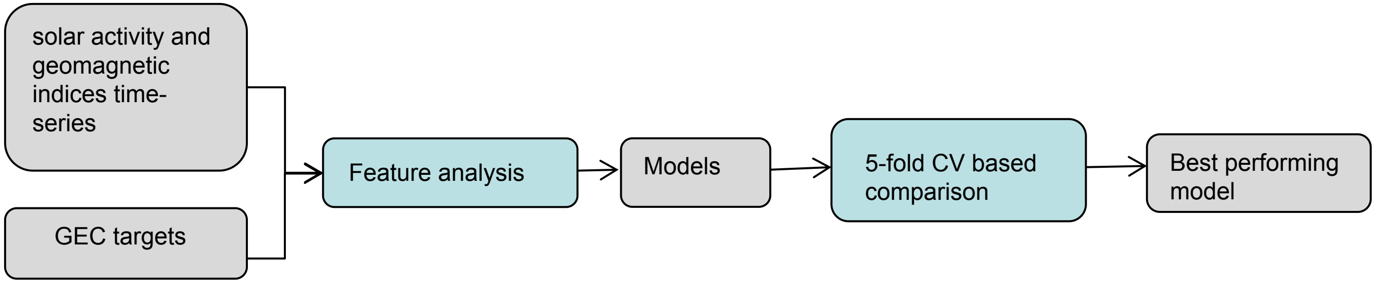


Local modeling

- magnetic latitude
- magnetic local time
- cos(magnetic latitude)
- sin(magnetic latitude)
- solar elevation angle
- cos(solar elevation angle)
- sin(solar elevation angle)
- cos(geographic longitude)
- sine(geographic longitude)



Global modeling


solar activity and geomagnetic indices time-series
GEC targets
Feature analysis
Models
5-fold CV based comparison
Best performing model

Feature selection methods:

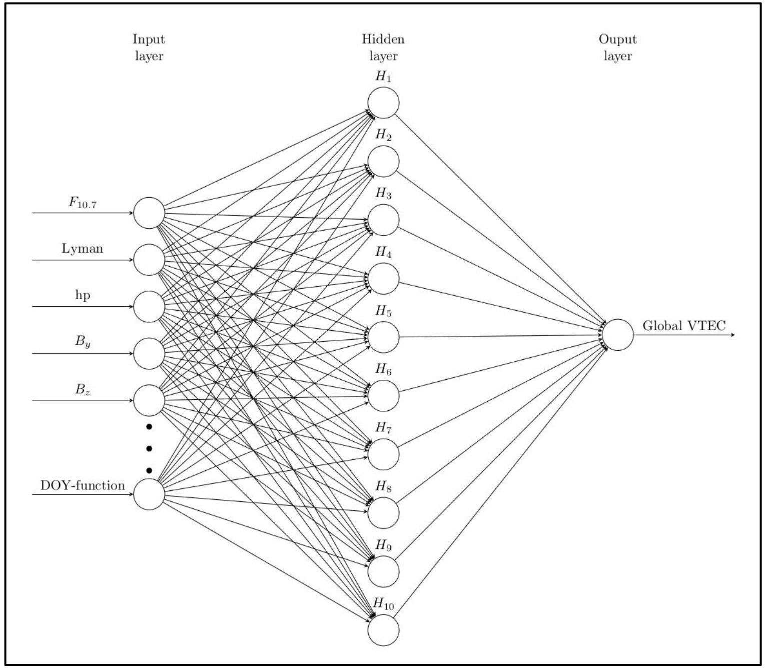
1. Related work of continuous 3D electron density model by Smirnov et al, 2020 adding time histories
2. Time-lagged Pearson cross-correlation
3. Permutation feature importance
4. Mutual information

X_A	X_B	X_C	Y
xa1	*xb1*	*xc1*	*y1*
xa2	*xb2*	*xc2*	*y2*
xa3	*xb3*	*xc3*	*y3*
xa4	*xb4*	*xc4*	*y4*
xa5	*xb5*	*xc5*	*y5*
xa6	*xb6*	*xc6*	*y6*

Permutation feature importance illustration
Source: Cerliani M., Feature Importance with Neural Network, Towards Data Science

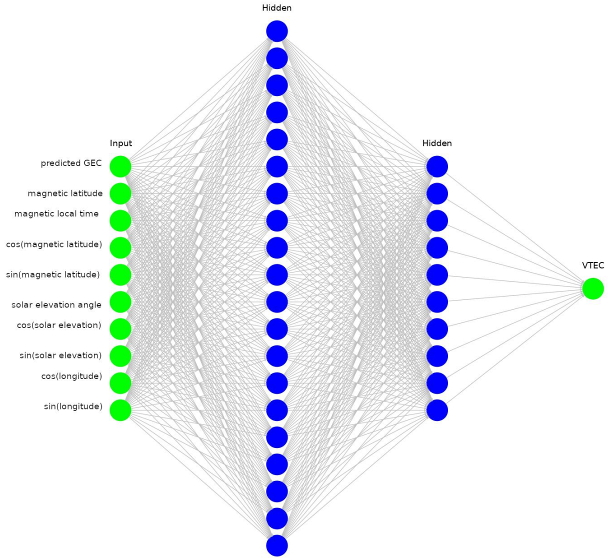
- Neural network consists of ten neurons

- Feature set consists of Lyman alpha, F 10.7 , B_y , B_z , V_x , SYM-H, Hp, trigonometric functions of DOY and universal time with time histories from the previous 72 and 96 hours

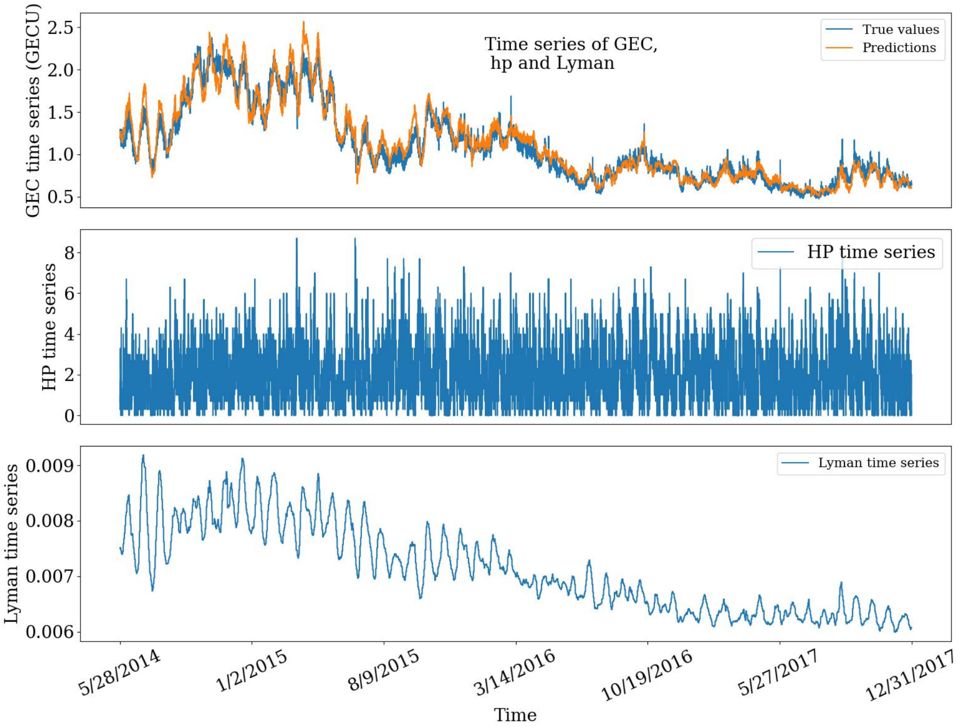


- Final neural network was tested on years 2004, 2006, 2011, 2016

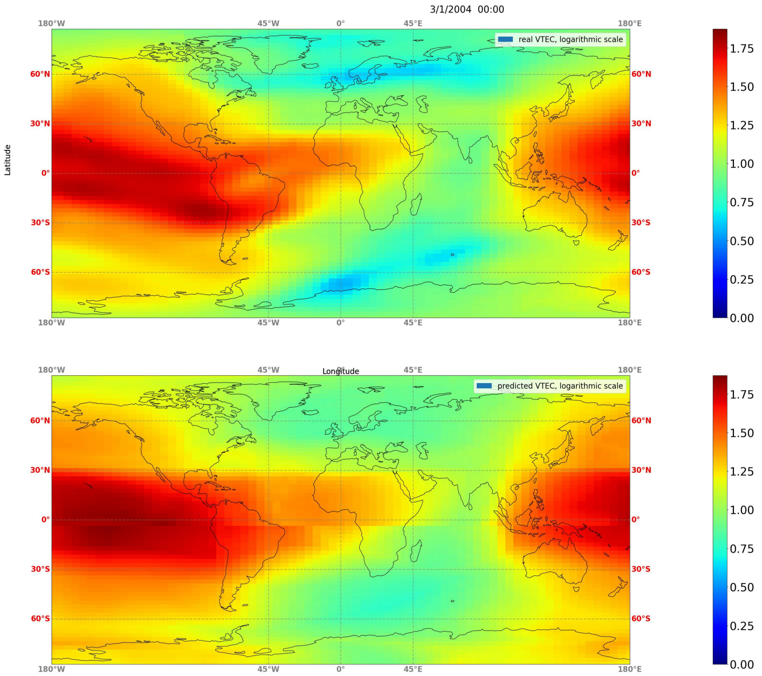
Period	RMSE	MAE
2004	4.9	3.6
2006	3.8	2.8
2011	6.6	4.7
2016	4.7	3.6
entire period	5.1	3.7



- Test data: 2014 - 2017
- Performance in test data expressed in correlation 97 %

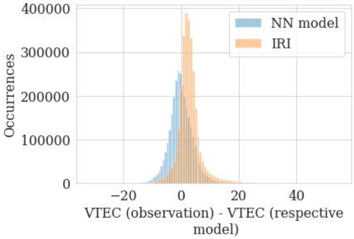


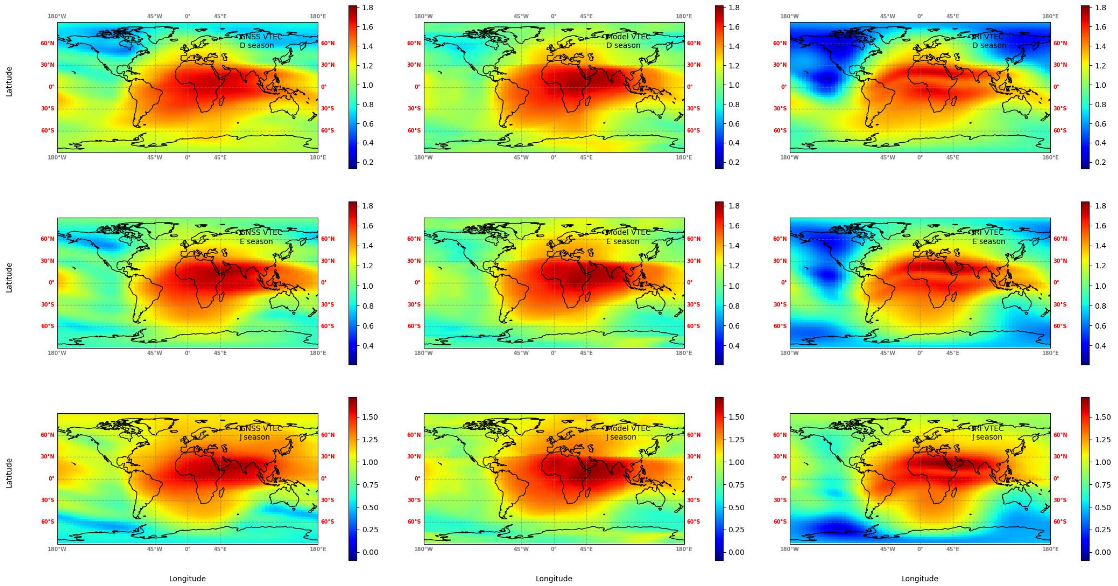
- Diurnal variation in logarithmic scale
- Model captures reasonably well the variations of the target
- Model was compared to 1-step variant and has better performance and reduces overfitting by 62%



- D-season or December solstice: January, February, November, December
- E-season or Equinoxes: March, April, September, October
- J-season or June solstice: June, July, May, August

Type	IRI	NN
RMSE	5.3	4.3
Dist. mean	2.8	-0.09





Future directions

- Incorporate information from tidal waves into the model
- Experiment extensively with data rebalancing techniques for a storm-time model

Summary

- A new approach for modeling VTEC is introduced with separation of global and local component
- The approach introduces significant advantages in terms of computational complexity
- In the global component, the GEC is predicted based on geomagnetic and solar indices
- The agreement of observations and model for GEC is 97 % in terms of correlation
- In the local component, the VTEC is predicted based on GEC and geographic and geomagnetic coordinates
- The final model achieves good results for different solar cycle activity periods

Acknowledgments

This research is supported by the Helmholtz Pilot Projects Information & Data Science II, MAchine learning based Plasma density model project (MAP) - ZT-I-0022.

Additional Slides

Measurements of VTEC

- TEC can be derived from electron density $$\mathrm{STEC}(x_r, x^s, t) = \int_{x_r}^{x^s} N_e(s,t)\,ds$$

- TEC can be derived from GNSS measurements $$P_1 - P_2 = \frac{40.3(f_2^2 - f_1^2)}{f_1^2 f_2^2} \cdot mf(z) \cdot VTEC + c(DCB_s + DCB_r)$$

where P 1 and P 2 are the smoothed dual-frequency code measurements; f 1 and f 2 are the carrier frequencies of the L1 and L2 signals, respectively; m f is the ionospheric mapping function, which depends on the zenith distance z at the receiver’s location; VTEC is the vertical TEC at the IPP; c is the speed of light; DCB s and DCB r are the differential code biases of satellites and receivers, respectively.

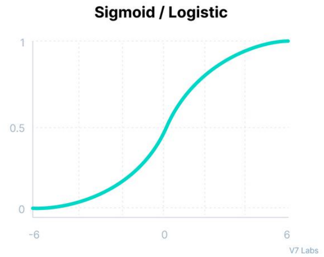
Mutual information and or pearson

- Mutual information in discrete case

$$\mathrm{I}(X;Y) = \sum_{y \in \mathcal{Y}} \sum_{x \in \mathcal{X}} p_{(X,Y)}(x,y) \log\left(\frac{p_{(X,Y)}(x,y)}{p_X(x)\, p_Y(y)}\right), \quad \textbf{(Eq.1)}$$

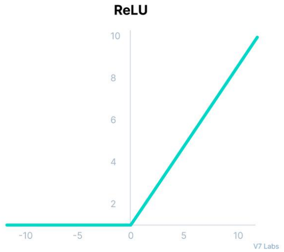
activation functions

- Sigmoid activation function $f(x) = \dfrac{1}{1+e^{-x}}$



Sigmoid/Logistic Activation Function

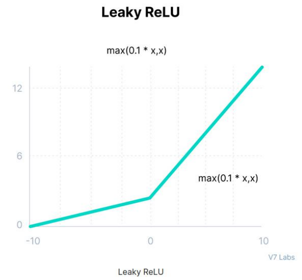
- Rectifier linear unit $f(x) = max\,(0, x)$



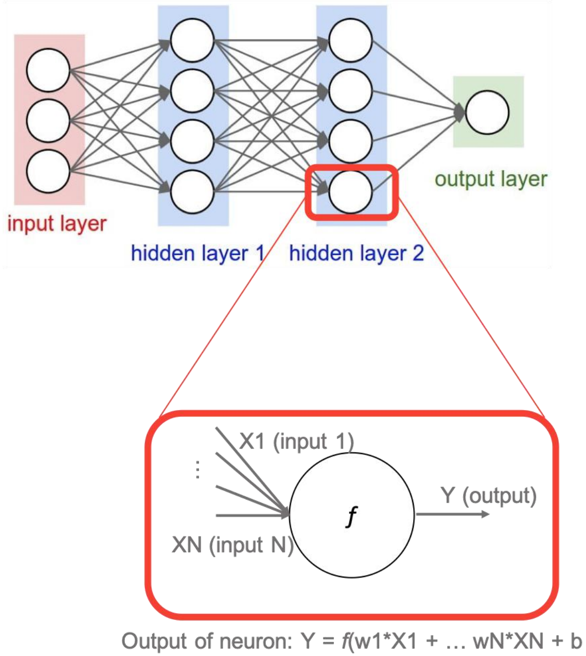
ReLU Activation Function

activation functions

- Leaky RELU $f(x) = max\ (0.1x, x)$



- Powerful algorithms used for classification, function approximation, pattern recognition, outlier detection etc
- Consist of input, one or more hidden layers and output layer
- Each hidden layer computes linear combination of the previous layer inputs and applies non-linear transformation
- Updates of weights and biases through gradient descent applied on difference between observation and prediction



Source: Zhelavskaya I. (2020)

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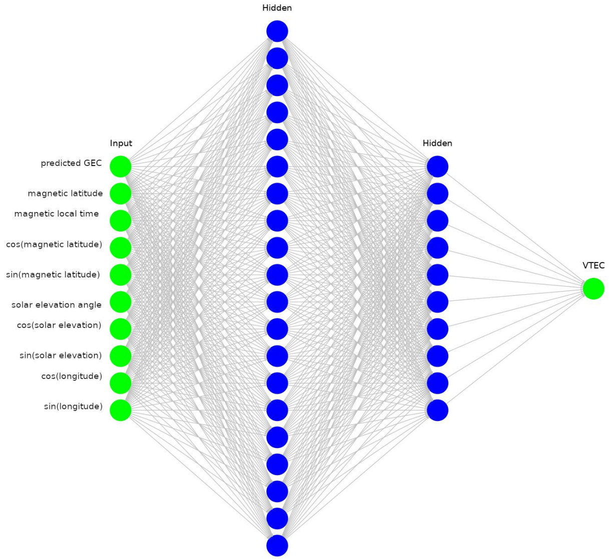

pearson correlation