Research Article

Discussing Total Electron Content over the Solar Wind Parameters

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Modeling and forecasting of Total Electron Content (TEC) values by an Artificial Neural Network model (ANNm) have high agreement on November 2003, 2004 superstorms. The work discusses Solar Wind Parameters (SWp) from OMNI (Operating Missions as a Node on the Internet) and TEC (TECU) data (International Reference Ionosphere) IRI-2012, IRI-2016 on November 20, 2003 (Dst = -422 nT) and on November 08, 2004 (Dst = -374 nT) Geomagnetic Storms (GSs). The paper commences with a 120-hour GS exhibition of SWp and proceeds with the correlation data of the variables, their hierarchical tracks, and inner dispersions. The ANNm with SWp as the input and TEC data as the output are introduced. The performance of the ANNm for 2003 and 2004 superstorms is adequate. The Correlation Coefficient (R) and Root Mean Square Error (RMSE) of the ANNm are 97.5%, 1.17 TECU (IRI-2012), and 97.9%, 1.09 TECU (IRI-2016) for the 2003 GS and 97.0%, 0.89 TECU (IRI-2012), and 98.0%, 1.61 TECU (IRI-2016) for 2004 GS. Parameters effect of the R constant of TEC data points out to the dynamic pressure (nPa), the magnetic field B_z component (nT), the flow speed (km/s), and the proton density ($1/\text{cm}^3$). Besides, the absolute total error and the variance of the predicted TEC data for November 2003 and November 2004 GSs are 0.06 (0.30%) with 0.013 variance (IRI-2012), 0.09 (0.49%) with 0.016 variance (IRI-2016) for 2003 storm and 0.13 (0.73%) with 0.033 variance (IRI-2012), and 0.11 (1.06%) with 0.035 variance (IRI-2016) for 2004. It means that the paper models TEC data with considerable consistency over the SWp.

1. Introduction

Briefly, a geomagnetic storm (GS) [1–11] is the effect of the solar wind to the magnetic field of the Earth. The solar wind traveling through the interplanetary medium has tremendous energy-charge density. The GS is named by the southward peak value of the disturbance storm time (Dst (nT)) zonal geomagnetic index after the B_z (nT) magnetic field is rushed from the northward (positive direction) to the southward (negative direction). The GS initiates with the deceleration of the flow wind velocity v (km/s). Meanwhile, the dynamic pressure P (nPa) and the proton density N ($1/\text{cm}^3$) respond with the sudden acceleration called coronal mass ejection (CME). The high-speed solar wind reaches the ionosphere with CME and causes ionospheric instabilities through intense currents [12]. The ionosphere coat, which covers from 50 to 1000 km, is the layer of the Earth's upper atmosphere. The total electron content (TEC) is one of the principal ionospheric parameters. The TEC (TECU) describes the electron density at a cross-section zone of 1 m^2

during the transferring of the signal. The unit of TEC is specified by 10^{16} electrons/ m^2 [1, 13–15]. The electric field fluctuation in lower latitudes induces ionospheric-magnetospheric disturbances that may be classified as negative or positive. While the electron density diminishes in the negative disturbances, the electron density enhances in the positive ones [16]. Ionospheric storms, which alter depending on the solar action, the Earth's turning, and spatial, regular, monthly, and seasonal circumstances, have different impacts in the ionosphere [17, 18]. The TEC values, which change over time and ought to be evaluated along with their location in space, are the principal factors for solar activity and ionosphere-magnetosphere-Sun interaction [3, 19–36]. This essay predicts the TEC values through an artificial neural network model (ANNm) [7, 8, 37–45] over the superstorms of November 20, 2003 (Dst = -422 nT) and November 08, 2004 (Dst = -374 nT). The predicted TEC values are criss cross checked with the values attained from the IRI-2012 and 2016 [31, 46–48] model. The IRI model, which has been incessantly improved after its first version

was produced in 1978, was created by the collaboration of the International Union of Radio Science (URSI) and the Committee on Space Research (COSPAR). The last open data-based version of the model is the IRI-2016 model. IRI may introduce various parameters concerned with the ionosphere, holding the TEC value for ionosphere altitudes between 50 km and 2000 km along with time, date, and position [47].

The solar wind parameters (SWp) and the TEC values of the IRI-2012, 2016 model are utilized in the ANNm that performs the backpropagation iteration of Rumelhart et al. [49]. The Scaled Conjugate Gradient (trainscg) training algorithm is used with thirty-five neural members supplying inner dealings of the ANNm. The TEC data is gained as the output while the SWp (B_z , E , P , N , v , T) are selected as the input to the ANNm, where B_z (nT) is the magnetic field (B) and component (z), N is the proton density ($1/\text{cm}^3$), T is the temperature (K), v is the plasma flow velocity (km/s), P is the dynamic pressure (nPa), and E is the electric field (mV/m). The TEC values are related to the IRI-2012 and 2016 data, and the consistency of the consequence is evaluated with the aid of the correlation coefficient (R) and the root means square error (RMSE (TECU)). After that, the data attained from the ANNm is pictured with the absolute error rate.

The purpose of the paper is to model and compare the TEC (TECU) values of the two declared geomagnetic phenomena by the ANN. The work obeys the causality principle [50–52]. In the light of this principle, the cause is the SWp and the effect is TEC variables. In the ANNm established, the paper is governed by the physical facts of the GSs. The novelty of this paper is that it predicts TEC data for two superstorms with considerable consistency, obeying the causality principle, based on the solar wind parameters. In estimating IRI-2012 and IRI-2016 TEC data, the same ANN framework has modeled different TEC data with RMSE scores under two and with variance under one.

The first part scans the background, the next section tries to comprehend the dynamics of the GSs, and the third part handles the binary relations, hierarchical clusters, and scattering of the SWp, TEC variables. The ANN investigation is utilized for the modeling of the TEC variables. In the last section, the work is concluded by discussions of the results.

The hourly version of data is employed in the essay.

2. Data

TEC values gained from IRI-2012 and 2016 for the related day were calculated online from URL 1 by entering the latitude and longitude of the station used in the application. TEC values calculated from IRI-2012-2016 are gained along with the latitude and longitude of the epicenter of the earthquakes that happened in Papua New Guinea-New Britain ($5.581^\circ\text{S}/150.88^\circ\text{E}$) on November 25, 2003, and Indonesia-Alor Island ($8.152^\circ\text{S}/124.868^\circ\text{E}$) on November 11, 2004.

This paper uses 450 km as F-peak height to define total electron content. “IRI TEC values are obtained for a specific time and location hourly from the latest version, the IRI-2012 and IRI-2016 online model” (https://ccmc.gsfc.nasa.gov/modelweb/models/iri2012_vitmo.php and https://ccmc.gsfc.nasa.gov/modelweb/models/iri2016_vitmo.php). This paper uses “NeQuick” as “electron density profile” at the top, “URSI” as “Ne F-peak (on)”, and “AMTB2013” as “F-peak height”.

The performances of IRI-2012 and IRI-2016 in this paper do not differ significantly. In general, minor differences are expected [53–56]. Under 300 km [55], the IRI models predict a little less than the observed TEC value. While this deviation in estimation increases for IRI-2016 around the equinoxes, it decreases during solar minimum. So, IRI-2016 is relatively more accurate at the solar minimum than IRI-2012. Again, under 300 km, IRI-2016 is closer to the observed TEC values over the plot for bins [55].

In the modeling of TEC data obtained during the 24th solar cycle from Guntur (India), Sukkur (Pakistan), and Agartala (India), the results obtained with IRI-2016 are more consistent than the results of IRI-2012 [53, 54, 56].

Figure 1 exhibits the 120-hour (five-day) scene of the SWPs of the two super GSs. The phenomenon day is centered at the five-day storm period. The paper employs SPEDAS (Space Physics Environment Data Analysis Software) to indicate oscillations in the SWp of GSs.

By looking at Figure 1, something can be said about the process of the super GSs. At 07:00 UT on November 19, a sudden acceleration in the dynamic pressure (nPa) occurs with the assistance of the proton density ($1/\text{cm}^3$). This means that the first CME commences the November 2003 superstorm. Meanwhile, the B_z (nT) magnetic field straightly orients from the negative northward to the positive southward. The B_z magnetic field immediately catches its deep value (-50.9 nT) and the Dst (nT) index takes place in the center of the storm that the Dst index shows its negative peak values (-422 nT) within a couple of hours. On November 20, 2003, the time shows 20:00 UT when the Dst index hits its negative peak. The smallest value time of the Dst index is the main phase of the GS.

Once again, by looking at Figure 1 for the November 2004 superstorm, on November 06, at 15:00 UT, the first CME commences with an unpredicted jump in the dynamic pressure (from 1.11 nPa to 5.31 nPa) and the proton density (from 5.3 $1/\text{cm}^3$ to 18.0 $1/\text{cm}^3$). The CME of the November 2004 superstorm is far more shocking than that of the November 2003 storm. On November 07, another CME bursts at 03:00 UT. November 08 (06:00 UT) is the storm day in which the Dst index indicates its supreme value of -374 nT after the orienting of the B_z magnetic field from the northward to the southward.

3. Modeling

Dual relation with the Pearson correlation matrix for the variable of the November 20, 2003, and November 08, 2004, super GSs are displayed in Tables 1 and 2. Tables 1 and 2 tell the mutual relation of the variables. Table 1 values closer to ± 1 show stronger correlations. The hierarchical presence of GSs data and scattering of variables are exhibited in Figures 2(a) and 2(b) and Figure 3, respectively. Each line shows the correlation of data by means of the dendrogram.

After that, in the statistical corporation of data, one can need to recall the ANNm (Figure 4).

FIGURE 1: The B_z (nT), the E (mV/m), the P (nPa), the N ($1/\text{cm}^3$), the v (km/s), and T (K) SWp for (a) November 20, 2003 (b) November 08, 2004.

TABLE 1: Data correlation matrix (November 20, 2003).

	B_z	T	N	V	P	E	TEC(2012)	TEC(2016)
B_z (nT)	1	0.149	-0.533**	-0.068	-0.508**	-0.998**	0.319**	0.305**
T (K)		1	-0.024	0.571**	0.152	-0.135	-0.190*	-0.179
N ($1/\text{cm}^3$)			1	-0.003	0.949**	0.524**	-0.089	-0.101
V (km/s)				1	0.238**	0.082	-0.026	0.015
P (nPa)					1	0.505**	-0.136	-0.140
E (mV/m)						1	-0.317**	-0.304**
TEC (TECU)							1	1

TABLE 2: Data correlation matrix (November 08, 2004).

	B_z	T	N	v	P	E	TEC(2012)	TEC(2016)
B_z (nT)	1	0.205*	0.167	-0.265**	0.001	-0.992**	-0.309**	-0.260**
T (K)		1	0.172	0.268**	0.436**	0.203*	-0.194*	-0.173
N ($1/\text{cm}^3$)			1	-0.109	0.686**	-0.125	-0.132	-0.101
V (km/s)				1	0.443**	0.220*	-0.083	-0.198*
P (nPa)					1	0.004	-0.177	-0.193*
E (mV/m)						1	0.312**	0.267**
TEC (TECU)							1	1

**The 0.01 level (2-tailed) and *the 0.05 level (2-tailed).

FIGURE 2: (a) Cluster of the variables (Left side is IRI-2012 and the right side is IRI-2016, November 20, 2003 storm). (b) The cluster of the variables (Left side is IRI-2012 and the right side is IRI-2016, November 08, 2004 storm).

The ANNm is inspired by the human brain that connects via neurons. The ANNm has sheets that are named input, hidden, and output layers (Figure 4) as they resemble the brain regions. This complex organization learns by training with the support of mathematical instruments, especially nonlinear ones. The ANN inputs-outputs do not need any info or homework for modeling [37].

This ANNm employs the following equation:

$$y_{ij} = \sum_{k=1}^n w_{kj} x_{ik} + b_j, \quad (1)$$

where w is the weight vector, y is the independent variable of the activation function (as an output), x is the input, and B is the bias. The sigmoid transfer function [57] is f :

$$f(y) = \frac{1}{1 + e^{-y}}, \quad (2)$$

where f is the logistic function.

The instructional learning technique is extensively used [58]. The ANN background includes some layers and a predefined quantity neural cell that is utilized for inner contact. The input layer is commonly the first layer. The

hidden layer [37] is the other layer. One hidden layer is frequently preferred rather than multiple layers [59]. The last layer is the output layer. While the input layer includes the independent variables (SWp: B_z , T , N , v , P , E), the output layer comprises the dependent variable (TEC) in this essay. The output layer utilizes the sigmoid transfer function. The author employs 120 (hours) data totally; 84 hours (70%) are used for training ANN, 24 hours (20%) for testing, and 12 hours (10%) for validating. The essay commits the back-propagation algorithm that learns feedback reiteration for the prediction. The gradient reduction method that utilizes the weights of the variables piles up the all iterations. Newton's approach [60] and gradient decrease are commonly used as a standard optimization in backpropagation algorithms. Feedback training-learning employing constant input minimalizes the total error residue by backward cluster. The work uses the Scaled Conjugate Gradient (trainscg) training algorithm.

After generating the training algorithm, the amount of the hidden layer of the neurons ought to be assigned. The number of neurons is stated as an involved amount. While few neurons reason insufficient learning, large numbers of neurons cause memorizing the ANNm. The appropriate

FIGURE 3: Scattering of the variables.

amount of neurons allows the ANN to develop its generalization facility [61, 62]. The number of the layer's neurons is addressed as thirty-five, in which the Mean Square Error (MSE) value inclines to be stable. The MSE is as follows:

$$\text{MSE} = \frac{1}{n} \sum (y_{\text{observed}} - y_{\text{estimated}})^2. \quad (3)$$

The ANN yields satisfactory results after its own training. All updates should be as free from memorization as possible. Updates of the time series are interrupted as soon as they reach the stability of the training-test-validation iterations (Figure 5). When the MSE (equation (3)) optimization model reaches stability, the iteration (period, update) step is terminated. Figure 5 shows the MSE (TECU) values of TEC data for the November 20, 2003, and November 8, 2004, superstorms.

The considerable researches introduce remarkable RMSE consequences in the estimation of TEC values. One may discover some forecasting in Tulunay et al. [35] with 1.975 TECU, Ansari et al. [19] with 1.797 TECU, Inyurt and Sekertekin [42] with 3.92 TECU, Razin and Voosoghi [45] with 1.756 TECU.

We consider that our consequences merit the readers' evaluation. The relatively small RMSE (TECU) rates, with the margin of error of the prediction reliability of the TEC data, are exhibited in Figure 5. The TEC values are compared with the IRI-2012 and 2016 data.

According to Figure 5, TEC value estimation RMSE scores are 1.17 TECU (IRI-2012) and 1.09 TECU (IRI-2016) for November 20, 2003 GS.

For November 08, 2004, GS, TEC value estimation RMSE scores are 0.89 TECU (IRI-2012) and 1.61 TECU (IRI-2016) for November 20, 2003, GS.

FIGURE 4: The ANN framework for the variables.

Figures 6(a) and 6(b) display the yielding of the discussion gained from IRI-2012, 2016 and the estimated TEC values. It may be realized from Figures 6(a) and 6(b) that there is an agreement among the R values of the training, testing, and output target.

One may discover R correlation constant of some forecasts in Tulunay et al. [35] with 99.0%, Ansari et al. [19] with 91.6%, Inyurt and Sekertekin [42] with 88.0%, Razin and Voosoghi [45] with 88.1%.

The prediction R coefficient of the training, validation, and testing of TEC (TECU) values that were gained to November 2003 GS are 99.5%, 98.3%, 94.6% (IRI-2012), and 98.5%, 99.4%, 95.8% (IRI-2016), respectively (Figure 6(a)).

The prediction R coefficient of the training, validation, and testing of TEC values that were gained to November 2004 GS are 96.6%, 99.6%, 97.1% (IRI-2012), and 98.3%, 98.3%, 96.8% (IRI-2016), respectively (Figure 6(b)).

The TEC values ANN estimation model outcomes of the super GSs seem comparable. The model not only exhibits the suitability of the IRI (2007)-estimated TEC outputs but also shows the reliability of the consequences.

Validation of the ANN model: In this part, one can see to validate the ANN model with the null hypothesis and different location extrapolation. Except for the locations discussed in the paper, the ANN model can be validated for the North Pacific, Hawaii, 5.581°N/150.88°W and Australia offshore, Coral Sea, 21.759°S/156.38°E. Figure 7 shows that the ANN model is also useful in many different locations.

Are the R coefficients obtained in the paper significant and purely event-related, or are they calculated by accidental (random)? This significance test can be done with the classical null hypothesis (H_0) and t -score. Three separate steps should be followed: (i) The null hypothesis is put forward. (ii) The t score is calculated. (iii) A comparison of the t -score with the table value is made. If the t -score is greater than the table value, the hypothesis is rejected. If it is less, it is accepted.

- (i) H_0 : The correlation coefficient is an accidental (calculated by random) value.

(ii) $t = (R/S_R)$ where $S_R = \sqrt{(1 - R^2)/(n - 2)}$ and n is all hours ($n = 120$ hours), $n - 2$ is the degree of freedom. For the 2003 storm, IRI-2012 and IRI-2016 t -scores, $t = 4.766$ and $t = 5.217$, respectively. For the 2004 storm, IRI-2012 and IRI-2016 t -scores, $t = 4.334$ and $t = 5.350$, respectively.

(iii) t -scores with 0.05 and 0.01 errors from the table are 1.66 and 2.36. The calculated t -scores are considerably larger than the table value. In this case, the null hypothesis H_0 is rejected. Ultimately, the R correlation coefficients obtained in the discussion are important and relevant, not accidental.

From another point of view, TEC data obtained from different locations for the validation of the model gives satisfactory results such as the null hypothesis when modeled with the approach used in the study. Figure 7 displays the results.

For 2003 superstorm IRI-2012: North Pacific, Hawaii, 5.581°N/150.88°W

For 2003 superstorm IRI-2016: Australia offshore, Coral Sea, 21.759°S/156.38°E

For 2004 superstorm IRI-2012: North Pacific, Hawaii, 5.581°N/150.88°W

For 2004 superstorm IRI-2016: Australia offshore, Coral Sea, 21.759°S/156.38°E

Figure 8, where the first line is IRI-2012 and the second line is IRI-2016, indicates the IRI 2012 and 2016 estimated TEC values with their average absolute errors. The absolute error of the predicted TEC values in line with the IRI-2007 ones may be shown with the Error = $|\text{TEC}_{\text{est}} - \text{TEC}|$, where TEC_{est} is the estimated TEC value. The satisfactory absolute error rates in the ANNm can be seen.

Absolute error rates in Figure 8, together with their variance values, are 0.06 (0.30%) with 0.013 variance (IRI-2012) and 0.09 (0.49%) with 0.016 variance (IRI-2016) for November 20, 2003 superstorm. For November 08, 2004 superstorm, absolute errors are 0.13 (0.73%) with 0.033 variance (IRI-2012) and 0.11 (1.06%) with 0.035 variance (IRI-2016).

The formula (4) [63] relates to the effect of the variables. It is expressed as follows:

$$\% \text{Effect} = 100 \cdot \left(1 - \frac{R_n}{R_{\text{diff}}} \right). \quad (4)$$

Equation (4) is employed by ignoring the variables from the investigation. In this way, the impact strength of the relevant variable is revealed. The R correlation constant is centered in equation (4). R_n is the correlation rate attained by assuming the related input. R_{dif} is the basic correlation ratio between predicted and observed variables in equation (4). The variables' impact on the ANNm can be seen in Table 3.

In addition to the training, validation, and testing R correlation coefficients of the investigation (result) can be

FIGURE 5: The MSE (TECU) of the ANN model (The first line is IRI-2012 and the second line is IRI-2016).

seen in Figure 9. 2003 and 2004 superstorms, IRI 2012 and 2016 correlation ratios are 97.5%, 97.0% (first and second one) and 97.9%, 98.0% (third and last one), respectively. The suitability of the result R rates with the training, validation, and testing ones can be noticed.

In Table 2, B_z (nT), N ($1/\text{cm}^3$), v (km/s), P (nPa) SWp are the magnetic field (B_z), the proton density, the flow speed, and the dynamic pressure, respectively. The two superstorms to be handled separately:

3.1. November 20, 2003, Superstorm

- (i) IRI-2012 TEC values: The prediction model of the TEC (TECU) data is substantially influenced by the B_z (nT), the v (km/s), the P (nPa), and the N ($1/\text{cm}^3$) SWp. When these SWp are ignored, the R rate of the TEC is influenced by 20.89%, 14.12%, 12.42%, and 11.69%, respectively (Table 2). This means that the R constant is much exceedingly

FIGURE 6: (a) Training, validation, and testing correlations for TEC (TECU). (b) Training, validation, and testing correlations for TEC (TECU).

influenced by the B_z (nT) and highly influenced by the v (km/s), the P (nPa), the N ($1/\text{cm}^3$). The B_z (nT), the v (km/s), the P (nPa), and the N ($1/\text{cm}^3$) are dynamic-effective estimator for the TEC [64–68].

Physically, after the decrease in the flow velocity of high-speed (v) energetic particles, the GS commences with an unexpected rise in the dynamic pressure (P) and the proton density (N). Then in a few hours, the SW speed begins to increase. That is, the directing of the B_z magnetic field from the negative northward to the positive southward corresponds to the sudden acceleration of the SW speed [2]. In the main phase of the GS, which begins directly after the mentioned time period, the TEC data reacts (Figure 7-black arrow) to this situation with a

serious decrease [67]. Accordingly, in the main phase of the GS following the sudden commencement, TEC data answer back to a raise in the dynamic pressure (P), the proton density (N), and the flow speed (v) with a decrease like there were a quadruple physical mechanism. At last, in the main phase of the GS is an ascendant plasma flow that decreases the ionospheric electron density till the magnetic reconnection [61] procedure initiates, which reestablishes the pressure stability [64–67].

- (ii) IRI-2016 TEC values: The ANN prediction model of the TEC is considerably influenced by the B_z (nT), the N ($1/\text{cm}^3$), the P (nPa), and the v (km/s) SWp. When these SWp are ignored, the R rate of the TEC is influenced by 21.31%, 12.26%, 12.06%, and 11.18%, respectively (Table 2). This means that the R constant

(a)
FIGURE 7: Continued.

(b)

FIGURE 7: The MSE (TECU) and correlation constants of the ANN models.

is much highly influenced by the B_z (nT) and highly influenced by the N ($1/\text{cm}^3$), the P (nPa), and the v (km/s).

3.2. November 08, 2004, Superstorm

- (i) IRI-2012 TEC values: The prediction model of the TEC (TECU) data is substantially affected by the P (nPa), the B_z (nT), the v (km/s), and the N ($1/\text{cm}^3$) SWp. When these SWp are neglected, the R rate of the TEC is influenced by 12.78%, 12.27%, 10.76%, and 9.07%, respectively (Table 3). One can realize

that the R constant is much exceedingly influenced by the P (nPa) and highly influenced by the B_z (nT), the v (km/s), and the N ($1/\text{cm}^3$).

- (ii) IRI-2016 TEC values: The ANN prediction model of the TEC is considerably influenced by the B_z (nT), the v (km/s), the P (nPa), and the N ($1/\text{cm}^3$) SWp. When these SWp are ignored, the R rate of the TEC is influenced by 17.98%, 12.25%, 10.35%, and 9.77%, respectively (Table 3). This means that the R constant is much highly influenced by the B_z (nT) and highly influenced by the v (km/s), the P (nPa), and the N ($1/\text{cm}^3$).

FIGURE 8: The estimated-observed TEC values and their absolute errors.

TABLE 3: The effect of each variable on the model

Variable	IRI-2012		IRI-2016	
	R	Effect on R (%)	R	Effect on R (%)
November 20, 2003				
Basic value	0.975	—	0.979	—
B_z (nT)	0.771	20.89	0.770	21.31
T (K)	0.964	1.14	0.974	0.51
N ($1/\text{cm}^3$)	0.861	11.69	0.859	12.26
v (km/s)	0.837	14.12	0.870	11.18
P (nPa)	0.854	12.42	0.861	12.06
E (mV/m)	0.972	0.32	0.972	0.72
November 08, 2004				
Basic value	0.970	—	0.980	—
B_z (nT)	0.851	12.27	0.804	17.98
T (K)	0.959	1.34	0.965	1.53
N ($1/\text{cm}^3$)	0.882	9.07	0.884	9.77
v (km/s)	0.866	10.76	0.860	12.25
P (nPa)	0.846	12.78	0.879	10.35
E (mV/m)	0.960	1.03	0.965	1.53

FIGURE 9: Correlation coefficients of the superstorms.

4. Conclusion

This essay estimates TEC variables with the help of the solar wind parameters (SWp) in two superstorms (November 20, 2003, and November 08, 2004) compared with IRI-2012, IRI-2016 data. The TEC values predicted over Papua New Guinea-New Britain (5.581°S/150.88°E) and Indonesia-Alor Island (8.152°S/124.868°E) location with the artificial neural network model (ANNm) presents notable results. The performance of the ANNm is assessed by the correlation coefficient (R), root mean square error (RMSE), and absolute error. In summary, the results are as follows.

- (i) The IRI-2012 forecast R values as 97.5% and 97.0% for storms 2003 and 2004. IRI-2016 forecast R as 97.9% and 98.0% for storms 2003 and 2004.
- (ii) The IRI-2012 TEC RMSE (TECU) values are 1.17 TECU and 0.89 TECU for storms 2003 and 2004. The IRI-2016 TEC RMSE is 1.09 TECU and 1.61 TECU for storms 2003 and 2004.
- (iii) IRI-2012 absolute error rates are 0.06 (0.30%) with 0.013 variance and 0.13 (0.73%) with 0.033 variance for storms 2003 and 2004. IRI-2016 absolute error rates are 0.09 (0.49%) with 0.016 variance and 0.11 (1.06%) with 0.035 variance for storms 2003 and 2004.
- (iv) The effects of independent variables in the estimation of both IRI-2012 and IRI-2016 TEC data overlap with physical facts in both superstorms dynamic, by pointing out the magnetic field B_z component (nT), the flow speed v (km/s), the dynamic pressure P (nPa), and the proton density N ($1/\text{cm}^3$) SWp.

Works on the modeling-predicting of TEC values give way to a better comprehension of the relationship between the Earth's crust and the ionosphere.

Data Availability

The data can be accessed through OMNI web: <https://omniweb.gsfc.nasa.gov/form/dx1.html>.

Conflicts of Interest

The author declares no conflicts of interest.

Authors' Contributions

Data are collected and analyzed by the author. All interpretations and explanations belong to the author. The author read and approved the final manuscript.

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