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TEC prediction with neural network for equatorial latitude station in Thailand

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This paper describes the neural network (NN) application for the prediction of the total electron content (TEC) over Chumphon, an equatorial latitude station in Thailand. The studied period is based on the available data during the low-solar-activity period from 2005 to 2009. The single hidden layer feed-forward network with a back propagation algorithm is applied in this work. The input space of the NN includes the day number, hour number and sunspot number. An analysis was made by comparing the TEC from the neural network prediction (NN TEC), the TEC from an observation (GPS TEC) and the TEC from the IRI-2007 model (IRI-2007 TEC). To obtain the optimum NN for the TEC prediction, the root-mean-square error (RMSE) is taken into account. In order to measure the effectiveness of the NN, the normalized RMSE of the NN TEC computed from the difference between the NN TEC and the GPS TEC is investigated. The RMSE, and normalized RMSE, comparisons for both the NN model and the IRI-2007 model are described. Even with the constraint of a limited amount of available data, the results show that the proposed NN can predict the GPS TEC quite well over the equatorial latitude station.

Key words: Neural network, total electron content, low solar activity period, IRI-2007 model, GPS.

1. Introduction

The variation of electron density in the ionosphere has significant effects on a radio signal propagating through the Earth's atmosphere. The total electron content (TEC) is one of the quantities which can describe the ionospheric ionization content. The equatorial region is an anomaly area where the most significant discrepancy of experimental and modeled data has been observed (Yasukevich, 2008). At present, there exist several ionosphere models including IRI-2001 and IRI-2007, which allow calculations of the electron density profile and the TEC. The IRI-2007 is the new release of the IRI model and has many new features. IRI-2007 now offers various options to compute the electron density in the topside ionosphere, the region above the F_2 maximum, which is an improvement over the limitations in previous versions of the model (Bilitza, 2004; Coisson *et al.*, 2009).

TEC derived from GPS data has been collected to construct empirical models. Neural network (NN) techniques have been applied to various topics in the study of the upper atmosphere. A number of works employ the NN to predict atmospheric parameters and determine the optimum parameters for modeling, such as the temporal and spatial forecasting of the f_oF_2 values up to twenty-four hours in advance and near-real time prediction (Tulunay *et al.*, 2000; Oyeyemi *et al.*, 2006), to make operational forecasts of ionospheric variations (Nakamura *et al.*, 2007), the topside ionospheric variability and electron-density modelling (McKinnell and Poole, 2001; Maruyama, 2002), solar proxies pertaining to an empirical model (McKinnell, 2008; Maruyama, 2010), and regional TEC modeling with the NN (Leandro and Santos, 2004; Tulunay *et al.*, 2004b; Maruyama, 2007; Habarulema *et al.*, 2007, 2009b; Watthanasangmechai *et al.*, 2010).

Recently, TEC data have become available in Thailand and some neighboring countries as a result of the SEALION project. This provides the opportunity to study the TEC prediction. Moreover, the availability of historic TEC data is important for the development of the IRI model (Mosert, 2007), as well as the NN model which can learn from prior data (Watthanasangmechai *et al.*, 2010). Better representations of the region above the F peak are of critical importance for many investigations that require TEC predictions (Bilitza, 1997). Thus, we hope that this research will not only lead to a prediction of the TEC over Thailand, but also will contribute to the data pool for this area as well. In this paper, the TEC is measured by the JAVAD-GPS receiver installed at the GPS receiver station, namely; Chumphon (10.72°N, 99.37°E, dip latitude 3°), equatorial latitude station, Thailand. To predict the TEC value, a neural network (NN) was applied in this work. The results of the NN are compared with the observed value (GPS TEC) for NN efficiency testing. In addition, we employ the TEC from the IRI-2007 model, the widely-used ionosphere model for comparison as well.

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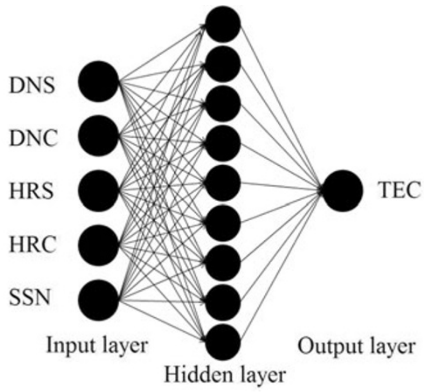

Fig. 1. Schematic diagram of the artificial neural network for TEC prediction.

2. Artificial Neural Network

2.1 Neural Network

Neural Networks (NN) is an information processing system consisting of nodes or neurons. A neuron is an information processing unit which consists of a connecting link, adder and activation function. The neuron patterns are similar to biological neural nets and are modeled after the human brain (Tulunay *et al.*, 2004a). NN is an important tool for nonlinear approximation when it is trained with sufficient historic data (Habarulema *et al.*, 2007). TEC is one of the nonlinear ionospheric parameters which have been previously predicted by using NN (Habarulema *et al.*, 2007, 2009a; Maruyama, 2007; Watthanasangmechai *et al.*, 2010). Among the various NN structures, we have used a basic structure known as a feed-forward network with a back propagation algorithm, the well-known algorithm, for our model. In order to achieve the optimum NN, a comparison of the Root-Mean-Square Error (RMSE) was used. RMSE is defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{TEC_{pred}} - \mathrm{TEC_{meas}})^2}, \qquad (1)$$

where N is the number of data points, $\mathrm{TEC_{pred}}$ is TEC predicted by a model and $\mathrm{TEC_{meas}}$ is the vertical TEC (VTEC) estimated from GPS observations by using the technique described in Otsuka *et al.* (2002).

This NN composes of one input layer, one hidden layer and one output layer. Figure 1 presents a schematic diagram of the proposed NN for this work. The input layer consists of five nodes, or neurons, corresponding to five input parameters each with 32,112 data points, while the hidden, and the output, layers consists, respectively, of nine and one nodes, or neurons. The expositions about NN and its algorithms are well described in Tulunay *et al.* (2004a) and Watthanasangmechai *et al.* (2010). In this paper, we will only focus on the NN application for predicting the TEC over the Thailand equatorial latitude station. On the other hand, the main purpose is to model the NN and compare the NN TEC with GPS TEC and IRI-2007 TEC, so as to validate the NN model. The data set is divided into training, validating and testing sets. The training and validating sets are the TEC data in 2005, 2006, 2008 and 2009 while the TEC data in 2007 are reserved for the testing process. The performance of our NN model is also considered from the RMSE as well.

2.2 NN inputs and output

The input space was collected from the parameters that have an impact on the TEC data such as the hour number (HR, diurnal variation), the day number (DN, seasonal variation) and the sunspot number (SSN, measure of solar activity). To make the data continuous, the first two parameters were each split into sine and cosine components, two cyclic components (McKinnell and Poole, 2000; Habarulema *et al.*, 2007, 2009a; McKinnell, 2008) as follows:

$$\begin{aligned} \mathrm{DNS} &= \sin\left(\frac{2\pi\,\mathrm{DN}}{365.25}\right), \quad \mathrm{DNC} = \cos\left(\frac{2\pi\,\mathrm{DN}}{365.25}\right) \\ \mathrm{HRS} &= \sin\left(\frac{2\pi\,\mathrm{HR}}{24}\right), \quad \mathrm{HRC} = \cos\left(\frac{2\pi\,\mathrm{HR}}{24}\right) \end{aligned}, \qquad (2)$$

where DNS, DNC, HRS and HRC are the sine and cosine components of DN and HR, respectively. The studied years include the leap year, a year having 366 days, thus the quantity 0.25 appears in Eq. (2).

The daily SSN, which indicates the solar activity, is collected from the site: ftp.ngdc.noaa.gov. It is considered as one of the input parameters for the first neural network (NN1). Since the amplitude of short-term solar-proxy variations are induced by solar rotation, one solar rotation is equal to 27 days, and the long-term variations follow the 11-year solar activity period (Maruyama, 2010), we choose the 27-day mean SSN as one of the input parameters for the second neural network (NN2) to represent the solar activity. Besides, the sunspot number is more effective for periods longer than 27 days (Maruyama, 2010) for training the neural network, thus we also choose an 81-day mean SSN, three solar rotation periods, as another input parameter for the third neural network (NN3). All of the input parameters are fed into the input space for the TEC prediction. The output of each NN is VTEC. The RMSE values of which are investigated to achieve the optimum NN.

3. Results and Discussions

In this work, the NN model is developed for Chumphon as a single-station model near the magnetic equator in Thailand. The daily SSN, as shown in Fig. 2, is applied for NN1, while the 27-day mean SSN, as shown in Fig. 3, and the 81-day mean SSN, as shown in Fig. 4, are applied for NN2 and NN3, respectively. To achieve the optimum NN, the RMSE comparison of NN1, NN2 and NN3, each with 6 to 12 cells in the hidden layer, is made as shown in Fig. 5. All data used in NN processes are the data from 2005 to 2009. Since the achievement of the trained network depends not only on the selection of input parameters but also on the initial weights (Maruyama, 2010), the initial random weights are used for this work, thus we run each NN ten times to choose the best NN for the best result. From Fig. 5, we found that NN3 with nine hidden cells performs as the best NN for Chumphon station for the studied period with the RMSE 2.269 TECU and the normalized RMSE 0.161 from the testing process. We will henceforth refer to NN3 as the proposed NN.

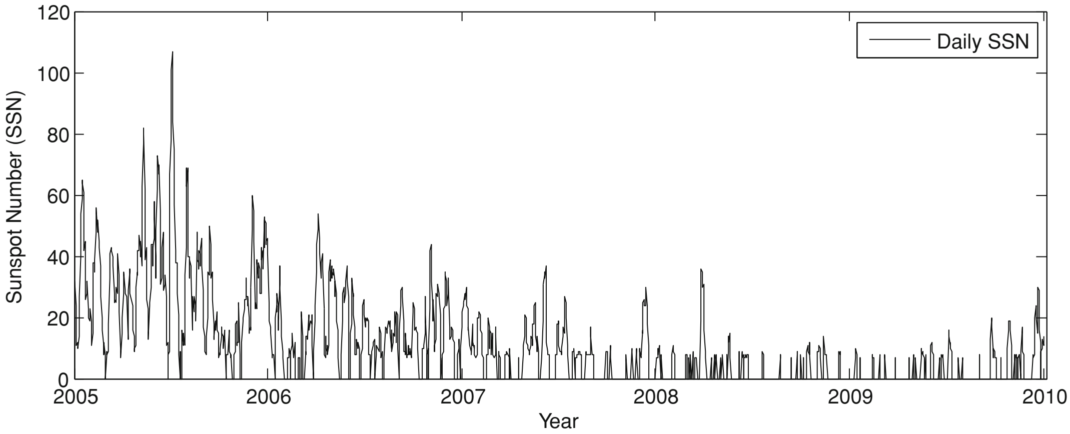

Fig. 2. The daily SSN during 2005 to 2009 which is applied for NN1.

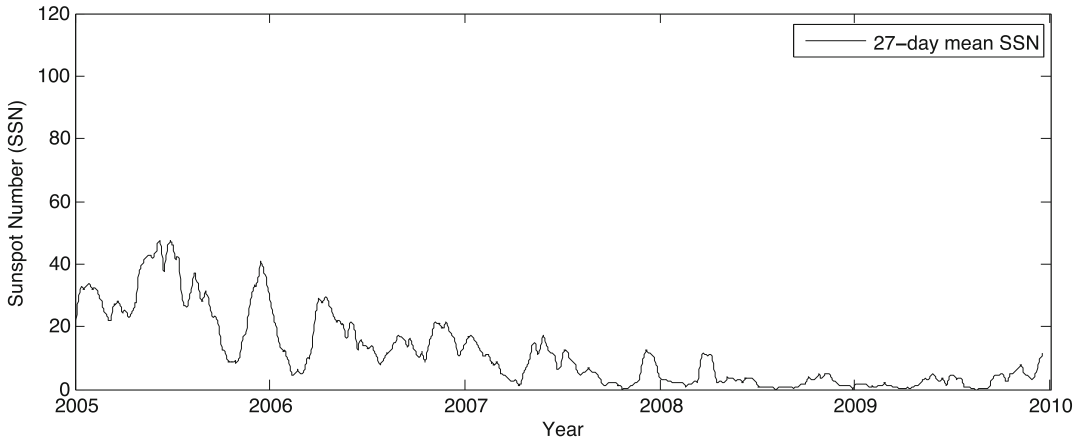

Fig. 3. The 27-day mean SSN during 2005 to 2009 which is applied for NN2.

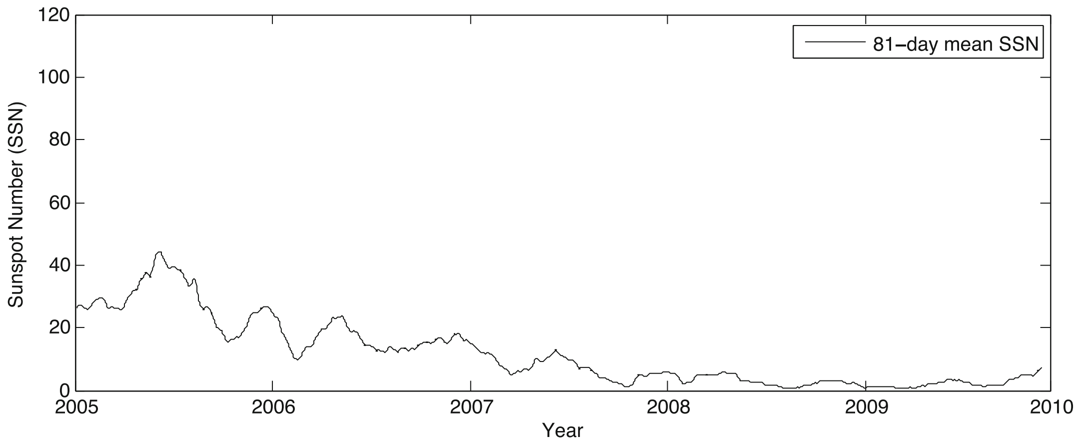

Fig. 4. The 81-day mean SSN during 2005 to 2009 which is applied for NN3.

The proposed NN (NN3) is the feed-forward network with a back propagation algorithm. It consists of five nodes or neurons in the input layer, nine nodes in the hidden layer, and one output node in the output layer, as shown in Fig. 1. The input layer is fed with the sine and cosine components of the day number and the hour number, and the 81-day mean SSN. The initial weight and biases for the training process are set to be random values. The Levenberg-Marquardt algorithm is applied as the training function. The output of the proposed NN is compared with GPS TEC and IRI-2007 TEC. We take the normalized RMSE into account for the result comparison. The normalized RMSE is the RMSE value divided by the background TEC to avoid the effect from the TEC background.

In this work, we set the upper boundary height for the IRI-2007 model to be 20,000 km, the maximum value which the IRI-2007 model allows, to include not only the electrons in the ionosphere, but also in the plasmasphere as

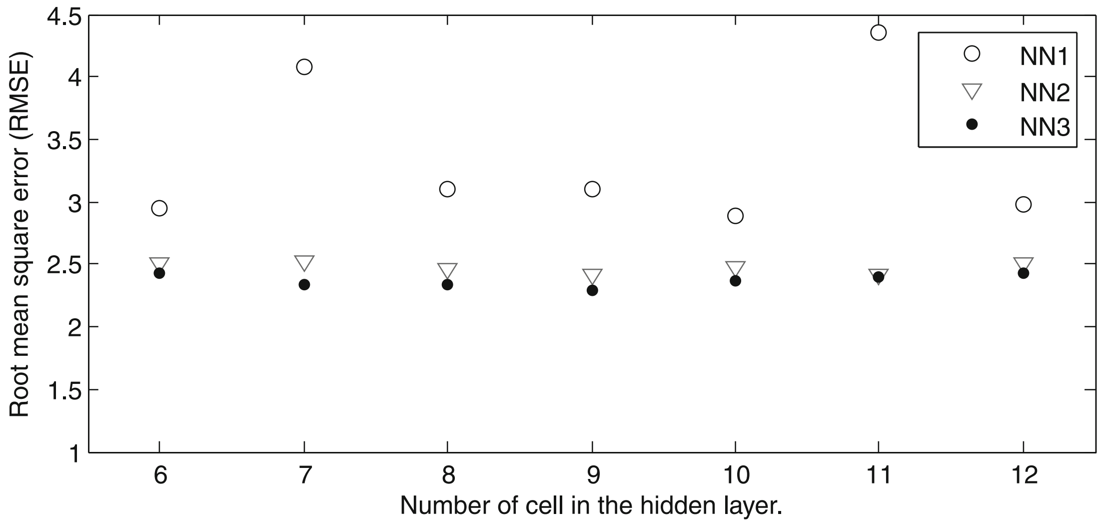

Fig. 5. RMSE values computed for an NN model with 6 to 12 neurons in a single hidden layer.

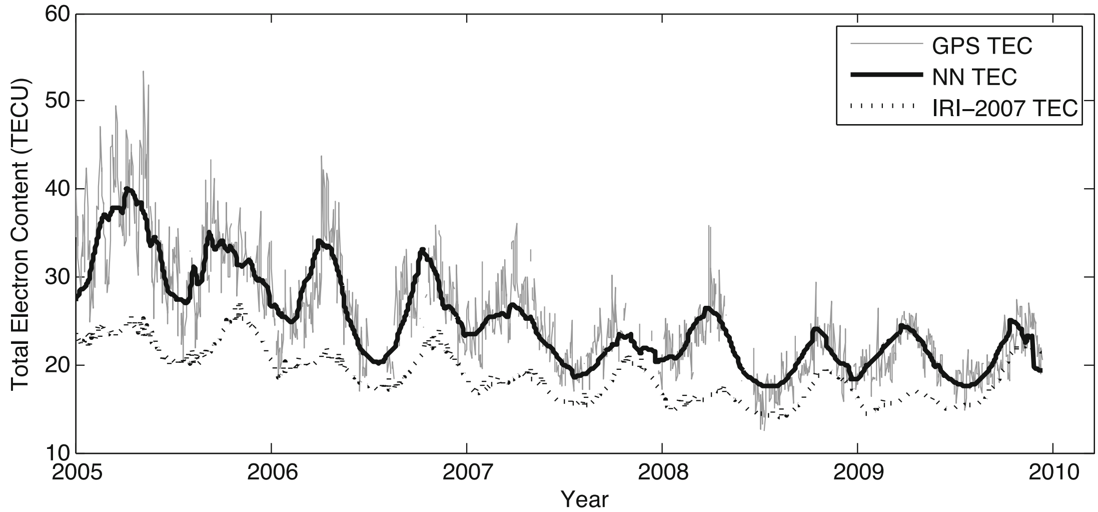

Fig. 6. GPS TEC, NN TEC and IRI TEC over the 5-year period, 2005 to 2009, at 1230 LT for Chumphon station.

well. The results in the years 2005, 2006, 2007, the last period of the solar cycle 23, and in the years 2008, 2009, the start period of solar cycle 24, from the NN processes are plotted versus the GPS TEC and the IRI-2007 TEC at 1230 LT as shown in Fig. 6. Hereafter, we introduce seven comparison results which are hourly comparison, seasonal comparison, 0030 LT comparison, 0630 LT comparison, 1230 LT comparison, 1830 LT comparison and TEC comparison on an individual day, respectively.

3.1 Hourly comparison

To evaluate the performance of NN, the hourly model is constructed. The data set for the learning process comprises TEC in 2005, 2006, 2008 and 2009. Following the learning process, NN output is compared with GPS TEC and IRI-2007 TEC on equinox and solstice days in 2007. In 2007, equinox days occur on March 20 and September 23, while solstice days occur on June 21 and December 22 (U.S. Naval Observatory; http://www.erh.noaa.gov/box/equinox.html), respectively. However, we compare the results on December 25 for the solstice day due to a loss of data on December 22. The hourly NN TEC is plotted with the GPS TEC and the IRI-2007 TEC to see the effectiveness of the hourly model, as shown in Fig. 7(a)–(d). The RMSE and normalized RMSE of the NN TEC and the IRI-2007 TEC for each of the four proposed days are shown in Table 1. The NN TEC with the smallest RMSE (1.468 TECU) and the smallest normalized RMSE (0.135) is on December 25, a solstice day. The NN TEC with the largest RMSE (2.797 TECU) and the largest normalized RMSE (0.195) is on March 20, an equinox day. The average TEC values on December 25 and March 20 are equal to 10.805 TECU and 14.281 TECU, respectively, and are considered as the background TEC values of December 25 and March 20.

Among various methods to predict TEC, the results prove that the hourly model yields one of the appropriate tools for TEC prediction purposes. Even though there is a considerable difficulty for NN to learn during the TEC prediction process on equinox days during this period due to the occurrence of an equatorial plasma bubble, which includes various ionospheric irregularity scales, causing a large day-to-night variation and a drastically-fluctuating component of

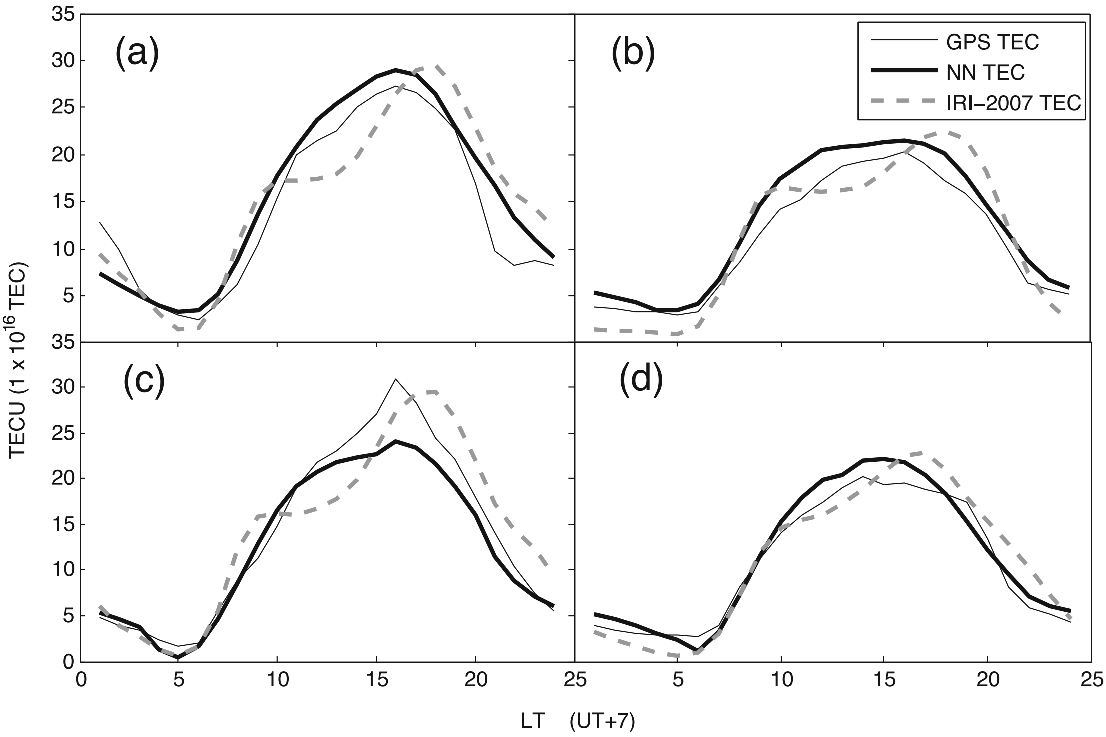

Fig. 7. (a–d) GPS TEC, NN TEC and IRI-2007 TEC at Chumphon station (a) on 20 March 2007 (equinox day), (b) on 21 June 2007 (solstice day), (c) on 23 September 2007 (equinox day), (d) on 25 December 2007 (solstice day).

Table 1. Background TEC, RMSE and normalized RMSE values of GPS TEC and predicted values (NN TEC and IRI-2007 TEC) for different days (equinox and solstice days) in 2007 over Chumphon station.

Date	Background TEC (TECU)	RMSE (TECU) between		Normalized RMSE between	
		NN TEC	IRI-2007 TEC	NN TEC	IRI-2007 TEC
March 20	14.281	2.797	4.164	0.195	0.291
June 21	10.904	1.965	2.743	0.180	0.251
September 23	14.006	2.430	3.412	0.173	0.243
December 25	10.805	1.468	2.142	0.135	0.198
4 studied-day	12.499	2.165	3.115	0.173	0.249
All year 2007	14.078	2.296	3.881	0.163	0.275

the TEC, the hourly model is still able to predict TEC quite well. If we consider in terms of the normalized RMSE as shown in Table 1, the normalized RMSE from the hourly model is smaller than that from the IRI-2007 model for the entire year over Chumphon. We do not mean to imply that the IRI-2007 model is not appropriate to use for TEC prediction, however, we presume that the IRI-2007 database may not cover Southeast Asia data and, in particular, over Chumphon equatorial latitude station, for example. However, our NN TEC performs well during the period studied since the NN model learns from the local TEC value. This is a reason why the hourly model can well predict TEC values as mentioned above.

3.2 Seasonal comparison

Since seasonal variation plays an important role in TEC variation, we also carry out a seasonal TEC comparison to investigate the possibility of NN to predict the seasonal TEC. In this paper, there are four distinct seasons, which are the March equinox, the June solstice, the September equinox and the December solstice. Each season is represented by a monthly median value. Meaning, we take the median to each hourly data of 31-day TEC data in March, predicted from the method described in Fig. 1, in order to obtain the 24-hour seasonal TEC for the March equinox, for example. Thus the 24-hour monthly median TEC values are cited as the seasonal TEC. For the seasonal comparison, hereafter, we refer to the NN as the seasonal model.

For this model, the 5:9:1 architecture with a 81-day mean SSN is still taken. TEC in 2005, 2006, 2008 and 2009 are applied in the learning process, while the seasonal TEC in 2007 is used as the target for this seasonal model. The NN TEC (seasonal TEC) is plotted to compare with the GPS TEC and the IRI-2007 TEC. Figure 8 shows that the IRI TEC values are clearly underestimated during 0430 LT to 0630 LT and 1130 LT to 1630 LT for the March equinox, during 0530 LT to 0730 LT and 1030 LT to 1630 LT for the June solstice, during 0230 LT to 0530 LT and 1130 LT to 1530 LT for the September equinox, and during 0330 LT to 0630 LT for the December solstice, while during 1730 LT and 2130 LT for the June solstice, 1730 LT and 2330 LT for the September equinox, and 1530 LT and 2330 LT for the December solstice, IRI-2007 TEC are overestimated. From

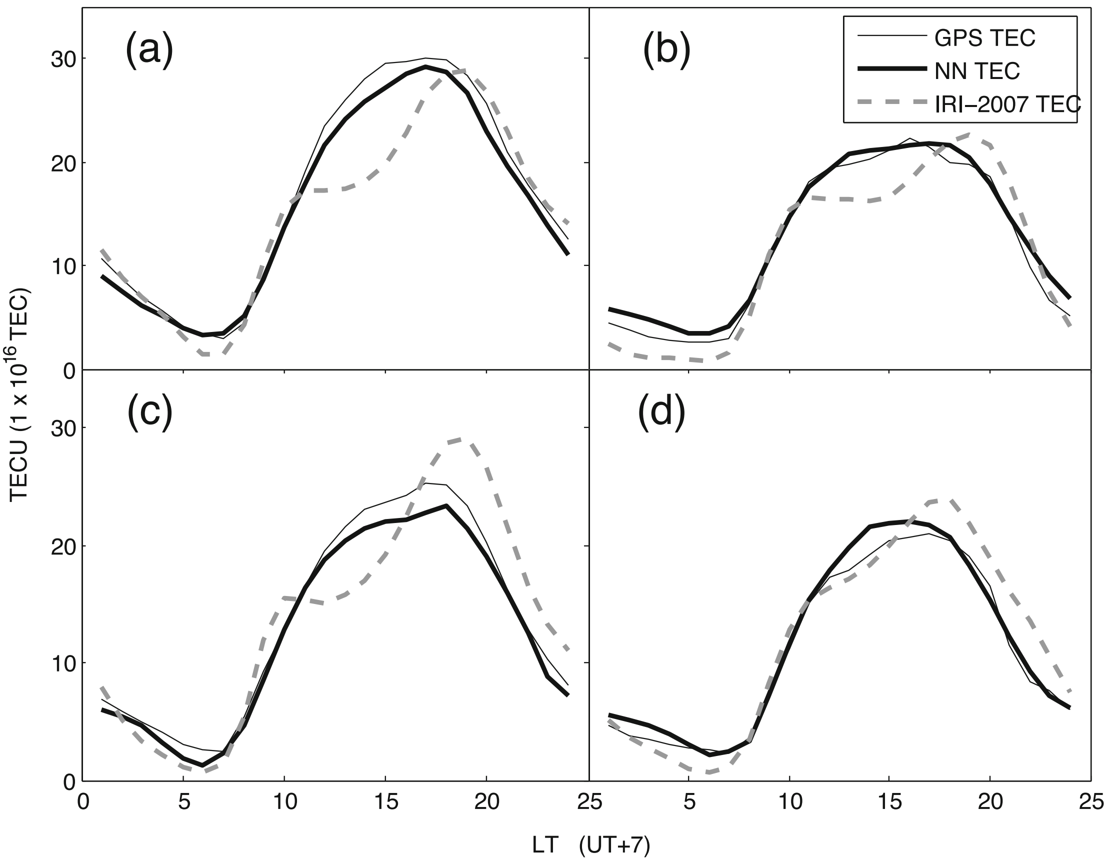

Fig. 8. (a–d) GPS TEC, NN TEC and IRI TEC at Chumphon station for (a) March (b) June (c) September (d) December.

Table 2. Background TEC, RMSE and normalized RMSE values of GPS TEC and predicted values (NN TEC and IRI-2007 TEC) for different seasons which are March (representing the March equinox), June (representing the June solstice), September (representing the September equinox) and December (representing the December solstice), respectively, in 2007 over Chumphon station.

Month	Background TEC (TECU)	RMSE (TECU)		Normalized RMSE	
		NN TEC	IRI-2007 TEC	NN TEC	IRI-2007 TEC
March	16.923	1.385	4.025	0.081	0.237
June	12.163	1.107	2.485	0.091	0.204
September	13.639	1.208	3.513	0.088	0.257
December	11.083	1.012	2.135	0.091	0.192

this investigation, we can conclude that the IRI-2007 model underestimates around the local pre-sunrise and the local midday, and overestimates around after the local sunset. For the remainder of the time, the IRI-2007 model predicts TEC quite well. When we take the seasonal NN TEC into account, we find that the NN performs quite well for seasonal TEC prediction. However, the NN underestimates TEC during 1130 LT to 2030 LT for the March equinox, as well as during 1230 LT to 1830 LT for the September equinox, and the NN overestimates TEC during 0030 LT to 0630 LT for the June solstice and during 1230 to 1630 LT for the December solstice. The shapes of the NN TEC and the GPS TEC for all seasons resemble each other. The RMSE values of the NN TEC and the IRI-2007 TEC are shown in Table 2. The best estimation for the NN occurs during the March equinox with a normalized RMSE of 0.081 while that for the IRI-2007 model occurs during the December solstice with a normalized RMSE of 0.192. The worst estimations occur during the December solstice for the NN and during the September equinox for the IRI-2007 model with normalized RMSEs of 0.091 and 0.257, respectively.

3.3 0030 LT comparison

The difference between universal time and the local time at Chumphon is seven hours. We consider 0030 LT (1730 UT) to be local midnight for this paper. To see if NN is applicable for TEC prediction, the first comparison at 0030 LT in 2007 is described. We show the comparison of 365-day variation of the GPS TEC, the NN TEC and the IRI-2007 TEC at local midnight in Fig. 9. It is shown that the NN model predicts the TEC over Chumphon at 0030 LT for the year 2007 fairly well with a RMSE of 1.996 TECU, and a normalized RMSE of 0.334. The IRI-2007 TEC is underestimated at local midnight during mid-year. The IRI-2007 model predicts TEC for Chumphon station at 0030 LT in the year 2007 with an RMSE of 2.469 TECU, and a normalized RMSE of 0.413. The average TEC values of the GPS TEC, the NN model and the IRI-2007 model, at local midnight in 2007, are equal to 5.971 TECU, 5.612 TECU

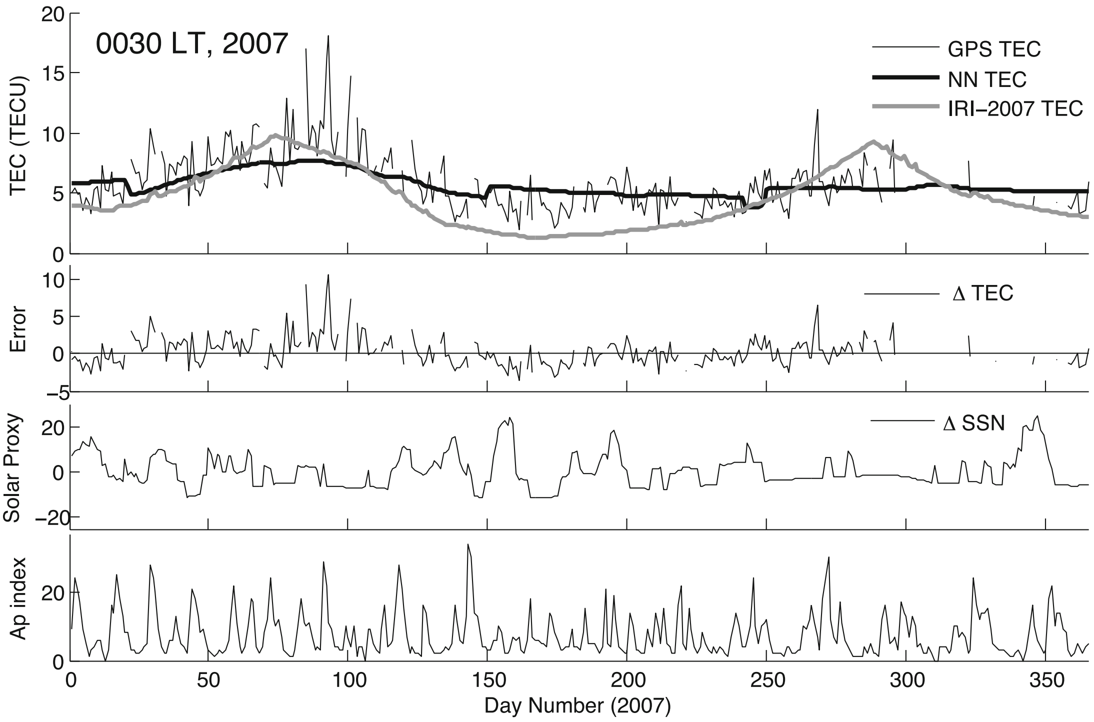

Fig. 9. GPS TEC, NN TEC and IRI-2007 TEC, the difference between the GPS TEC and the NN TEC (ΔTEC), and the difference between the daily SSN and 81-day mean SSN (ΔSSN), all at 0030 LT, and the A_p index, all in 2007 over Chumphon station.

and 4.729 TECU, respectively. The comparison results for local midnight reveal the worst estimation for both the NN model and the IRI-2007 model. This may be a result of the equatorial plasma bubble, which is always observed during the night time and causes drastic TEC variation. We presume that this is the main reason why the worst estimation, or prediction, occurs at local midnight.

3.4 0630 LT comparison

The comparison between the GPS-TEC, the NN TEC and the IRI-2007 TEC at 0630 LT is made to investigate the TEC variation, the effectiveness of the proposed NN model and the IRI-2007 model, at local pre-sunrise. From observations, GPS TEC values at local pre-sunrise are quite low with an average TEC value of 5.287 TECU for all year 2007. To see the TEC prediction performance of the IRI-2007 and the NN model, TEC from the NN model is plotted against GPS TEC and IRI-2007 TEC as shown in Fig. 10. We found that the NN is still able to predict TEC pretty well with an RMSE of 1.084 TECU and a normalized RMSE of 0.205, while the IRI-2007 model also predicts TEC pretty well with an RMSE of 1.246 TECU and a normalized RMSE of 0.235. The average TEC values of the NN model and the IRI-2007 model at local pre-sunrise in 2007 are equal to 5.064 TECU and 4.668 TECU, respectively.

3.5 1230 LT comparison

The same procedure with two previous comparisons was applied for 1230 LT, which is referred to as the local midday. The NN TEC and the IRI-2007 TEC at 1230 LT are compared with each other by plotting the GPS TEC as shown in Fig. 11. One can notice that both TECs predicted from the NN model and the IRI-2007 model have the same trend of data at local midday for year 2007. However, we can observe that the IRI-2007 TEC is evidently underestimated by both the GPS TEC and the NN TEC, while the NN TEC agrees with the GPS TEC with an RMSE of 2.718 TECU and a normalized RMSE of 0.114. The RMSE of the IRI-2007 model is equal to 7.135 and the normalized RMSE is equal to 0.299 at local midday for the entire year at this station. The yearly average at local midday of the GPS TEC is 23.791 TECU while those for the NN model and the IRI-2007 model are 22.593 TECU and 17.741 TECU, respectively. The best estimation of the proposed NN model can be seen here, at local midday, among other comparisons at 0030 LT, 0630 LT, 1230 LT and 1830 LT, as described in Table 3.

3.6 1830 LT comparison

The comparison of the NN TEC, the GPS TEC and the IRI-2007 TEC at local pre-sunset is shown in Fig. 12. The trends of the NN TEC from the 1830 LT model and the IRI-2007 TEC are similar, and follow the GPS TEC at local pre-sunset. If we consider only the RMSE value at 1830 LT, we will find that the RMSE of the NN TEC is pretty high with 3.300 TECU. However, this is affected by the high background TEC value at the local pre-sunset hour, which is equal to 20.939 TECU. To avoid this effect in the comparison, normalized RMSEs are considered. The IRI-2007 model also gives a high RMSE value, however, the corresponding normalized RMSE is equal to 0.211, which is the best approximation of the IRI-2007 model. The average TEC values for the NN model and the IRI-2007 model at local pre-sunset are equal to 18.934 TECU and 23.755 TECU, respectively. From Fig. 12, we can notice that the IRI-2007 model distinctly overestimates TEC for the period after the 250th day at 1830 LT which may be the reason for the fairly high RMSE value.

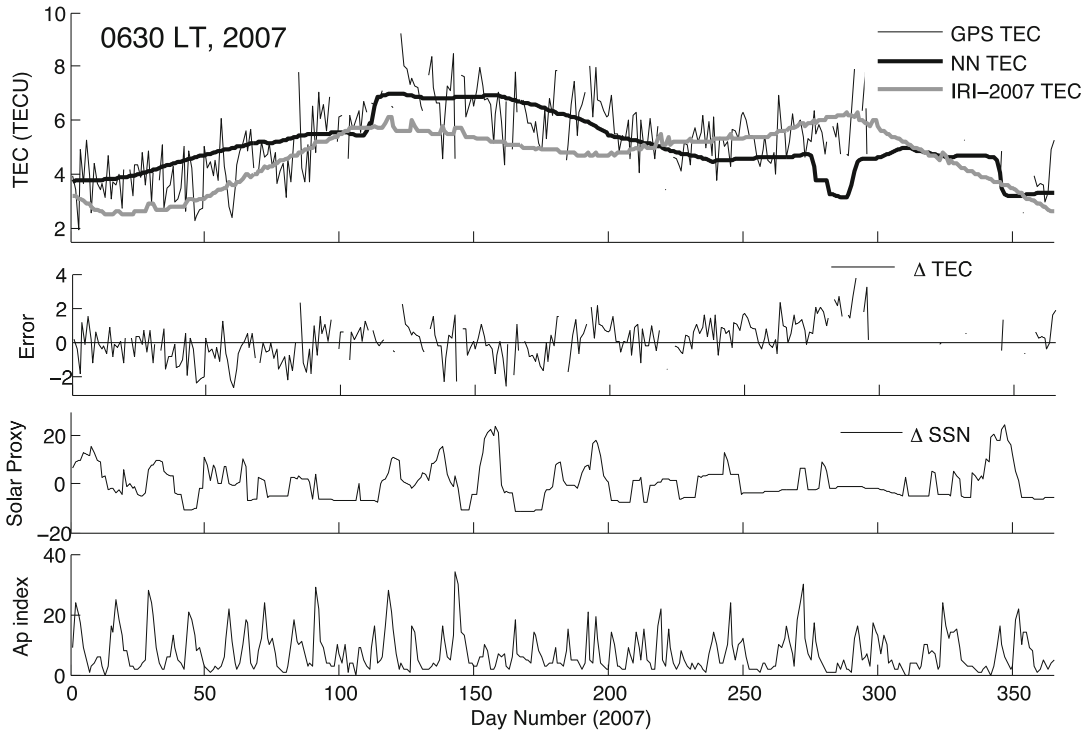

Fig. 10. GPS TEC, NN TEC and IRI-2007 TEC, the difference between the GPS TEC and the NN TEC (ΔTEC), and the difference between the daily SSN and 81-day mean SSN (ΔSSN), all at 0630 LT, and the A_p index, all in 2007 over Chumphon station.

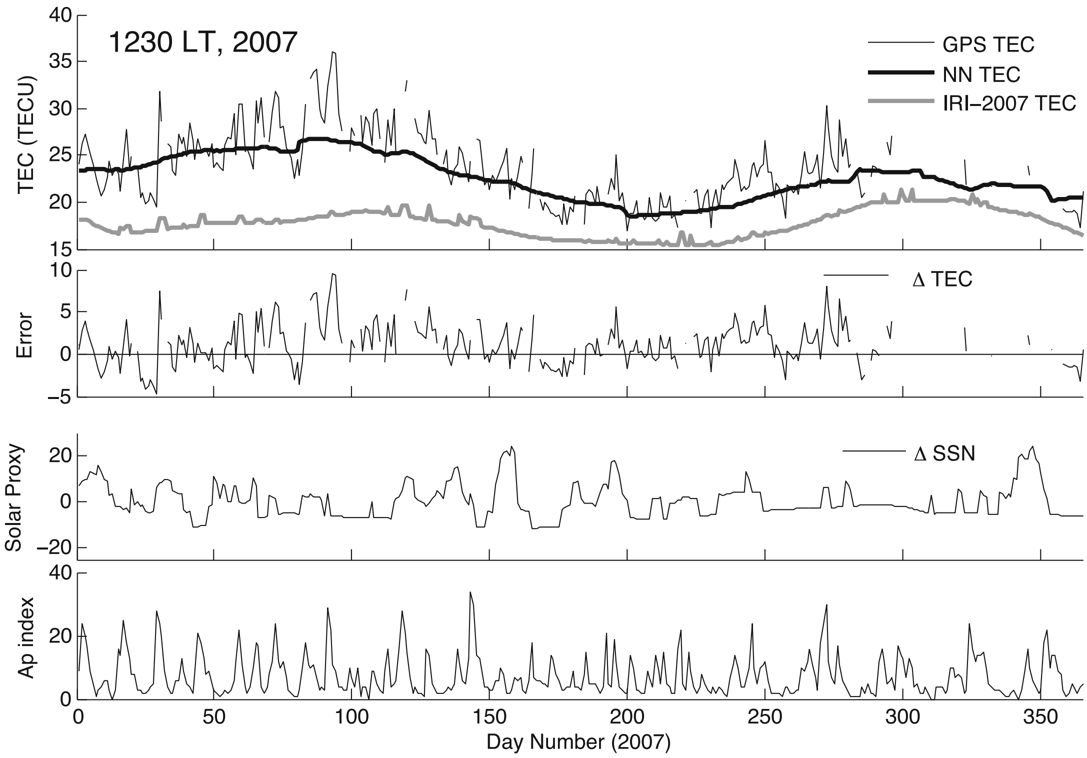

Fig. 11. GPS TEC, NN TEC and IRI-2007 TEC, the difference between the GPS TEC and the NN TEC (ΔTEC), and the difference between the daily SSN and 81-day mean SSN (ΔSSN), all at 1230 LT, and the A_p index, all in 2007 over Chumphon station.

The normalized RMSE values of the GPS TEC and the predicted values (NN TEC and IRI-2007 TEC) for each of the four comparisons of Subsections 3.3 to 3.6, over Chumphon station, are compared and shown in Table 3. We found that our NN model can be used to predict TEC values at different times of the year 2007 over Chumphon, the equatorial latitude station. The minimum normalized RMSE value is 0.114 from the 1230 LT comparison, while the maximum over is 0.334 from the 0030 LT comparison. We can infer that the proposed NN model can give the best

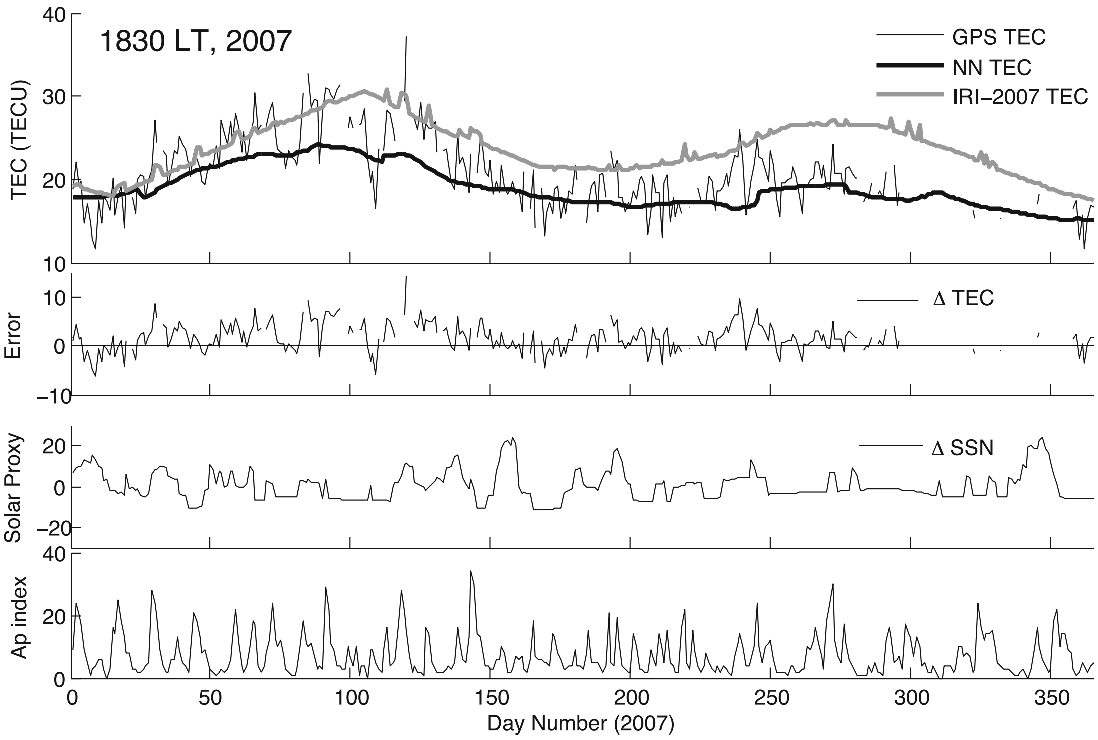

Fig. 12. GPS TEC, NN TEC and IRI-2007 TEC, the difference between the GPS TEC and the NN TEC (ΔTEC), and the difference between the daily SSN and 81-day mean SSN (ΔSSN), all at 1830 LT, and the A_p index, all in 2007 over Chumphon station.

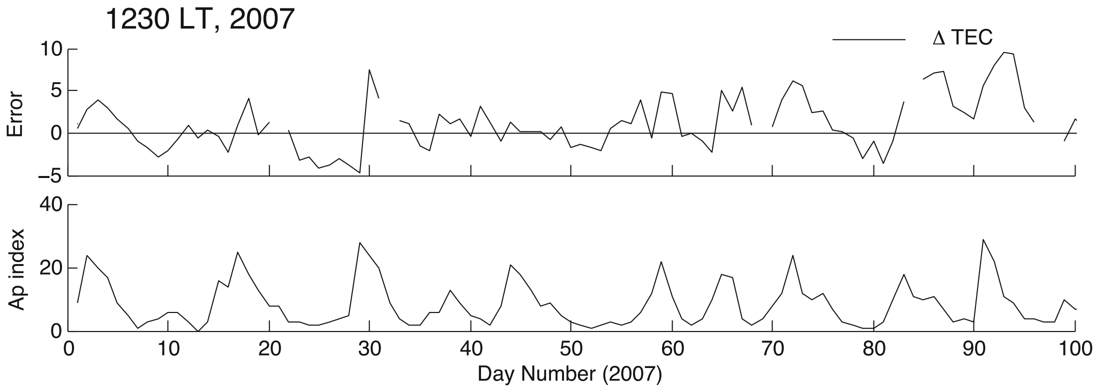

Fig. 13. Comparison between the daytime ΔTEC and A_p index in more detail (for days 1 to 100), all in 2007 over Chumphon station.

Table 3. Average TEC, RMSE and normalized RMSE values of GPS TEC and predicted values (NN TEC and IRI-2007 TEC) for different times in 2007 which are 0030 LT, 0630 LT, 1230 LT and 1830 LT, respectively, over Chumphon station.

Time (LT)	Average TEC (TECU)			RMSE (TECU)		Normalized RMSE	
	GPS TEC	NN TEC	IRI-2007 TEC	NN TEC	IRI-2007 TEC	NN TEC	IRI-2007 TEC
0030	5.971	5.619	4.729	1.996	2.469	0.334	0.413
0630	5.287	5.064	4.668	1.084	1.246	0.205	0.235
1230	23.791	22.593	17.741	2.718	7.135	0.114	0.299
1830	20.939	18.934	23.755	3.300	4.433	0.157	0.211

TEC approximation at local midday due to the smallest normalized RMSE value it gives. However, the NN TEC from the 0030 LT model needs to be leveled up to decrease the normalized RMSE value.

3.7 TEC comparison on an individual day

For Figs. 9 to 12, each of which includes (from top to bottom) the comparison between the GPS TEC, the NN TEC and the IRI-2007 TEC, the difference between the GPS TEC and the NN TEC (ΔTEC, the error of the NN model), the difference between the daily SSN and 81-day mean SSN (ΔSSN), and the daily geomagnetic-activity index, A_p, all in 2007. Positive errors, which are related to the solar proxy variation represented by ΔSSN, are noticed on the 35th day of the 0030 LT comparison in Fig. 9, and on the 195th day of the 1230 LT comparison in Fig. 11. For the 35th day in Fig. 9, the ΔSSN is about 10, while the ΔTEC is about 3 TECU (the background TEC is equal to 5.971 TECU). The background TEC is an average GPS TEC value for the whole year 2007 at any represented time. The ΔSSN is about 16, while the ΔTEC is about 5 TECU (the background TEC is equal to 23.791 TECU), on the 195th day in Fig. 11. The trend of the ΔTEC variation and the ΔSSN variation resemble each other during about 10 days before, and after, the 195th day of the 1230 LT comparison in Fig. 11, as well. The TEC error corresponding to the largest ΔSSN at around the 160th day is not prominent. Generally, daily errors caused by using an 81-day mean SSN as a solar input are not very significant.

Positive errors, which are related to the geomagnetic-activity index represented by the daily A_p index, are noticed on the 40th and 85th days of the 0030 LT comparison in Fig. 9, the 140th, 185th and 190th days of the 0630 LT comparison in Fig. 10, the 17th, 30th, 60th, 65th, 70th, 195th, 271st and 277th days of the 1230 LT comparison in Fig. 11, and the 30th, 72nd and 120th days of the 1830 LT comparison in Fig. 12. The largest ΔTEC, noticed on the 85th day in Fig. 9 and on the 120th day in Fig. 12, are clearly related to the geomagnetic activity, as well as during the 1st and 30th days of the 1230 LT comparison in Fig. 11, with three peaks of the ΔTEC and A_p variations resembling each other. The negative errors, which are related to the solar proxy variation, do not clearly appear in the study period but those related to geomagnetic activity can be seen on the 132nd, 140th, 147th, and 170th days of the 0630 LT comparison in Fig. 10. The large positive error noticed during the 270th and 290th days in Fig. 10, is absolutely not related to the solar proxy variation; however, may be related to the geomagnetic activity index for some of these days. Another large positive error on the 340th day correlates to the peak of the geomagnetic-activity index and an increase of the ΔSSN on this day. Figure 13 compares daytime ΔTEC and A_p in more detail (for days 1 to 100). The TEC increases occurred with a time delay of approximately one day, which strongly suggests the effect of a disturbance dynamo (Scherliess and Fejer, 1997). The weakened daytime eastward electric field might suppress the fountain effect, and cause a density increase at the magnetic equator.

An error, unrelated to both the solar proxy index and the geomagnetic-activity index, can be seen on the 270th day of the 0030 LT comparison in Fig. 9. We presume that such an error is attributed to other origins, such as forcing below the ionosphere including coupling with planetary wave activities (Lastovicka, 2006; Borries *et al.*, 2007; Maruyama, 2010). The remaining errors are caused by the large day-to-day variation of the TEC in the equatorial latitude region itself.

4. Conclusions

This work investigates an NN model which has 9 neurons in the single hidden layer for TEC prediction at Chumphon station, Thailand. The parameters which impact the TEC data were taken as the NN inputs. In this study, we have considered six comparisons to show the NN TEC. To investigate the effectiveness for using the NN as a TEC prediction tool, the RMSE and normalized RMSE of the NN TEC were computed and compared with those of the IRI-2007 TEC, as described. The result is that the proposed NN model, in the case of all of the comparisons described above, can well predict the TEC compared with the IRI-2007 TEC. For some periods, even though there is a considerable difficulty for the NN to learn during the TEC prediction process due to large variations of TEC, not only on equinox days, but also on solstice days, our model is still able to predict TEC quite well. This difficulty may be attributed to the occurrence of an equatorial plasma bubble and to day-to-day TEC variations in the equatorial region. Besides the TEC variation effect, three possible mechanisms, including the geomagnetic-activity index, the solar proxy and another effect which originated below the Earth's ionosphere, which contribute to the TEC prediction error are introduced as error sources for the equatorial latitude region. Moreover, this work adopts the method of Otsuka (Otsuka *et al.*, 2002) for deriving the GPS TEC. In this method, the hourly average of the VTEC is assumed to be uniform within the receiver surrounding area of approximately 1000 km. Since this assumption may be invalid at an equatorial region where a steep latitudinal variation of the TEC, caused by an equatorial anomaly, exists, it may be one of the possible reasons for the difference between the NN TEC and the IRI-2007 TEC. In the case of all comparisons, the NN model underestimates the GPS TEC, which needs to be leveled up in a newer version; however, the NN TEC agrees overall with the GPS TEC. The IRI-2007 model underestimates the GPS TEC as shown in all the comparisons, except the estimation at 1830 LT which the IRI-2007 model overestimates. In this research, we show that the NN is a potentially effective method for TEC prediction in an equatorial region.

5. Future Works

Future works include expanding the input space in order to include most of the impact factors of the TEC, developing the GPS TEC database for at least one solar cycle (∼11 years), and adding TEC data from other stations within Thailand. In addition, the study in Maruyama (2010) shows that other solar proxies besides the sunspot number may be more optimal, hence, we will experiment with various options in future works.

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