CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 INTRODUCTION

In this chapter, the results obtained from the neural network (NN) and the hybrid Seasonal Autoregressive Integrated Moving Average-Neural Network (hybrid SARIMA-NN) models are presented. In the first part, the performances of the NN models were analysed and the findings are presented in sections 4.2, 4.3, and 4.4. The results cover; (i) the capabilities of NN1 and NN2 in estimating the missing data, (ii) the predictability of seasonal TEC based on NN2, and (iii) the predictability of disturbed days TEC based on NN2. The performances of this NN2 model are validated by comparing the results obtained from part (ii) and (iii) with the IRI TEC values with respect to the GPS TEC.

Meanwhile, in the second part, the performance of the developed hybrid SARIMA-NN model in forecasting the GPS TEC values 3 days ahead for different condition days; (i) quiet days, (ii) moderate days and (iii) disturbed days is presented. The forecast TEC values from the hybrid model are compared with the corresponding output given by both the individual models; FCAST-NN and FCAST-SARIMA separately. The results obtained from this analysis are depicted in section 4.5.

4.2 RECONSTRUCTION OF MISSING GPS TEC DATA

Interpolation and extrapolation methods are used to fill the gaps in the dataset. Both methods are very important in recovering the missing and erroneous data in ionospheric studies in order to generate the complete behaviour of ionospheric TEC variations. Thus, in order to evaluate the interpolation and extrapolation capabilities of NN, the developed model is used to estimate the missing ionospheric TEC data in the dataset. The original GPS TEC data are removed and assumed to be missing to analyse the model's interpolation and extrapolation capabilities in estimating the missing data. In the first analysis, the developed models, NN1 and NN2 are used to estimate the hourly ionospheric TEC for 6 days (144 data points). Both the NNs consisted similar input parameters and architectures, but the datasets employed in the network during the training phase were different for both the models. The development of the NN1 and NN2 models are described thoroughly in subsection 3.4.4. In order to assess the performance of the estimation models NN1 and NN2 more extensively, further analysis on the incomplete data with higher number of missing data condition is carried out and the findings are discussed in the subsequent section.

4.2.1 Interpolate and extrapolate missing data up-to 6-day

Both, the NN1 and NN2 models are tested on the identical hourly TEC dataset (March 2006) for comparative purposes. Figure 4.1(a) and Figure 4.1(b) represent the GPS TEC with the corresponding estimated TEC, NN1 TEC (interpolation), and NN2 TEC (extrapolation) for the first 6 days in March 2006, respectively. The duration of

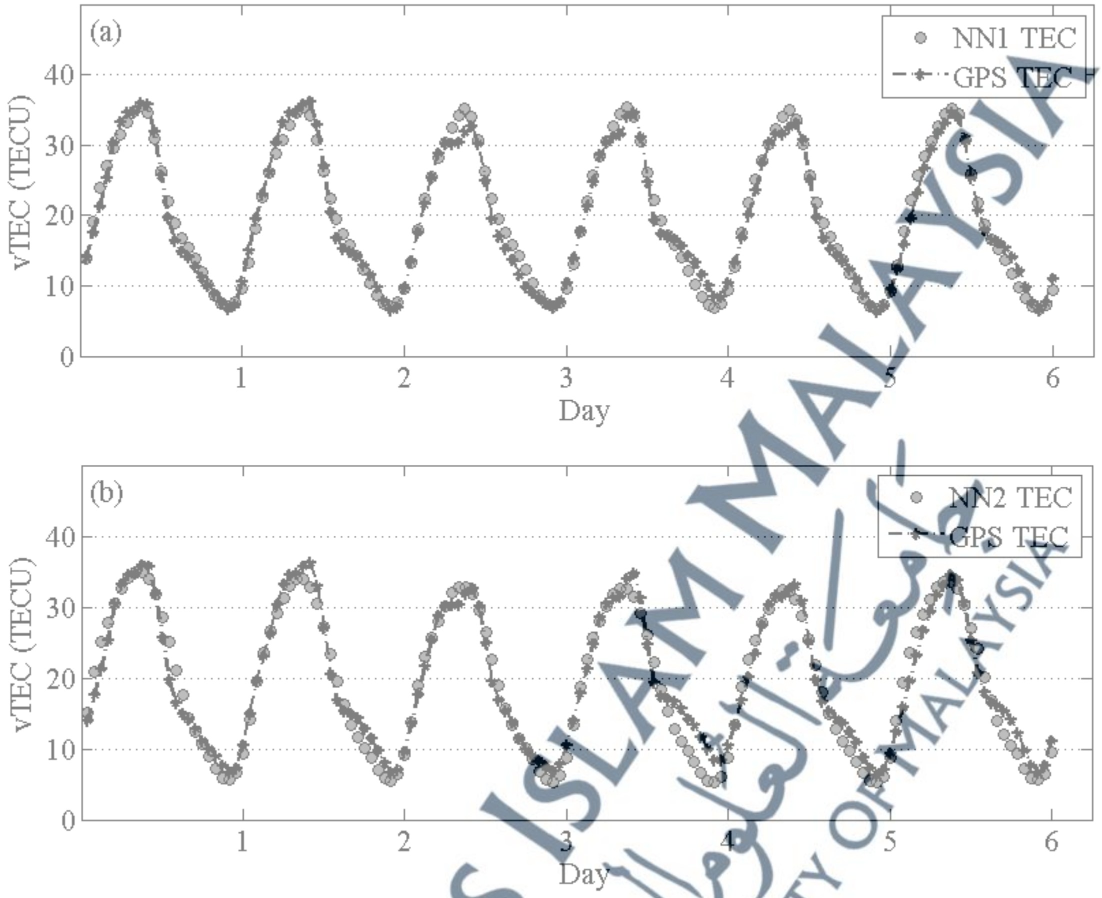

Figure 4.1: Comparison between (a) NN1 TEC (interpolation) and (b) NN2 TEC (extrapolation) against the GPS TEC values from 1 – 6 March 2006 over Parit Raja station

the data covered approximately 20% of the overall TEC data in March 2006. In this analysis, the particular period of the original TEC dataset is considered incomplete. The original data are removed and assumed to be missing, so that the real measurements would be still available and can be used for comparative purposes.

The plotted figures 4.1(a) and 4.1(b) indicate that the NN1 and NN2 are able to interpolate and extrapolate the missing values fairly well and there is insignificant difference between the GPS TEC and the estimated TEC for the first 6 days in March

2006. The minimum and maximum deviations between the GPS TEC and corresponding estimated values are between ~-3.146 and ~3.911 TECU for NN1 model, while ~-5.128 and ~5.473 TECU for NN2 model. The normalised RMSE values are calculated for both models using the average GPS TEC (~19.735 TECU) and the values are 0.075 and 0.105 for interpolation and extrapolation, respectively. The comparison results showed that NN model has the tendency to estimate the missing data well within the input space than estimating the sample outside the input range. Even though the NN2 model fits the missing data fairly well with relative correction (Crel) at about ~88.9%, yet the model has still shown inaccuracies at certain data points. In Figure 4.1(b), slight discrepancies are found on the 2nd, 4th, 5th and 6th days. The NN2 model tend to underestimate the GPS TEC at about ~1600 UT extending to pre-sunrise at about ~2200 UT. The absolute errors during these hours are ranging between ~2 and ~5 TECU. Difficulties in estimating TEC during this period might be due to the fact that ionospheric TEC fluctuates rapidly during the equinoxes.

Olwendo et al. (2012a), analysed TEC over Malindi (2.9˚S, 40.1˚E) and Nairobi (1.2˚S, 36.8˚E), the equatorial latitude stations in Kenyan, and reported that the variability of TEC at night time was larger and more significant in the equinoxes compared to solstices. The enhancement in total electron contents during night hours is not due to solar radiations, but it might be related to other sources that could highly influence the night time ionospheric variations, e.g. the evening pre-reversal enhancement (PRE). This phenomenon could be a factor that causes the level of electron density to remain high at night-time at the equatorial region. According to Kelly (2009), the evening pre-reversal enhancement is observed during the postsunset, where during this period the enhancement of eastward electric field is quite significant prior to the change of zonal electric field to the west. This enhancement is very prominent especially during equinoxes as they can cause the F-layer plasma lift to higher altitudes. In consequence, the recombination process slows down and leads to infrequent ion-neutral collisions. Since, this study only employed the primary factors, such as solar, magnetic, diurnal and seasonal proxies to describe the TEC variations, additional input parameters that could influence the TEC variability especially during night hours at the equatorial region need to be considered to enhance the predictability of the NN model.

In order to explore the interpolation and extrapolation capabilities of the NN models more extensively, the NNs are evaluated over longer periods of missing data in March 2006. The performances of the models are analysed and the findings are discussed in the following section.

4.2.2 Interpolate and extrapolate missing data up-to 30-day

The capabilities of the NNs to interpolate and extrapolate data for a whole month of March 2006 are investigated. Figure 4.2 describes the findings of the analysis, (i) The bar graphs denote the RMSE values against the percentage of missing data in a month, and (ii) the line graphs represent the relative correction, Crel with respect to the percentage of missing data. The overall results show that the NN model is better in interpolation than extrapolation. The RMSE values are computed for both the models across different percentage of missing data in the datasets. The results show that the NN1 model used for interpolation technique has lower RMSE

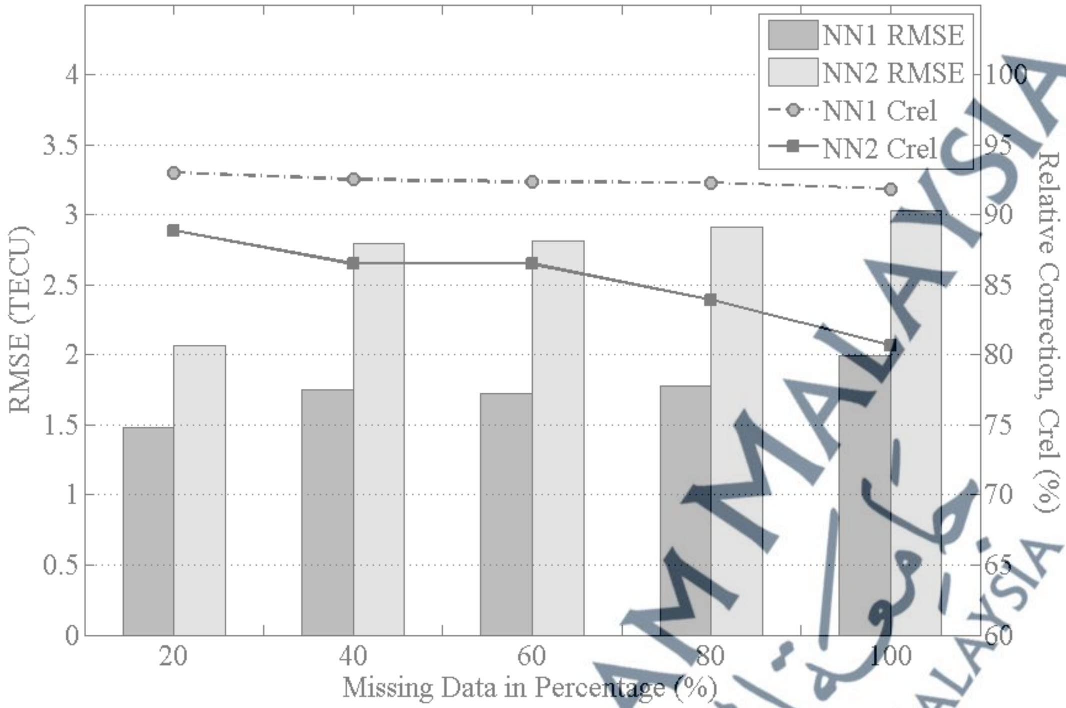

Figure 4.2: RMSE and Crel values versus the percentage of missing data for NN1 (interpolation) and NN2 (extrapolation) model for March 2006 over Parit Raja station

values compared to the NN2 model used for extrapolation technique. The NN1 model does not exhibits large error variations to estimate the TEC values. However, the NN2 shows degradation by ~35% in the RMSE values as the missing data increased from 6 to 12 days. For above 40% of missing data, the NN2 model tends to produce small error(RMSE) variations. In general, the percentage of missing data is directly proportional to the average error (RMSE) for both techniques. The errors between the observed and estimated values become larger as the number of missing value increases.

The relative correction exhibits the effectiveness of a estimation model and in this analysis, the relative correction for both models decreased as the percentage of missing data increases. This shows the Crel is inversely proportional to the percentage of missing data. The changes in Crel is very insignificant in the NN1 model, where for 20%, 40%, 60%, 80%, and 100% missing data, the Crel are ~93.0%, ~92.5%, ~92.3%, ~92.3%, and ~91.8%, respectively. Conclusively, the TEC estimated by the NN1 model able to fill up the data gaps fairly well and satisfactorily since the relative corrections for the NN1 model are more than 90 percent for all ranges of missing rate.

Meanwhile, it is apparent from Figure 4.2 that the overall relative correction values for extrapolation are lower than interpolation. The lowest estimation accuracy of NN2 is observed when all the 30-day data were assumed missing and the model shows degradation by ~11.8% compared to NN1. Although the Crel values in NN2 exhibit a decline trend, the value remained constant as the missing data increased from 40% to 60%. For missing data above 60%, the NN2 model has Crel below than 85% and the value dropped to a lower value as the missing data increased. The quality and the performance of the NN2 model degraded as the rate of missing values increased. However, the average estimation accuracy of the NN2 model is ~85.3%, which still close to an optimum model. An estimation model with Crel equivalent to 100% is defined as an optimum model.

Overall, the NN model offered better results for interpolation than extrapolation. In fact, similar NN capabilities result has been reported by Habarulema et al. (2007) based on a single station model in South Africa by using a five-year data period. The capability of NN in estimating the ionospheric TEC might be affected by other factors, but yet to be discovered at this stage. In order to assess the predictability of the model more thoroughly, the NN2 model is further used to estimate the seasonal

TEC and geomagnetically disturbed days TEC, since it is well-known that the ionospheric TEC variability can significantly be affected by factors, such as solar, diurnal, seasonal, as well as magnetic variations.

4.3 SEASONAL TEC ESTIMATION

Since the equatorial ionospheric is found to manifest remarkable seasonal variations due to solar radiations and zenith angle, the developed hourly NN2 is used to estimate the seasonal TEC values for the same station. The main intention of this analysis is to investigate the capability of the NN2 model to estimate the TEC values over both the equinox and solstice seasons. The performance of the NN2 model to estimate the TEC values during the four seasons in 2006, namely; March representing the March equinox (vernal), June representing the June solstice (summer), October representing the October equinox (autumn) and December representing the December solstice (winter) is analysed. Due to unavailability of data for certain days in September, the testing on autumn equinox is conducted in October 2006. The estimated TEC values yielded by the NN2 model are compared with the most commonly used global model known as IRI (International Reference Ionosphere) with reference to the GPS TEC, in order to validate the NN2 model. Both, the IRI and NN2 models produce monthly median TEC values and the results are illustrated in Figure 4.3(a) - (d).

The average GPS TEC, RMSE, relative correction, and normalised RMSE values of IRI TEC and NN2 TEC with respect to GPS TEC are computed for all the four seasons and summarised in Table 4.1. Overall, the results show that the NN2

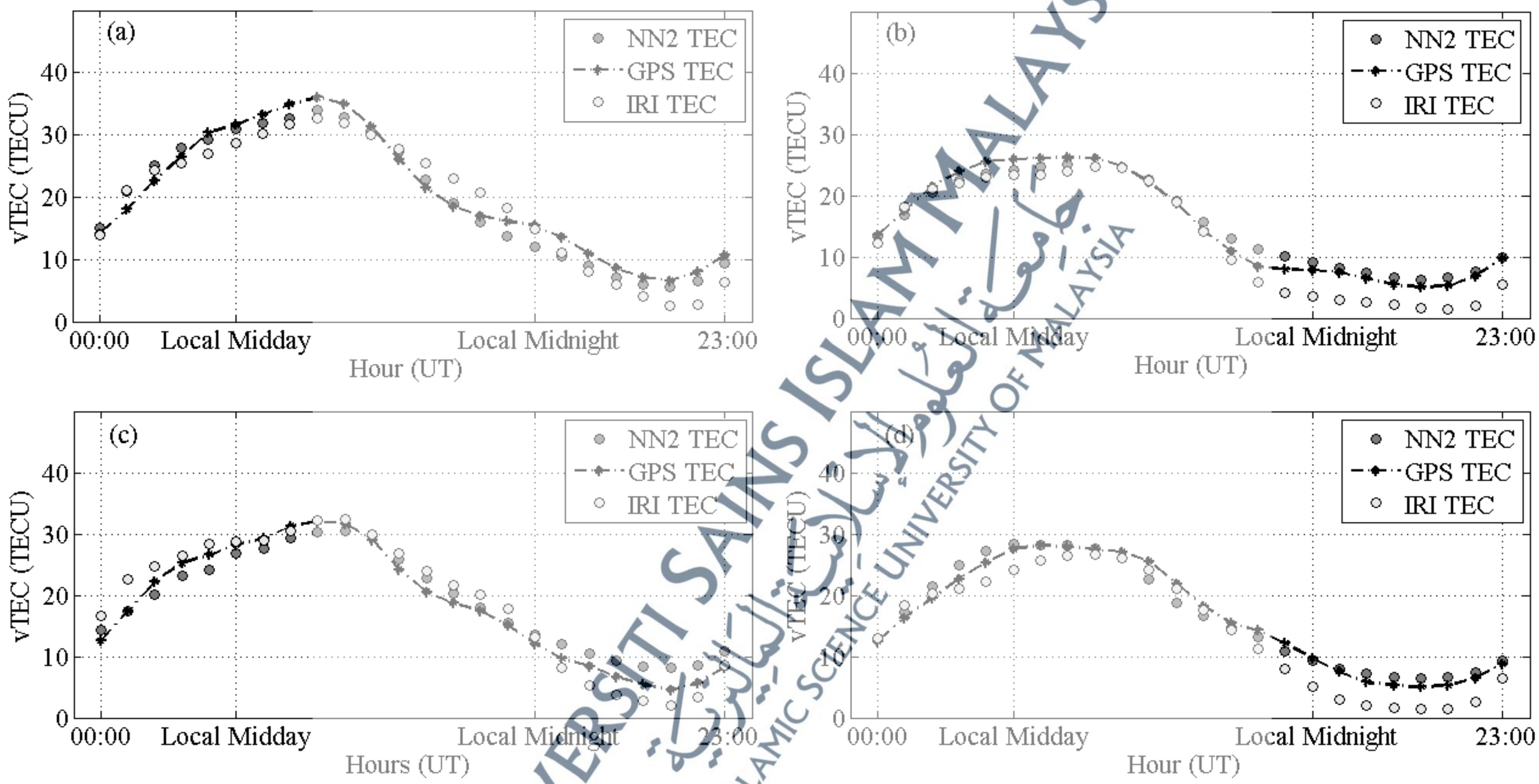

Figure 4.3: Comparison seasonal TEC variations between GPS TEC, NN2 TEC, IRI TEC at Parit Raja station for (a) March (Vernal Equinox), (b) June (Summer Solstice), (c) September (Autumn Equinox), and (d) December (Winter Solstice) in 2006.

model tends to estimate the seasonal GPS TEC values more accurately than the IRI model. The statistical observation from Table 4.1 shows that the average RMSE for NN2 and IRI for all the four seasons in 2006 are ~1.666 and ~2.772 TECU, respectively. In average the NN2 model shows an improvement of ~39.9% compared to the IRI model over the four seasons in 2006. This result proves that the developed NN2 has learned and the model able to generalize well for “unseen” data with high accuracy. The NN2 was trained using the local TEC values, which could have contributed to the success of the developed model compared to the IRI.

According to Watthanasangmechai et al. (2012), the discrepancy between the IRI TEC and the GPS TEC could also be partly due to lack of equatorial ionospheric measurement in the IRI-2007 model, in particular over Southeast Asia. As a result, the IRI model finds difficulty in estimating TEC values over the equatorial latitude station. Apart from that, the difference in the GPS TEC and IRI TEC might due to the altitude at which the ionospheric TEC is estimated in both cases. GPS at an altitude of 20,200 km allowed the measurement of the TEC while the IRI model estimated the TEC at an altitude of 2000 km only (Mosert et al., 2007). Besides, the assumption of ionosphere to be a single layer at a fixed height (Habarulema et al., 2009), could probably contribute to the difference between IRI TEC and GPS TEC, since the altitude of maximum electron density ($h_{max}F2$) varies significantly in equatorial and mid latitude regions (Rama Rao et al., 2006). These are factors that might have affected the estimation accuracy of IRI over Parit Raja, an equatorial latitude station.

The best estimation of the estimated models can be quantified in terms of normalized RMSE and Crel. The NN2 model gives the best TEC approximation

Table 4.1: Average GPS TEC, RMSE, normalized RMSE and relative correction between the GPS TEC and the estimated values; NN2 TEC and IRI TEC during March equinox, June solstice, October equinox and December solstice in 2006 over Parit Raja station

Season Month	Average GPS TEC (TECU)	RMSE (TECU)		Normalised RMSE		Crel (%)	
		NN2	IRI	NN2	IRI	NN2	IRI
March	20.579	1.895	3.080	0.092	0.150	87.13	80.62
June	15.319	1.338	2.789	0.087	0.182	89.08	73.07
October	18.420	2.037	2.421	0.111	0.131	82.41	82.14
December	16.486	1.394	2.797	0.085	0.170	90.34	74.13

during December solstice with the smallest normalized RMSE (~0.085) and largest Crel (~90%). The model poorly estimated the TEC during October equinox with the largest normalized RMSE (~0.111) and smallest Crel (~82%). In contrast, the IRI model is able to estimate the GPS TEC favourably well during the equinoxes compared to solstice seasons. There is a general agreement between both the estimated models during October equinox, where the models yielded approximately equal average relative correction. In terms of RMSE, the NN2 model shows a slight improvement of ~15.9% than the IRI model during this season. For analysis purposes, the error values more (less) than one standard deviation (1σ) between the observed and the estimated TEC are considered as overestimation (underestimation). The underestimation of GPS TEC by the IRI model during the solstices are observed during 0300 UT to 0700 UT and 1400 UT to 2300 UT in the range between ~2 and ~5 TECU for both June and December solstices. These values can clearly be seen in Figure 4.3(b) and Figure 4.3(d).

The seasonal shapes of NN2 TEC and GPS TEC for all seasons resemble each other, yet at certain instances, the NN2 mode displayed a tendency to under or overestimates the GPS TEC. Among the seasons, the NN2 model significantly overestimates the TEC about ~1.5 - 3.6 TECU between 1100 UT to 1300 UT and 1400 UT to 2300 UT for October equinox with the greatest deviation of ~3.596 TECU observed at 2100 UT. The NN2 underestimates the TEC between 0700 UT to 0900 UT and 1500 UT to 1800 UT for March equinox and between 1000 UT to 1200 UT for December solstice. The maximum difference of ~3.078 TECU and ~3.301 TECU is observed at 1100 UT for March equinox and 1600 UT for December solstice, respectively. The underestimation and overestimation of GPS TEC by the NN2 model during equinoxes and solstices are shown in Figure 4.3(a) - (d). However, the overall errors of the NN2 model remained less than 3.6 TECU for all seasons.

Nonetheless, it was discovered that the developed NN2 model experienced slight difficulty to estimate the TEC values during equinoxes. Two main factors that could have affect the performance of the NN2 model are; (i) first factor is as mentioned in the previous section, insufficient representation of TEC variations in NN modelling. TEC varies drastically during equinoxes. Generally, a few mechanisms that vary with the seasons contribute to the enhancement or depletion of electron densities in the ionosphere. For instance, changes in the solar zenith angle, the eastward electric field and the meridional component of neutral winds are some of the factors that contributed to the seasonal anomaly in this latitude (Bagiya et al., 2009). The indices that represent these factors have yet to be included in this NN modelling. Thus, insufficient of parameter(s) that represented the ionospheric TEC variations during this period led the NN2 model to experience slight difficulty in learning the trend of the data and in making an informed generalization. Next the second factor is (ii) the NNs model offered better interpolation than extrapolation (Habarulema et al., 2007). Since the model is referred as a data-driven model, they learn and generalize from experiences. Sufficient data or observations, which cover all possible TEC variations, increase the predictability level of the model. Thus, relatively small dataset in this work might have affected the extrapolative capability of the model. To further investigate on the predictive capability of the NN2 model, the ionospheric TEC estimation during the geomagnetic storms is analysed and the results are discussed in the following section.

4.4 DISTURBED DAYS TEC ESTIMATION

Apart from solar, diurnal, and seasonal variations; the external perturbation, such as geomagnetic storms and solar storms, is even a significant factor that influences the ionospheric dynamics and variations. This phenomenon can cause drastic changes in the plasma densities. Generally, the GPS TEC measurement is expected to show monotonic TEC variations during undisturbed ionospheric conditions, since the formation of ionospheric TEC primarily depends on the interaction of solar radiations with atoms and molecules in the ionosphere layer. However, the energetic solar flares and the high velocity solar wind stream (coronal mass ejections) that affect the earth’s magnetic field cause geomagnetic storm, which has a profound influence on the upper atmosphere.

The geomagnetic storm is known as a global disturbance in the Earth's magnetic field. During this event, the ionosphere exhibits complex and unpredictable behaviour, while the perturbation can cause severe degradation to GPS signals that traverse through ionosphere. Thus, it is important to comprehend the dynamics of these storms, as well as their impacts upon human technologies. In order to explore the feasibility of the NN2 model during geomagnetic storm, the developed NN2 model is applied to estimate the TEC variations during the impulsive event.

The geomagnetic storms considered in this thesis are access based on the disturbance storm time (Dst) index. Significant depression in the Dst index due to enhancement of ring current intensity and energy are used to classify the magnetic storm severity. The Dst values drop to lower negative as the intensity of the magnetic storm increases. In this analysis, the Dst < -100 nT on a particular day is categorised as a storm day. The index is calculated at hourly basis and expressed in nanotesla (nT) unit (Sugiura, 1964). These hourly values were obtained from the National Geophysical Data Centre (NGDC) at their anonymous FTP site: ftp.ngdc.noaa.gov/STP/GEOMAGNETIC_DATA/INDICES/DST. A standard geomagnetic storm can be classified into three phases; (i) initial phase shows a sudden increment in the Earth's magnetic field known as sudden commencement (SC) and certain storms only start gradually, namely gradual commencement (GC); (ii) main phase exhibits persistent decrease in the Earth's magnetic field over a time span of a few hours to a day or two, and (iii) recovery phase is the period when the Earth's magnetic field increases from its minimum value to quiet time value and usually may extend slightly longer than the main phase (Lakhina et al., 2006; Rama Rao et al., 2009; Pandey and Dubey, 2009). In this analysis, the main phase is used as the indicator of storm onset (the time storm begins in UT (hours)).

In order to evaluate the accuracy of the estimation models to estimate the ionospheric TEC during magnetic storm, a diurnal plot of the hourly median NN2 TEC and IRI TEC for three consecutive days; pre-storm, storm and post-storm days is plotted against the GPS TEC. In Figure 4.4, the upper panel shows the Dst values, while the lower panel shows the GPS TEC with corresponding NN2 TEC and IRI TEC models during the geomagnetic disturbances from 14 to 16 December 2006. This storm is considered as the most intense storm in year 2006. A sudden increment in the Dst value is observed on 14 December at 1500 UT, whereas the onset of the main phase is observed two hours later on the same day. The Dst value dropped to the minimum (-146 nT) at about 16 hours after the storm onset. The GPS TEC significantly depleted on the storm day with reference to the relatively quiet days before and after the storm shows a strong negative ionospheric storm.

The NN2 model is able to capture the behaviour of the ionospheric TEC fairly well during the initial and recovery phases of the storm compared to the IRI model, which are on 14 and 16 December. The performance of the NN2 model is quantified in terms of RMSE and the results show that the developed model exhibits improvement of ~22.3% and ~26.4% than the IRI model on both days, pre- and post-storm, respectively. However, on the storm day, the performance of the NN2 model degrades severely. The results obtained for the three consecutive days; 14, 15, and 16 December 2006 are summarised and depicted in Table 4.2. On the storm day, both the estimated models overestimate the GPS measurements, yet from the illustrations the results clearly demostratre that the NN2 model shows tendency to overestimate the GPS TEC significantly higher than the IRI-2007 model. The NN2 model overestimates the TEC values on the storm day with reaching a maximum deviation

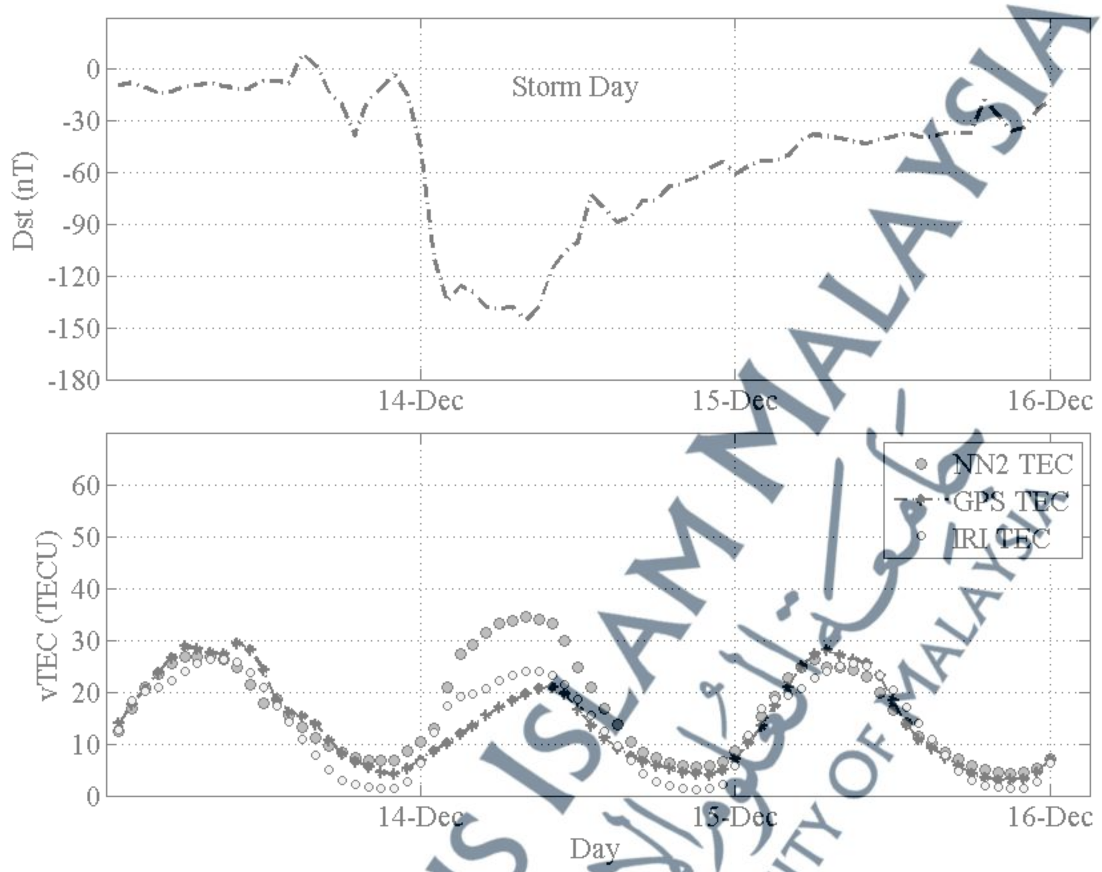

Figure 4.4: Dst and the corresponding GPS TEC, NN2 TEC and IRI TEC from 14-16 December 2006 over Parit Raja station

of ~16.251 TECU observed at local noon (0500 UT), while the IRI model overestimates the GPS TEC values on the storm day between 0000 UT to 1200 UT, with maximum difference of ~ 7.7 TECU. Notably, the estimation accuracy or the Crel of the IRI model is ~25% higher than NN2 model, which signifies that the IRI model is able to estimate the GPS TEC more favourably than the NN2 on the storm day. The IRI TEC generated by the IRI-2007 version model contains an empirical ionospheric storm-time correction model (STORM), which was driven by the prior history of the geomagnetic index ap and the design also includes seasonal

Table 4.2: Average GPS TEC, RMSE, normalized RMSE and relative correction between the GPS TEC and the estimated values; NN2 TEC and IRI TEC during the geomagnetic storm from 14-16 December 2006 over Parit Raja station

Days	Average GPS TEC (TECU)	RMSE (TECU)		Normalised RMSE		Crel (%)	
		NN2	IRI	NN2	IRI	NN2	IRI
14-Dec-06	17.120	2.662	3.429	0.155	0.200	82.49	72.72
15-Dec-06	11.491	9.668	3.791	0.841	0.330	40.88	64.20
16-Dec-06	14.054	1.656	2.251	0.118	0.160	83.48	79.18

and regional dependence in the migration of composition bulge by the diurnal wind field (Araujo-Pradere and Fuller-Rowell, 2002; Araujo-Pradere et al., 2002; Miro Amarante et al., 2007) have enhance the predictability of the model during negative ionospheric storm.

In identifying the factor(s) that could have affected the performance of the NN2 model, the corresponding TEC values on the disturbed days are retrieved from the training data and are illustrated in Appendix C. The observed GPS TEC on the pre-, post- and on- storm days are plotted against the seven quiet-day median hourly TEC prior to the storm. Meanwhile, in case of two storms fall within the ten days of each other, the quiet-day median values prior to the first storm are used for both storm periods (Vijaya Lekshmi et al., 2011). The plots depicted in Appendix C clearly indicate that there were no or insufficient representation of negative phase geomagnetic storms in the training data, except for the magnetic storm in May 15, 2005, where there is a sharp increment of TEC at 0800 UT and it depleted significantly after 0900 UT until the recovery phase. The enhancement in the number of total electron contents during all disturbed conditions in the training data conclusively confirmed the occurrence of positive ionospheric storms. As stated before, learning from the experiences is one of the main criteria that contribute to the achievement of NN modelling. Lack of experiences in the learning phase may affect the generalization of new data in NN modelling. With regard to the aforesaid factor, the NN2 model experienced difficulty in learning the trend during negative phase ionospheric storm, which cause the data-driven model unable to generalize the unseen data well. In conclusion, the NN2 tend to overestimate the ionospheric TEC values during the storm period as it has been trained.

In order to validate the capability of the NN2 model further during disturbed periods, the magnetic storm on 14 April 2006 which appeared to be a positive ionospheric storm effect with a minimum Dst value -111 nT at 1000 UT is examined. The analysed results are plotted in Figure 4.5 and the summary of the statistical observations for the three days (13-15 April) are tabulated in Table 4.3. The overall results indicate that the NN2 model is able to capture the measurement of TEC more accurately than the IRI model during the positive ionospheric storm. The underestimation of the TEC values by the IRI model during the geomagnetic storm from 13 to 15 April appear to be prominent and can be clearly seen from Figure 4.5. Although, the NN2 model has over and underestimates the GPS TEC for certain periods, it still closely resembled the observed TEC for some of the periods that have been considered. The developed NN2 model overestimates the GPS TEC between local pre-sunrise and post-sunrise for all days, as well as during local midnight on the storm day. In contrast, the NN2 model underestimates the TEC between~0400 UT

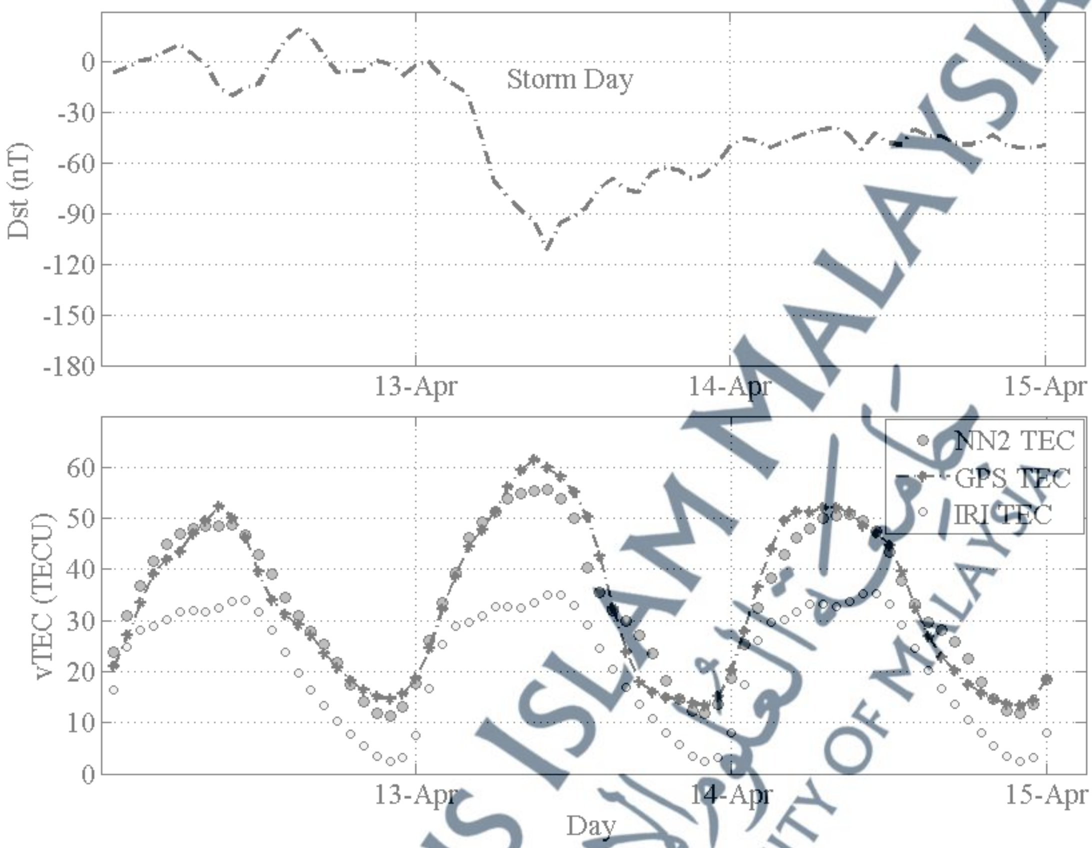

Figure 4.5: Dst and the corresponding GPS TEC, NN2 TEC and IRI TEC from 13-15 April 2006 over Parit Raja station

- ~1400 UT on storm and post-storm days. Even though both the estimation models generated the highest error on the storm day, the error margin for the NN2 model is still lower than the IRI model. From the statistical observations, the average RMSE are computed for the three days and the results indicate that the NN2 model (~3.469 TECU) offered more reliable TEC estimations than the IRI-2007 model (~13.525 TECU). In terms of relative correction, the effectiveness of the NN2 model is about ~30 to 35% higher than the IRI model for all days. This achievement may attribute to the training data in the NN modelling which mostly consisted of positive storms.

Table 4.3: Average GPS TEC, RMSE, normalized RMSE and relative correction between the GPS TEC and the estimated values; NN2 TEC and IRI TEC during the geomagnetic storm from13-15 April 2006 over Parit Raja station

Days	Average GPS TEC (TECU)	RMSE (TECU)		Normalised RMSE		Crel (%)	
		NN2	IRI	NN2	IRI	NN2	IRI
13-Apr-06	31.425	2.650	11.420	0.084	0.364	91.09	60.78
14-Apr - 06	35.996	4.513	16.352	0.125	0.454	87.82	56.35
15-Apr - 06	33.553	3.244	12.804	0.097	0.382	90.92	59.48

The comparison between both the negative and positive ionospheric storms has proven that a well trained neural network model with appropriate input parameters would contribute to a reliable estimation. However, the errors during the disturbed conditions are still higher compared to some other periods, especially during quiet conditions. Including additional input parameters in the NN modelling that are able to describe the complex behaviour of ionosphere during disturbed conditions may enhance the predictability level of the model. Furthermore, the difficulty of estimating TEC values during impulsive events could be overcome by widening the area of training through inclusion of more disturbed conditions in the training data.

Overall, the developed NN2 model revealed high competence in estimating the TEC dynamics at this region, yet at certain periods the model still showed inappropriateness, for instance, TEC variations during night time, equinox season TEC variations, TEC dynamics during negative ionospheric storm, etc. The inefficiency of the model may be due to the factors discussed thoroughly in the above sections. Therefore, in order to capture the TEC variability and the dynamics more accurately, certain aspects should be taken into consideration to improve the NN2 model to be a better representative of TEC estimation model in this region. Those aspects are described as future works in Chapter 5.

4.5 FORECASTING GPS TEC

In the previous section, the neural network models with appropriate input parameters and architectures have been used to estimate the ionospheric TEC. In this section, the observed TEC associated with the NN2 TEC values are employed to forecast a short-term period TEC time series in advance. For this feasibility study, a new hybrid technique is developed to forecast the hourly ionospheric TEC values up to 3 days or 72 hours ahead during medium solar activity using a single station data. In brief, based on a time series analysis, a hybrid methodology that combines the linear model; seasonal autoregressive integrated moving average (SARIMA), and the non-linear model; neural network (NN), is developed to perform short term ionospheric TEC forecasting. The first performance comparison between the hybrid model and the individual models FCAST-SARIMA and FCAST-NN to forecast the ionospheric TEC ahead are carried out based on three independent datasets; quiet days, moderate days, and disturbed days in October, November, and December, respectively in this feasibility study. The FCAST-SARIMA represents the forecast seasonal autoregressive integrated moving average model, while the FCAST-NN denotes the forecast NN model. The results are illustrated in Figure 4.6 to Figure 4.8, respectively. In all figures the top panel shows the comparison between the hybrid

SARIMA-NN TEC (Hybrid TEC) and the GPS TEC values, while in the second and third panels exhibit the comparison between the FCAST-SARIMA TEC (SARIMA TEC) and FCAST-NN TEC (NN TEC) with reference to the GPS TEC, respectively. A summary of these results are also tabulated in Table 4.4.

4.5.1 Forecasting GPS TEC during quiet condition

In order to evaluate the performance of the hybrid forecast model, the GPS TEC versus the forecast values are compared during the magnetic quiet days and the obtained results are illustrated in Figure 4.6. Moreover, in order to validate the forecasting performance of the hybrid model, the output from the hybrid model is compared separately with both the individual models used in hybrid SARIMA-NN model development. In the hybrid model, the SARIMA model is used to analyse 15 days prior TEC data to forecast the linear components, while the residuals from the SARIMA model are used in the NN model to forecast the non-linear components. Eventually, the forecast values from both the components are integrated to obtain the end results; hourly forecast ionospheric TEC values ahead.

The days from 10 - 12 October 2006 are considered as quiet conditions since the 3-hour planetary magnetic index of Kp ranged from 0 to 2+, while the Dst mean value on these particular days are -5nT, -1nT, and -2 nT, respectively. The main reason both the indices are taken into consideration because Huttunen et al. (2002) concluded that both the indices have been widely used as a storm indicator and they have different sensitivity to different storms–time current systems. The dominant causes of the magnetic storm is due to the interplanetary counterparts of the coronal

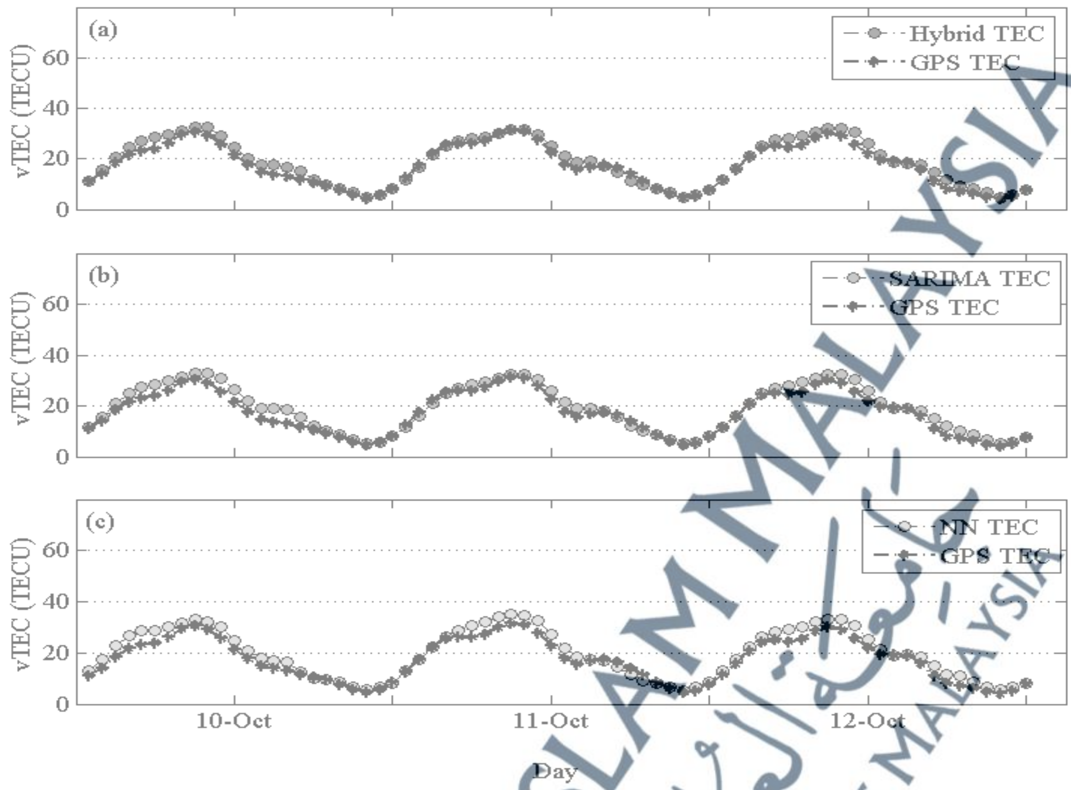

Figure 4.6: Comparison between GPS TEC and the hourly forecast TEC values produced by (a) hybrid SARIMA-NN model, (b) FCAST-SARIMA model, (c) FCAST-NN model during quiet days (10 - 12 October 2006) over Parit Raja

mass ejections (CME). However, Tsurutani et al. (1988) and Huttunen et al. (2002) have pointed out that post shock streams and sheath regions can even cause the most intense and big storms when the solar wind disturbance is sufficiently intense and long-lived. Since a few factors contribute to the intense magnetic storms, therefore, both the indices are considered to categorize a disturbed day.

The results show that during the quiet condition all the three forecast models able to forecast the TEC variations over time. In fact, it is interesting to observe in Figure 4.6 that all the forecast values could follow the trend of the GPS TEC very closely. This may be due to invariant of TEC values during the quiet condition. There is no any impulsive events that could cause stochastic variations in the TEC values. The hybrid SARIMA-NN model agrees with the corresponding GPS TEC with Crel of ~88.48% while, for the single models FCAST-SARIMA and FCAST-NN are ~86.63% and ~84.56%, respectively. This shows the accuracy of the hybrid model to forecast the GPS TEC is better than the individual models used separately. Meanwhile, the RMSE values are calculated for all the three forecast models for three consecutive days during the quiet period and the values are presented in a bar graph in Figure 4.9. The average RMSE for hybrid SARIMA-NN, FCAST-SARIMA and FCAST-NN models during the quiet days are 2.204, 2.497, and 2.912 TECU, respectively. It terms of average RMSE, the percentage improvements of the hybrid model over FCAST-SARIMA and FCAST-NN are ~11.7% and ~24.3%, respectively. Overall, the forecasting capability is improved during the quiet days via the hybrid model.

4.5.2 Forecasting GPS TEC during moderate condition

The second period is selected during the ionospheric moderate condition which is from 9 - 11 November 2006. In this case, the Kp index ranged from 0 to 6 and the Dst mean values on the 9^{th}, 10^{th}, and 11^{th} November 2006 are 4nT, -44nT and -36 nT, respectively. The forecast TEC values from all the three models are plotted in Figure 4.7. The results indicate that the hybrid SARIMA-NN model has tendency to forecast the ionospheric TEC values fairly well and the forecasting accuracy is better than both the individual models. Besides, the results from the Figure 4.7 clearly depicts that both the individual models are able to forecast the TEC variations for the first 24 hours (1 day ahead). The forecasting accuracies of both the models degraded

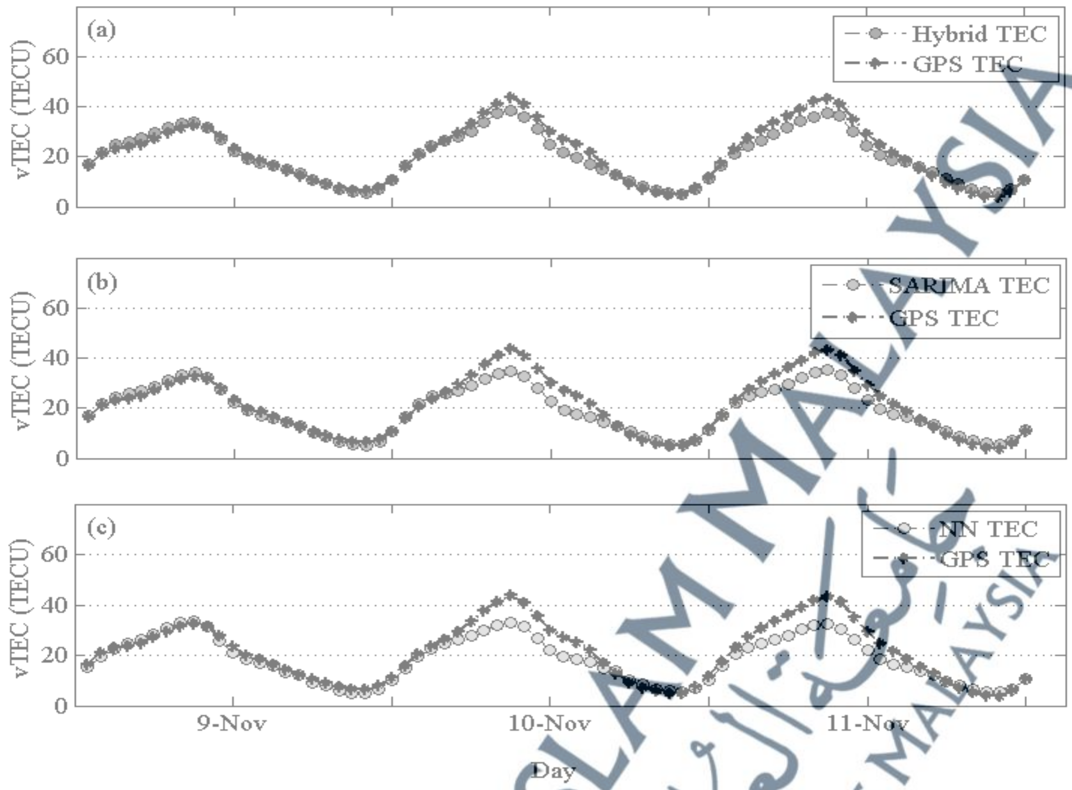

Figure 4.7: Comparison between GPS TEC and the hourly forecast TEC values produced by (a) hybrid SARIMA-NN model, (b) FCAST-SARIMA model, (c) FCAST-NN model during moderate days (9 - 11 November 2006) over Parit Raja

for the consecutive hours and days. The underestimation of TEC values on the second and third days appear to be more prominent on both the individual models than the hybrid SARIMA-NN model. The effectiveness of the forecasting model can be quantified in terms of relative error (Erel) and relative correction (Crel). The lesser the relative error, the better the performance of the forecasting model used. In this case, it is discovered that the Erel of the hybrid model is ~10.36%, the SARIMA model is ~12.51% and the NN model is ~14.33%. In other words, the hybrid SARIMA-NN, the FCAST-SARIMA and the FCAST-NN models are able to forecast the GPS TEC at about ~87.64%, ~85.45%, and ~83.67%, respectively which are satisfactory in common model application.

The RMSE values produced by the FCAST-NN approach during the moderate periods are ~1.376, ~5.292 and ~5.815 TECU on 9, 10, and 11 November 2006, respectively, while the RMSE values yielded by the FCAST-SARIMA model for the similar moderate days are ~1.080, ~4.792 and ~4.522 TECU. Overall, the forecasting errors are found to be increased for both the single models as the time horizon is enlarged. Besides, the results indicate that the FCAST-SARIMA model is able to forecast the GPS TEC trend ahead more accurately than the NN model during this period, even though the SARIMA model is specifically designed for linear approach and unable to capture the non-linear pattern. The limitation of the FCAST-NN model to forecast the ionospheric TEC variations 3 days in advance may due to insufficient of historical data in the training phase which could have affect the generalization ability of the model. Besides, inappropriate of input parameter may also increase the forecasting error of the NN model since input-output mapping is an important criterion in NN modelling. With the implementation of hybrid SARIMA-NN model, the RMSE values improved for all the three consecutive days. The values are ~1.226, ~3.126, and ~3.478 TECU on 9, 10, and 11 November, respectively. By integrating the linear and non-linear components, the hybrid model improved the forecasting by ~24.7% and ~37.3% over the individual models; SARIMA and NN model, respectively in terms of average RMSE.

4.5.3 Forecasting GPS TEC during disturbed condition

Unpredictable variability of the ionospheric TEC due to space weather is generally difficult to capture by using a simple model. Hence, taking into account the complexity during adverse space weather, the effectiveness of the developed models to forecast the GPS TEC ahead during geomagnetic storm are assessed. All the three forecast models are examined from 14 to 16 December 2006. These days are considered as disturbed days since the Kp ranged from 1- to 8+, while the Dst mean value for these particular days are -12nT, -99nT, and -38 nT, respectively. The forecast results are plotted in Figure 4.8, while the performance of the models is quantified in terms of errors as in Table 4.4. On visual inspection, all the forecast models yielded mixed results to forecast the impulsive event.

The hybrid SARIMA-NN and the FCAST-SARIMA models show good agreement during the storm day (15 December). However, both these models indicate large forecasting errors on the last day, which is on 16 December (post-storm). The result illustrated in Figure 4.9 shows that the hybrid and FCAST-SARIMA models yielded the least RMSE on the storm day and the values are larger on the pre- and post- storm days. This means; both the models are able to follow the GPS TEC trend more precisely during the depletion of TEC (negative phase storm), but are found not in reasonable agreement for the other two days, which increased the overall errors. In contrast, the FCAST-NN modelling approach is able to forecast the GPS TEC more precisely on the 1st day compared to the other two models, but the RMSE values increased significantly on the storm day, where the model overestimates the TEC values. However, on the consecutive day (16 December 2005), the forecasting error of the FCAST-NN model decreased by ~42.1% from the previous day and has the tendency to forecast the GPS TEC more favourably than the single model FCAST-SARIMA. The average RMSE are computed for the disturbed days and the findings are compared to determine the best performance model. The hybrid model produced ~2.830 TECU, while both the individual models; FCAST-SARIMA and FCAST-NN

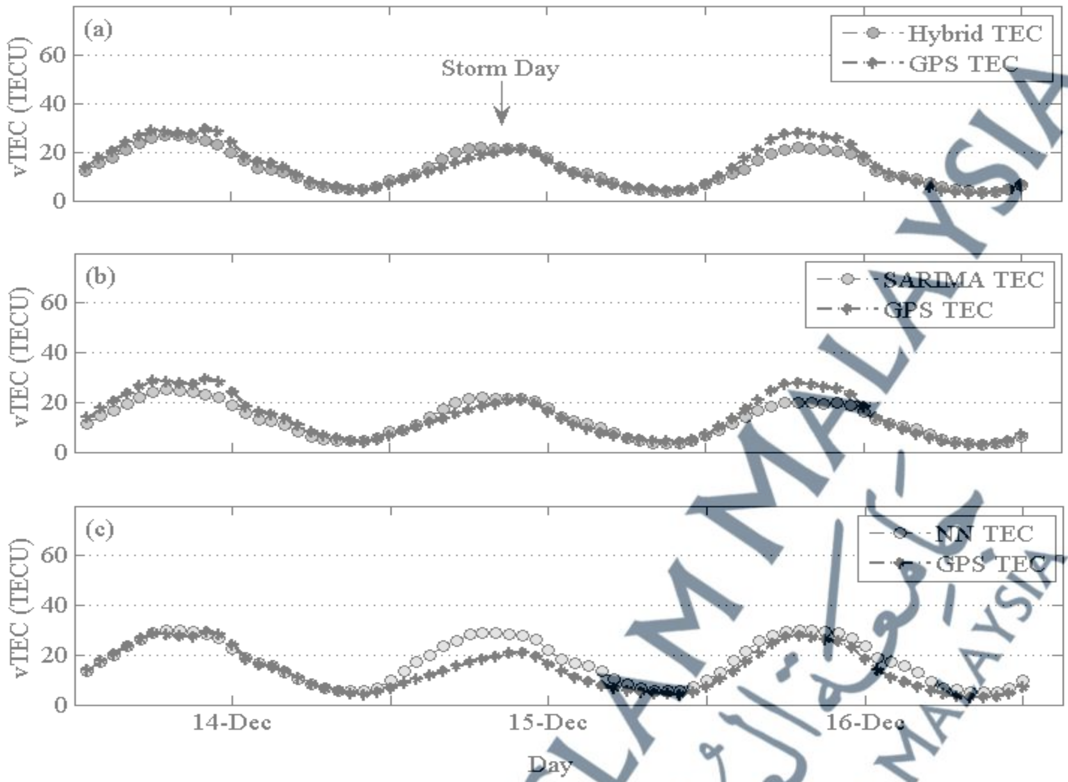

Figure 4.8: Comparison between GPS TEC and the hourly forecast TEC values produced by (a) hybrid SARIMA-NN model, (b) FCAST-SARIMA model, (c) FCAST-NN model during disturbed days (14 - 16 December 2006) over Parit Raja

yielded ~3.267 TECU and ~3.829 TECU, respectively. In terms of average RMSE, the percentage improvements of the hybrid model over FCAST-SARIMA and FCAST-NN during the disturbed conditions are ~13.4% and ~26.1%, respectively. These results indicate that the hybrid SARIMA-NN model has the tendency to forecast the TEC dynamics ahead more accurately during the disturbed conditions compared to the other individual models.

Furthermore, in order to examine the performance of the model, the Crel is assessed for each forecast model and found that the values appeared to be lower for all the three forecast models during this disturbed period compared to the other two

Table 4.4: Average GPS TEC, normalized RMSE and relative correction between the GPS TEC and the forecast values; Hybrid TEC, SARIMA TEC and NN TEC during quiet, moderate and disturbed conditions over Parit Raja station

Days	Average GPS TEC (TECU)	Normalised RMSE			Crel (%)		
		Hybrid	SARIMA	NN	Hybrid	SARIMA	NN
Quiet Days	17.360	0.127	0.143	0.167	88.48	86.63	84.56
Moderate Days	21.179	0.123	0.164	0.196	87.64	85.49	83.67
Disturbed Days	14.222	0.199	0.230	0.269	83.82	79.37	67.99

conditions; quiet and moderate. Overall, the performance of models is found to deteriorate during the impulsive events. This deterioration is more pronounced in the individual models than the hybrid model. This may be due to the fact that the SARIMA model is a linear based technique and this limitation may cause the model fails to forecast the stochastic behaviour of the TEC ahead. On the other hand, even though NN model is a non-linear based technique, insufficient experiences in the learning phase may affect the generalization of new data in NN modelling as stated in the section 4.4. However, owing to its ability in recognizing the linear and non-linear characteristics effectively, the hybrid model tends to forecast the unpredictable variability of the ionospheric TEC ahead more accurately. Apart from the RMSE and relative correction values, the performances of the forecast models are also quantified in terms of normalised RMSE. The errors are computed by dividing the RMSE value over the TEC background. This is done mainly to avoid the effects of high or low TEC background. The normalised RMSE values for three different ionospheric conditions indicate that the developed hybrid model could be an effective way to improve the forecasting accuracy than employing either of the individual models

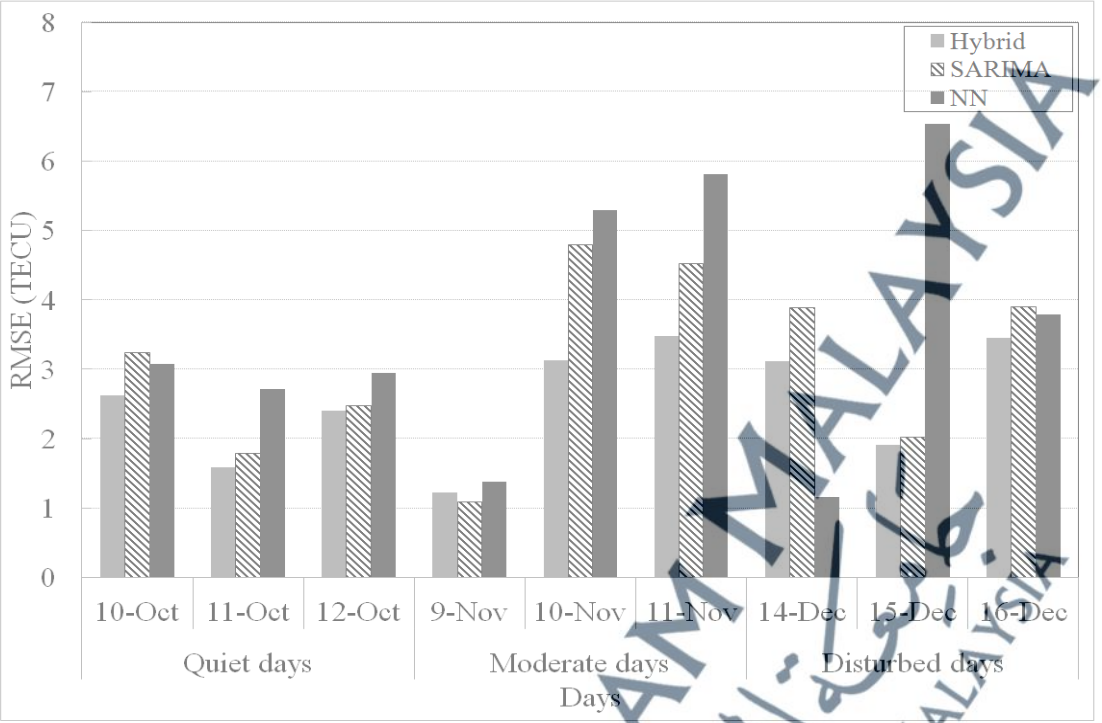

Figure 4.9: RMSE values for Hybrid, SARIMA and NN models during the quite, moderate and disturbed days in 2006 over Parit Raja

separately. This may be due to the fact that each individual model carries its own signatures and features, which are able to characterize the time series pattern in their own way. By integrating these different features into a single framework, enhance the performance of the hybrid model. The hybrid SARIMA-NN model is found to be a promising tool in forecasting the ionospheric TEC variability in Parit Raja, Malaysia.

4.6 SUMMARY

Generally, this chapter depicts the performance of the developed models; namely NN and hybrid SARIMA-NN. The NN model is analysed on the estimation of GPS TEC over Parit Raja station for certain scenarios. Firstly, the capabilities of the developed NN model to interpolate and extrapolate the missing GPS TEC data are examined and the findings are compared with the corresponding observed TEC extracted from the Parit Raja station. The results showed that the NN model offered better finding for interpolation than extrapolation. Hence, in order to further investigate the extrapolative capability of the NN2 model, a comparison between the NN TEC and the estimation TEC from the IRI-2007 model is assessed for the four seasons in 2006. Overall, the NN2 model is able to estimate the GPS TEC values fairly well than the IRI-2007 model. In terms of average RMSE, the percentage improvement of the NN2 model over the IRI model for the four seasons is ~39.9%. Besides, the NN model exhibited the highest predictability during December solstice with a relative correction at ~90% and the model experienced difficulty during equinoxes. Insufficient input parameter(s) to represent the equinoxes TEC and short observation data (a year) in the training phase could have affected the performance of the developed NN model. The performances of the NN2 and IRI models are further investigated during the impulsive events from 14 to 16 December, and the results show that the NN model estimated the GPS TEC more accurately than the IRI during pre- and post-storm. However, the NN model significantly overestimated the TEC on the storm day with a maximum deviation of ~16.251 TECU observed during local midday. The overestimation of the NN model is generally due to lack of information representing the negative phase storms in the training data. In order to verify the predictability of the developed model more thoroughly during ionospheric disturbed condition, the NN model is examined from 13 to 15 April 2006. The results from this analysis proved that the developed NN model has learned and is able to generalize the TEC values with high accuracy during positive ionospheric storms.

In the second section a feasibility study is carried out to investigate the possibility of forecasting the GPS TEC ahead for single GPS receiver station based on hybrid and single models. All the forecast models are examined on three different ionospheric conditions; quiet, moderate, and disturbed conditions. The condition of these three periods are categorised based on the Kp and Dst values. The overall results between the hybrid model and the single models with reference to GPS TEC indicated that the combining approach is more reliable than a single model. All the three forecast models achieved their maximum forecasting accuracy during quiet conditions and among the models, the hybrid model effectively improved the forecasting performance by ~11.7% and ~24.3% compared to both the single models; FCAST-SARIMA and FCAST-NN, respectively in terms of average RMSE. The accuracy and the performance of the forecast models during moderate conditions are also quantified in terms of RMSE, relative correction and the normalised RMSE values. The results revealed that the hybrid SARIMA-NN model is able to capture the non-linearity in the GPS TEC more precisely than each single model used in isolation. During the moderate condition, the forecasting errors are found to increase for both the single models as the time horizon is enlarged. Finally, the possibility of forecasting the GPS TEC three days ahead during geomagnetic storm is executed and the comparison analysis indicated that all the forecast models yielded mixed results in forecasting the stochastic TEC variations ahead. However, the hybrid model produced the least normalised RMSE value. The model forecast the complex and unpredictable behavioural of the GPS TEC more accurately than the single models even though the capability of the hybrid model to forecast the GPS TEC on the post-storm day is found not in reasonable agreement.