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A neural network approach for temperature retrieval from AMSU-A measurements onboard NOAA-15 and NOAA-16 satellites and a case study during Gonu cyclone

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RESUMEN

Se utilizó la técnica de redes neuronales (NN, por sus siglas en inglés) para obtener los perfiles verticales de temperatura a partir de las mediciones de la Advanced Microwave Sounding Unit-A NOAA-15 y 16 (AMSU-A, por sus siglas en inglés) sobre la región de la India. Los datos del correspondiente análisis global generados por el National Center for Environmental Prediction (NCEP) y los del AMSU-A de mayo a julio de 2007 se utilizaron para construir el conjunto de datos de entrenamiento de la red neuronal; el conjunto de datos independiente de mayo a julio de 2007 se dividió al azar en dos para entrenamiento (tierra) y prueba (océano). Los datos de los satélites NOAA-15 y 16 se obtuvieron en el formato de nivel 1b (información de conteo instrumental, navegación y calibración incluida) y preprocesada por el Advanced TIROS Operational Vertical Sounder (ATVOS) y el Advanced Very High Resolution Radiometer (AVHRR)_Processing Package (IAPP). El error medio de la raíz cuadrada (RMS) de los datos del perfil de temperatura recuperados con la NN se compara con los errores del International Advanced TOVS (ATOVS) Processing Package (IAPP). Los resultados globales basados en el análisis del entrenamiento y los conjuntos de datos independientes muestran que la calidad de los datos recuperados con la NN proporciona mejores resultados sobre la tierra y comparables sobre el océano. Se encontró que los errores RMS de la NN son menores a 3º en la superficie, entre 0.9 2.2º a 700-300 hPa y menores de 2º a 300-100 hPa. También se observó que la técnica de NN puede producir resultados notablemente mejores que los del IAPP en los niveles bajos y alrededor del nivel de 200 hPa. Finalmente, el brillo de temperatura (Tb máxima) con base en la red correspondiente a 54.94 GHz (canal 7) de la AMSU-A y la anomalía del núcleo cálido cercana al núcleo del ciclón se utilizaron para el análisis del ciclón Gonu que se formó sobre el Mar de Arabia del 31 de mayo al 7 de junio de 2007. Estas anomalías están relacionadas con la intensificación del ciclón. Se encontró que la anomalía de temperatura del canal único de la AMSU-A a 200 hPa puede ser un buen indicador de la intensidad del ciclón tropical. Por lo tanto, se puede establecer que una red neuronal optimizada puede ser aplicada con facilidad para la recuperación operacional de datos de la AMSU-A y que también puede ofrecer oportunidades sustanciales para mejorar el estudio de los ciclones tropicales.

ABSTRACT

A neural network (NN) technique is used to obtain vertical profiles of temperature from NOAA-15 and 16 Advanced Microwave Sounding Unit-A (AMSU-A) measurements over the Indian region. The corresponding global analysis data generated by National Center for Environmental Prediction (NCEP) and AMSU-A data from July 2006 to April 2007 are used to build the NN training data-sets and the independent dataset of May 2007 to July 2007 divided randomly into two independent dataset for training (land) and testing (ocean). NOAA-15 and 16 satellite data has been obtained in the form of level 1b (instrument counts, navigation and calibration information appended) format and pre-processed by ATOVS (Advanced TIROS Operational Vertical Sounder) and AVHRR (Advanced Very High Resolution Radiometer) Processing Package (AAPP). The root mean square (RMS) error of temperature profile retrieved with the NN is compared with the errors from the International Advanced TOVS (ATOVS) Processing Package (IAPP). The over all results based on the analysis of the training and independent datasets show that the quality of retrievals with NN provide better results over the land and comparable over the ocean. The RMS errors of NN are found to be less than 3 ºC at the surface, 0.9º to 2.2º between 700 and 300 hPa and less than 2 ºC between 300 and 100 hPa. It has also been observed that the NN technique can yield remarkably better results than IAPP at the low levels and at about 200-hPa level. Finally, the network based AMSU-A 54.94-GHz (Channel-7) brightness temperature (maximum Tb) and its warm core anomaly near the center of the cyclone has been used for the analysis of Gonu cyclone formed over Arabian Sea during 31 May to 7 June 2007. Further, the anomalies are related to the intensification of the cyclone. It has been found that the single channel AMSU-A temperature anomaly at 200 hPa can be a good indicator of the intensity of tropical cyclone. Therefore it may be stated that optimized NN can be easily applied to AMSU-A retrieval operationally and it can also offer substantial opportunities for improvement in tropical cyclone studies.

Keywords: NN, AAPP, IAPP, AMSU-MBT, brightness temperature (Tb), NOAA, AMSU.

1. Introduction

The vertical structure of temperature and water vapor plays an important role in the meteorological processes of the atmosphere. For years the radiosonde network has been the primary observing system for monitoring tropospheric temperature and water vapor. Routine observations are very difficult over the oceanic region due to logistic problems and high cost factors. The radiosonde networks are limited only over land regions. The Advanced Microwave Sounding Unit (AMSU) is the operational microwave sounder aboard the National Oceanic and Atmospheric Administration's (NOAA) polar-orbiting satellites. The first AMSU-A was launched on the NOAA-15 satellite, 13 May 1998, and measures outgoing radiation from the earth's surface and/or atmosphere in 15 spectral regions (four "window" channels at 23.8, 31.4, 50.3 and 89 Ghz and 11 temperature sounding channels from 52.8 to 58 Ghz), it is an advanced version over its predecessor, the Microwave Sounding Unit (MSU). These temperature sounding channels are used to derive atmospheric temperature profiles from the surface to an altitude of about 45 km in most situations. The window channels receive energy primarily from the surface and the boundary layer, and are used for deriving the products such as total precipitable water, cloud liquid water, snow cover, sea ice concentration, and precipitation rate. The India Meteorological Department (IMD) has shown the positive impact of these products in their limited area model. Impact study was carried out using high-resolution (80 km) TOVS temperature-humidity profile data, locally derived from High Resolution Picture Transmission (HRPT) station IMD, New Delhi (Bhatia *et al*., 1999). Preliminary results have also been obtained using AAPP installed at IMD, New Delhi for retrieval of temperature and moisture profile and AMSU data and NN (Singh *et al*., 2003).

In order to obtain atmospheric temperature profiles from a microwave instrument, it is necessary to develop a rapid and effective retrieval method. The physical retrieval methods have been applied to obtain temperatures from the sounding data (Li *et al*., 2000; Rosenkranz, 2001), while they generally require a good initial guess and a rapid and accurate direct transfer model. Furthermore, while the physical methods are used in the microwave band, the microwave surface emissivity is required as an input parameter, which has a significant effect on the calculation of brightness temperatures and is very difficult to obtain accurately. For retrieving temperature profiles from microwave radiances, another known technique is linear statistical regression (Rigone and Stogryn, 1977). Compared with the physical retrieval, the statistical retrieval is simple and robust in the presence of noise. But the linear statistical method lacks the capability of retrieving temperature profiles in extreme cases and fails to address non-linear problems (Zhigang *et al*., 2005). To overcome these problems, NN based technique has been used for the temperature retrievals in this study.

In the recent years NN have been used in an increasing number of meteorological applications and proved successful in the development of computationally efficient inversion methods for retrievals of atmospheric profile data (Motteler *et al*., 1995). Singh *et al*. (2003) have compared the results of NNs and other retrieval techniques from ATOVS data over Indian regions. Stogryn *et al*. (1994) presented their work of using fully connected, feed-forward NN to retrieve ocean surface wind speed based on the Special Sensor Microwave Imager (SSM/I) on board the Defense Meteorological Satellite Program (DMSP) satellites. Yang *et al*. (1997) used a neural network to estimate soil temperature. Hsieh and Tang (1998) reviewed the obstacles to adapting the NN technique to meteorological and oceanographic prediction and data analysis. Butler *et al*. (1996) obtained good results with a NN to retrieve temperature profiles from the Defense Meteorological Satellite Program Special Sensor Microwave Temperature Instrument (DMSP SSM/T-I). Kuligowski and Barros (2001) combined IR-microwave satellite data to retrieve temperature and dew point profiles by using an artificial NN. In a study of NN retrieval of atmospheric temperature profiles using collocated AMSU-A and NCEP (National Center for Environmental Prediction) data, Shi (2001) showed that back propagation NN could yield excellent results in retrieving temperature profiles from the 1000- to 10-hPa pressure levels.

In the present study, temperature profiles have been retrieved by two different retrieval schemes:NN and IAPP using NOAA15 and 16 measurements. The retrieval results have been evaluated by the root mean square (RMS) differences and bias deviation between the retrievals from International ATOVS Processing Package (IAPP) and NN with the collocated NCEP analysis for the months of May 2007 to July 2007. The collocated data sets are constructed based on the temperature profiles retrieved using neutral network and IAPP that are within 2.5 hour of time difference and within 2º x 2º Lat/Lon of NCEP analysis. Finally, NN retrieved AMSU-A 54.94-GHz (Channel-7) brightness temperature (maximum Tb) near the center of the cyclone has been used for the study of super cyclone Gonu formed over Arabian Sea during 31 May to 7 June 2007. The derived atmospheric temperature profiles are combined for land and ocean. In this paper, AMSU-A 54.94-GHz (Channel-7) maximum brightness temperature (Tb) will be referred to as an AMSU-MBT.

2. Temperature profile retrievals approaches

2.1 IAPP

In this study, NOAA-15 and 16 satellite data over the Indian region were used for reconstructing temperature profiles. Due to the absence of High Resolution Picture Transmission (HRPT) system, which was capable of receiving the data of NOAA satellites locally, we obtained the near-real time data in the form of level 1b (instrument counts, navigation and calibration information appended) format of NOAA satellite measurement's over the Indian region. Before the retrieval process, it is necessary to process the raw format. To accomplish this work NOAA-15 and 16 satellite data were pre-processed with the ATOVS and AVHRR Processing Package (AAPP) model (Klaes and Schraidt, 1999). The AAPP model was used to perform the ingestion and pre-processing of the level 1b data and the radiances are corrected from AMSU antenna correction procedure (Mo, 1999). The AAPP tasks perform the computation of the calibration coefficients, the satellite navigation (satellite position calculation on its orbit) and image navigation (longitude and latitude position of the pixels, taking into account the sensor geometry, solar angles, etc.). The pre-processing tasks achieve the conversion of the raw data (Earth and atmosphere visible [VIS] and infrared [IR] radiances) into physical parameters (brightness temperatures, albedo) and perform data mapping between the measurement grids of the different instruments (AVHRR/HIRS-High-Resolution Infrared Radiation Sounder), AMSU-MHS (Microwave Humidity Sounder/HIRS mapping). Finally AAPP supplies calibrated data for the same time periods of brightness temperature for all ATOVS channels (AMSU-A, AMSU-B/MHS and HIRS) located in the terrestrial coordinates (latitude and longitude) and mapped them in a common grid resolution. Angular variations including limb correction has been accounted for each channel in AAPP before using as input to IAPP scheme.

The IAPP developed by the Space Science and Engineering Center (SSEC) of the University of Wisconsin (Li *et al*., 2000) has been used to retrieve atmospheric parameters in both clear and cloudy atmospheres from ATOVS radiances from HIRS/3, AMSU-A, and AMSU-B, which were preprocessed by AAPP into the level 1d data format for retrievals. The retrieval algorithm for ATOVS data processing is composed of four steps: 1) HIRS/3 cloud detection and removal of cloud effects; 2) bias correction for the HIRS/3 radiative transfer calculations; 3) regression solution for parameters to be retrieved; and 4) nonlinear iterative physical retrieval of the atmospheric temperature profile, moisture profile, atmospheric total ozone, surface skin temperature and microwave surface emissivity through solving the radiative transfer equation (RTE). In the IAPP, a fast and accurate transmittance model is generated for the RTE calculation; it is called pressure layer optical depth (PLOD) (Hannon *et al*., 1996) and uses 42 pressure level vertical coordinates from 0.1 to 1050 hPa.

In this study, the ancillary data inputs that are used for retrievals are: high-resolution topography (supplied), and numerical model data from NCEP analysis. The IAPP performs temperature and moisture retrieval calculation on a 3 x 3 HIRS field of view (FOV) matrix. HIRS and AMSU-A radiances are used for cloud/clear FOV determination. Depending on clouds, an HIRS + AMSU-A retrieval, an AMSU-A only retrieval, or no retrieval is made for each 3 x 3 FOV matrix. If surface observations are not available, numerical model data is used to define surface conditions, or, with neither available, window channel radiances are used to best approximate surface conditions. Numerical model output can be used as a first guess field for the atmosphere and surface. Data have been selected to cover a larger geographic area from 60 to 90° E in longitude and from 2 to 32º N in latitude.

2.2 Neural network

A NN is a computer model composed of individual processing elements called neurons. The neurons are connected by links in terms of weights. A NN may consist of multiple layers of neurons interconnected with other neurons in the different layers. These layers are referred to as input layer, hidden layer, or output layer. The inputs and the interconnection weights are processed by a weighted summation function to produce a sum that is passed to a transfer function. The output of the transfer function is the output of the neurons. A NN is trained with input and output pattern examples. It then constructs a nonlinear numerical model of a physical process in terms of network parameters. The weights and the biases in the network are determined during the training process. They are obtained using a back-propagation algorithm that is described in detail by Shi (2001). In order to retrieve unique temperature profile by the network, we have chosen a network that is capable of modeling nonlinear data from example and is able to generalize and interpolate. The generalization of network makes it possible to train a network on a representative set of input/output pairs and get good results without training the network on all possible input/output pairs. The weights and biases are adjusted iteratively to reduce the difference between the actual training set output vectors and the estimated output vectors calculated by the network using the input vectors of the training set. The structure of a three-layer backpropagation NN is illustrated in Figure 1.

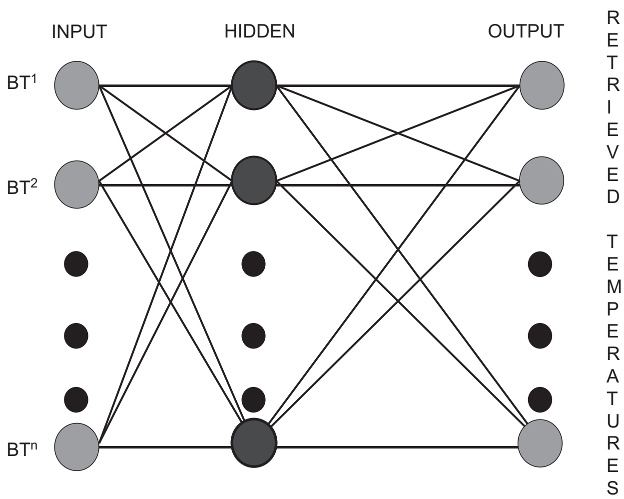


Fig. 1. Three layer backpropogation neural network.

In the figure, three layers mainly input, hidden and output have been used. The neuron of the input layer is represented by BT (brightness temperature, where 1, 2, . . ., n are the AMSU channels). The number of neurons in hidden layer is determined during network architecture design and adjusted to achieve best network performance. The number of neurons in output layer is the retrieved temperature profile. The number of transfer function has been examined in constructing the network architecture. It has been found that to propagate to the hidden-layer and output-layer, a tan-sigmoid transfer function and a linear transfer function in a three-layer back-propagation architecture gives the optimum network performance respectively for the type of data we used in this study. The training algorithm is the basic Levenberg-Marquardt method (Hagan *et al*., 1994), which has been used for the minimization of mean square error criteria. The neutral network technique proposed in this paper is based on the three-layer feed forward backpropagation described in Nath *et al*. (2008).

To optimize the training period and performance of the NN, those predictors with a weak physical relationship to the predictand have been eliminated from consideration. For instance, channel 20 of the HIRS (visible channel) is an obvious candidate for elimination, given that the radiance in the visible band is a function primarily of reflected rather than emitted radiation. The channels in the IR and microwave bands have been evaluated by examining the vertical weighting functions of the HIRS and AMSU-A instruments. In the processing steps of neutral network for the temperature retrieval, the AMSU-A 1d data consists of channels with weighting function peaking below 10 hPa, i.e., channels 1-12,15 and local satellite zenith angle has been considered in the retrieval of the temperature profile (i.e. n = 14). The local satellite zenith angle has been included in the input nodes, and as a result it is not necessary to adjust the measured brightness temperatures to the nadir direction. For the hidden layer, a large range of neurons have been tried between the range of 35 to 55 but good network performance has been achieved by setting 45 neurons in the hidden layer. Similarly, the output layer of the network contains 12 variables. The 12 elements are the temperatures at the 12 levels from 1000 to 100 hPa.

The NN algorithm is developed here to retrieve the atmospheric temperature profiles using AMSU-A observations at fixed pressure levels from 1000 to 100hPa. For this purpose, the AMSU-A 1d data are matched with the collocated NCEP analysis over the region 60 to 90° E in longitude and from 2 to 32º N in latitude. In the building of retrieval database, the NCEP analysis is selected instead of radiosonde observation for the following reasons. First, in the NCEP analysis, the grid values are adjusted to quality-controlled radiosondes, therefore the radiosondes over the Indian regions have their presence in NCEP analysis, second, unavailability of radiosondes over the oceanic region and third, the importance of having a statistically robust set for the training of neutral network, which requires a large number of profiles, much more easily obtainable with GFS than with RAOBS (RAwinsonde OBServation). However, pairings in which either the NCEP data or satellite data from any channel were missing were eliminated from the datasets.

3. Results and discussions

3.1 Comparison of neutral network and IAPP retrievals accuracies

The capability of retrieving temperature profiles may vary for different regions with seasons, thus, it is necessary to test the NN method with different datasets in order to fully investigate its capability. The purpose of this paper was also to test our model over the ocean region (Bay of Bengal and Arabian Sea), where cyclones are frequently formed in the months of pre-monsoon season (March to May).

Over the tropic, the atmospheric temperature and humidity distribution varies with season such as cold and dry in January in contrast with hot and humid in June. Therefore, coefficients derived for January can not be applied to the dataset for June. So we created diverse profile sets from the match-up data and then randomly divide them into two sets for training and testing. In this investigation, we considered two different collocated datasets, which are obtained from two different regions in the chosen domain. First, training data set is prepared for the months of July 2006 to April 2007 (trained dataset), and then secondly, this network architecture is applied for the independent (testing) datasets i. e. months of May 2007 to July 2007. The independent dataset is further divided randomly into two sets of training (land) and testing (ocean) separately. During the network design, to ensure that NN will generalize well to all cases that they have not been trained on, regularization and early stopping process have been incorporated. Which is used to modify the network performance function (the measure of error that the training process minimizes). By including the sizes of weights and biases, training produces a network that perform well with the training data and exhibits smoother behavior when presented with validation data. Similarly early stopping uses the training set, to update the weights and biases and validation set, to stop training when the network begins to over fit the data.

Retrieval results are evaluated by the RMS differences between the retrievals from IAPP and NN with the collocated NCEP analysis. The root mean square error of the retrieval is defined as:

$$\mathrm{RMS} = \sqrt{\frac{1}{K}\sum_{i=1}^{K}(X_{NCEP} - X_{RETR})^2}$$

where and X_{NCEP} and X_{RETR} are the NCEP analysis and retrieved temperature respectively and K is the total number of comparison.

Validation with independent testing dataset for the months of May 2007 to July 2007 has been done. Figure 2a shows the RMS retrieval errors for the training region (land) from the trained NN and IAPP. The NN temperature retrievals are found to be superior to the IAPP retrievals at all levels, especially at the low levels. This is because the network is trained using the maximum number of collocated data over the land. Another reason is, the physical method used in IAPP, significantly dependent on the microwave forward transfer model. Therefore it is very difficult

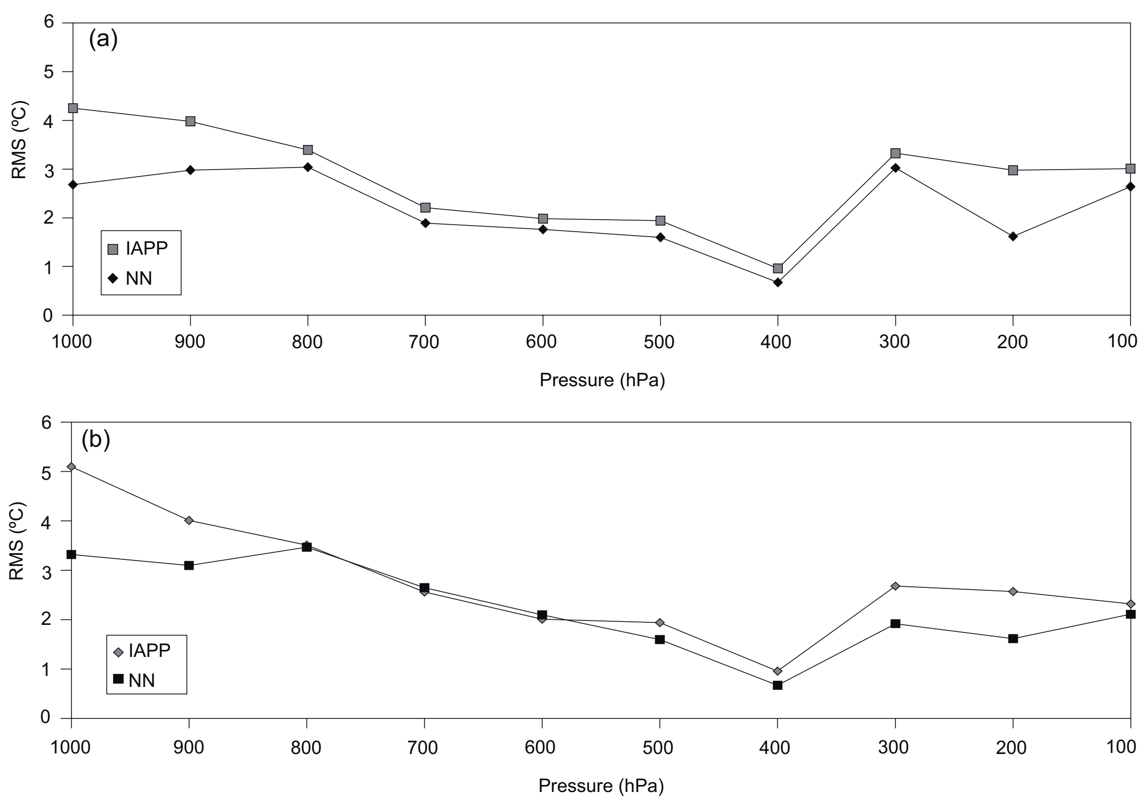


Fig. 2. The RMS errors retrieval of neural network and IAPP. (a) Over the land and (b) over the ocean, both for the months of May 2007 to July 2007.

to calculate accurate brightness temperatures of the low-level and window channels due to the difficulty of obtaining enough accurate surface parameters, especially the surface emissivity. The microwave emissivity varies with the surface conditions, local zenith angle and other factors. Due to these factors brightness temperature for surface-viewing channels can differ by several tens of degrees with a same atmospheric profile. Li *et al*. (2000) also pointed out that the retrieval could be subject to a large error especially in the low atmospheric levels due to some uncertainties, such as the failure of low-level cloud check, surface type uncertainty and emissivity error.

Figure 2b shows the RMS retrieval errors of the NN and IAPP over the testing region (ocean). The results are not satisfactory than those in training region over land. This is because the frequency of match-up data over the ocean are quite less in numbers. The purpose of choosing oceanic region as the testing region is to run our trained NN technique with unavailability of datasets. From the Fig. 2a, b, it can be stated that the retrieval results from the NN over the land are better than oceanic region, but they are still comparable. Especially the results from the NN are significantly better than those from IAPP at higher level near the 400-100 hPa. If enough collocated data of other region are available and used to train the NN, the retrieval results may improve. Note also that no limb corrections were performed on the data used in the neural-network retrievals, which is another potential source of improvement. Aires *et al*. (2002) also concluded that using a specialized NN for few different air masses was the appropriate strategy to adopt, but a larger dataset was then required to train these specialized models. The reason for the better results from neutral network is because of (a) the nonphysical retrieval methods depend heavily on collocated samples, while physical retrieval methods very strongly depend on the forward model and (b) the neutral network retrievals are independent of the surface type (Zhigang *et al*., 2005).

Figure 3 illustrates the overall RMS errors of the NN and IAPP schemes over land and ocean. The figure shows that the surface has the largest RMS value of approximately 3 ºC and steadily decreases to 2.2 to 0.9º between 700-300 hPa and less than 2 °C between 300-100 hPa. In order to reduce these errors, the difference between the time of observations (NCEP analysis match-up file) and NOAA passes should be less. Although the retrieval could be subject to a large error for different scheme of retrievals. Khanna *et al*. (1993) used the physical retrieval scheme using NOAA-11 and NOAA-12 data and found that the difference between profiles of satellite and radiosonde is about 3 to 4 ºC between 700 hPa and 200 hPa. However the difference is quite

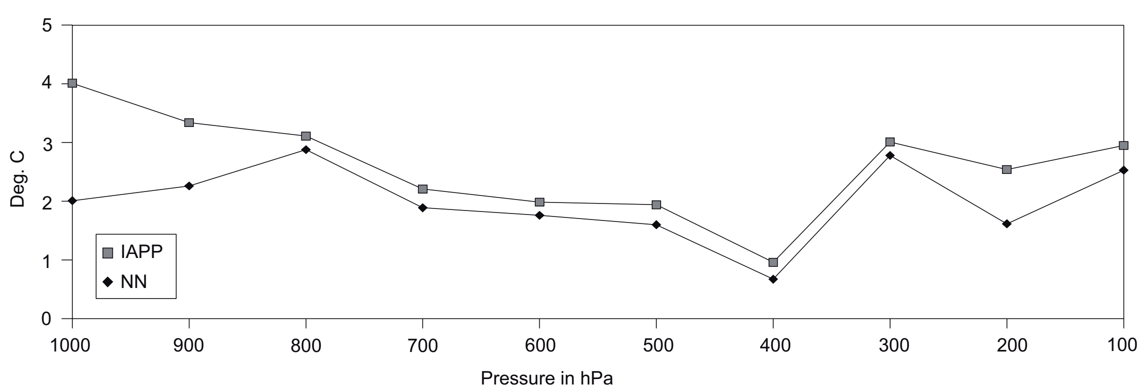


Fig. 3. Over all comparison of RMS errors retrieval of neural network and IAPP including land and ocean region.

large about 7 to 9 ºC below 850 hPa and above 150 hPa when 1000 hPa analysis is used as first guess. These errors are even higher when climatology is used as first guess in place of 1000 hPa analysis.

Figure 4 illustrates the bias deviation of the temperature profile retrieval from two schemes, i.e. NN and IAPP, for testing region. The collocated NCEP temperature profiles dataset are considered as truth data in calculating the bias deviation. In the statistics only those collocated are obtained which has not been used during training. It is clearly seen that the bias values of retrievals are within a ± 2 ºC. At surface and near surface levels, there is a negative bias trend with values in the range of −1 to −0.2 ºC.

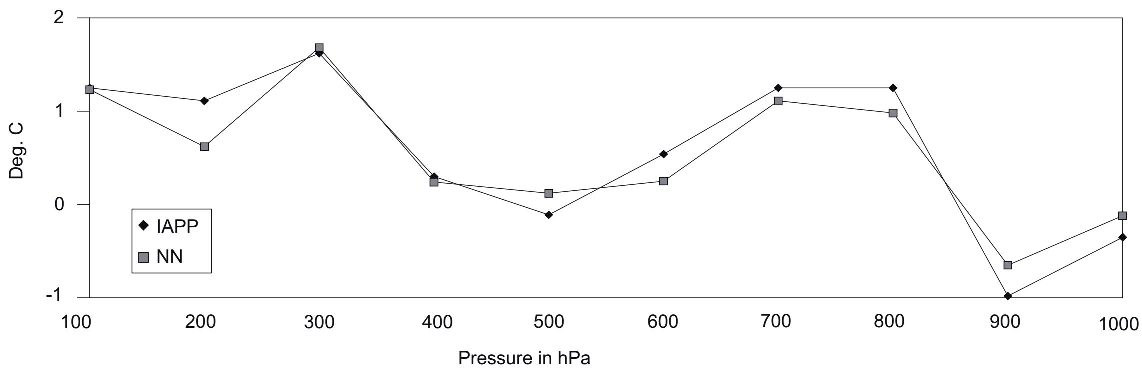


Fig. 4. Over all bias deviation based on testing region of neural network and IAPP at levels from 1000 to 100 hPa.

The NN retrievals have a lower bias than the IAPP at surface, between 850 and 600 hPa and above 400 hPa in the testing region; elsewhere the magnitude of the bias is similar. This may be due to the large horizontal gradients of temperature. The complex surface radiative properties represent the most diverse temperature features and are major factors leading to the largest values of the RMS deviations (Li *et al*., 2001). The bias deviation decreases steadily toward the middle troposphere. The increase of deviations in RMS and bias is mainly due to the much more different atmospheric conditions that are included in the database. The diversity of atmospheric conditions in the training database is an important factor in determining the generalized applicability of the trained NN. Therefore, despite the slight increase of the RMS deviations, the NN tested over the land and ocean by the testing dataset is considered a better retrieval network for operational applications than the network tested by the homogeneous dataset.

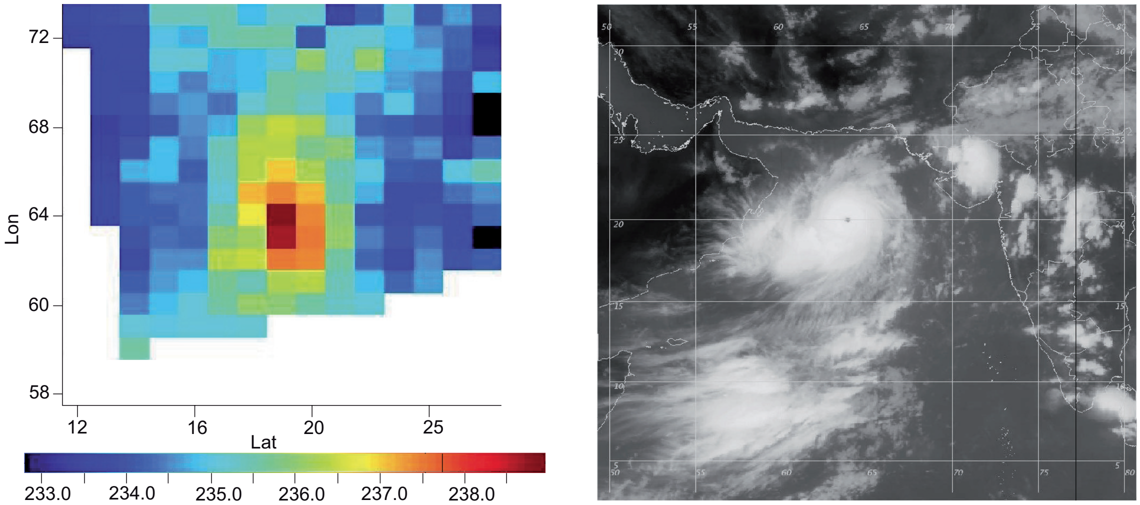
A comparison study (Lavanant *et al*., 1999) of the retrieval with French NWP center at 1000 to 10 hPa pressure levels indicate more than 15% deviation when the ICI (Inversion Coupled with Imager model) retrieval scheme compared to French ICI retrievals. This may be due to the possibility of high quality of ECMWF analyzed fields tuned over Europe as compared to the Asian region. The lower RMS error is possible only if better initial guess and refinements in retrieval techniques were used. It is not possible to achieve RMS less than 2.0 ºC in case proper initial guess is not available, large errors (up to 8 ºC) are seen near surface and above tropopause. So it is desirable to use the better retrieval approach such as NN to get the profiles of desired accuracies.

3.2 Analysis of tropical cyclone

One of the most exciting capabilities of the AMSU is the observation of tropical cyclones and it has been observed that the AMSU-A instrument, which was designed for temperature sounding can also observe the upper-level warm core of tropical cyclones (Kidder *et al*., 2000). A tropical cyclone (TC) is a warm core low-pressure system. The strength of the warm core is directly related to the storms intensity. Theoretically, contributions of upwelling terrestrial radiation sensed by the AMSU-A are largely comprised of two terms - the earth's surface and the overlying atmosphere. Satellite meteorologists typically relate the radiation sensed in individual AMSU-A channels/ frequencies to specific atmospheric layers by use of a term called a weighting function. Thus individual AMSU-A channels (i.e. frequencies) should be carefully chosen based on principles of radiative transfer theory. Each channel (frequency) is radiatively selective in the sense that it detects microwave radiation from discrete layers defined by the weighting function within the earth's atmosphere. Over the past two decades, several studies (Velden *et al*., 1991; Zhigang *et al*., 2005) have documented the TC intensities using satellite-borne passive microwave radiance data. Brueske *et al*. (2003) has outlined the single-channel AMSU approach and found (Channel –7, 54.96 Ghz ~200 mb [~12 km]) that AMSU-MBT radiances correspond well with the actual TC thermal structure and highly correlated with coincident TC minimum sea level pressure (MSLP). The weighting function for AMSU-MBT has a maximum amplitude (Kidder *et al*., 2000) at approximately 200 hPa (~12 km above the earth's surface). In the present analysis, we related specifically NN retrieved AMSU-MBT anomaly near the center of the cyclone, to MSLP and wind speed obtained from Ocean Vector Winds Science, USA (http://podaac.jpl.nasa.gov) for the Gonu cyclone. Further, the NN retrieved AMSU-MBT anomaly is related to the intensification of the cyclone.

Despite the limitations such as the coverage of a particular area of interest just once in 12 to 24 hours from a particular polar orbiter, the sounding information of the cyclone has been used by pooling the sounding data from other polar orbiters viewing the same areas of interest. We considered our area of interest on the cyclone center fell near around the center of ATOVS retrieval swath (2000 km). Based on the size of central clouds of Gonu cyclone seen from coincident Kalpana infrared (IR) image, the domain was set to 15º x 15º. After determining the domain of cyclone center cloud field according to the coincident IR image, the temperature anomalies were calculated by subtracting the average temperature of outer domain from the temperature of maximum Tb at each point inside the domain.

The retrieval data we selected began on 31 May when a low level circulation developed over southeast Arabian Sea was intensified into a vortex with intensity T 1.0 on Dvorak's scale, centered at 12.5N/75.5E. Initially it moved in the northerly direction, then it moved in the northwesterly direction and intensified at 1200 UTC on 1 June with intensity T 1.5 centre 14.5N/69.0E, and wind speed was about 40 knots at AMSU-MBT of –43.4 ºC. The vortex has again intensified at 00 UTC of 2 June to 12 UTC of 2 June with center at 15.1N/66.8E T 3.0. At this stage AMSU-MBT was observed near –42.9 ºC with increasing wind speed. At 18 UTC of 3 June with center 18.0N/66.5E intensity T4.0 the storm has been classified as very severe cyclonic storm with wind speed about 120 knots and the AMSU-MBT around –42.1 ºC. After this, it moved in northwesterly direction at 00UTC of 4 June and intensified very rapidly with center 18.4E/65.1E T 4.5 (eye visible) and T 5.0 at 03 UTC. Further intensification is seen at 12 UTC of 4 June: intensity T 6.5 center 20.2N/63.8E. At this it has been classified as super cyclone with wind speed about 140 knots; the AMSU-MBT around –38.2 ºC and pressure was 920 mb. After maintaining peak winds for about 9 hours, this has been downgraded to very severe cyclonic storm status early on June 5. It was further disorganized and crossed the coast on 7 June at 0400 UTC position 25.5N/58.1E with intensity T 2.5. On



(a) Retrieved AMSU-A 54.9 GHz image of NOAA-15

(b) Infrared image of Kalpana-1

Fig. 5. The coincident infrared and microwave image of 04-06-07 12 UTC.

geostationary platform, the much more frequent Kalpana-1 images could be an indispensable tool for monitoring such cyclones as it can be seen from Figure 5, which show the Kalpana-1 IR image of 4 June 2007 along with AMSU-MBT of same time, but as tropical cyclones intensified, they are characterized by upper tropospheric warming as a result of adiabatic warming/compression of air as it subsides (sinks) within the cyclone center. These subsidences within a tropical cyclone warms the overlying troposphere, suppressing clouds and leads to the characteristic eye which can be better seen by AMSU-MBT than Kalpana-1, because at this frequency scattering and precipitation effects is negligible and microwave instrument can measure this upper level warm core quite well. Tropical

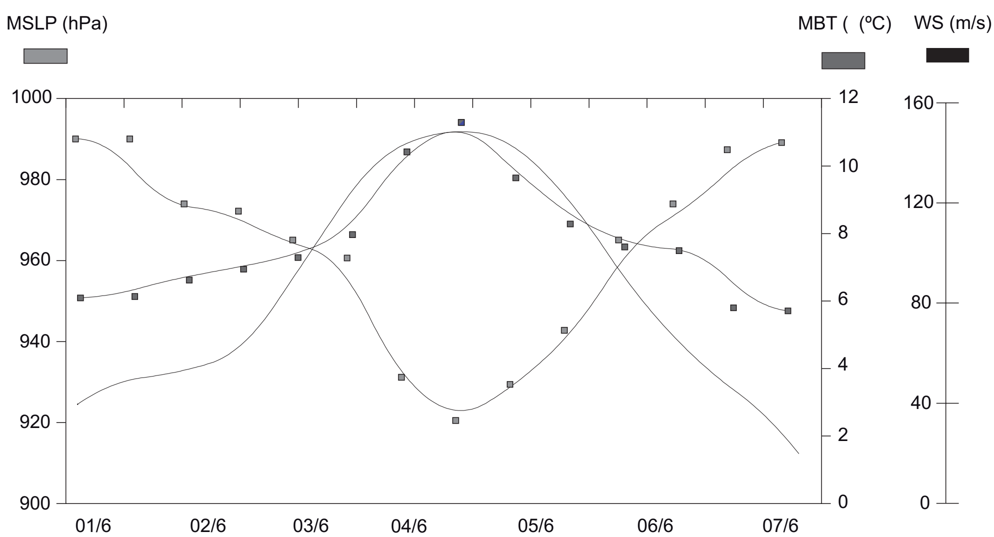


Fig. 6. Anomaly of the AMSU-MBT, wind speed(WS) and pressure during the cyclone. The figure clearly indicates that rising anomaly in AMSU-MBT could be well correlated with the pressure and wind speed.

cyclone typically have a deep tropospheric layer of warm anomalies relative to their surroundings, with warmest anomalies near 300-200 hPa and maximum wind speed near the surface (Hawkins and Rubsam,1968). Figure 6 shows the anomaly of AMSU-MBT, wind speed and pressure during the cyclone. Because of warming in the upper troposphere, which is responsible for the surface pressure drop in the tropical cyclones, the maximum temperature anomaly has correlation with MSLP. The figure clearly indicates that the rise in temperature anomaly of AMSU channel-7 could be well correlated with pressure and wind speed.

Finally, AMSU-MBT anomaly with cyclone intensity (T No) during the cyclone period have been computed and shown in Figure 7. The figure gives an indication of how well single AMSU channel can be utilized for the cyclones especially in the case of super cyclone. It is clearly seen that the order of warm core anomaly at 200 hPa was around 11 ºC. This is indicating the positive relationship of cyclone intensities with warm core anomaly of AMSU-MBT. The regression line indicates that for each 0.8 ºC rise in the AMSU-MBT, the cyclone advances in one category i.e. T. No. Although the categories are not large in this small sample of storms, the technique is simple to implement and could be very useful to operational forecasters. But there are some limitations: (a) Significant changes in the tropical disturbances can take place between two successive passes of polar orbiters viewing almost the same area with 24 hour periodicity. (b) Due to scan geometry limitations continuity is not maintained in AMSU observations between two successive passes. Hence the disturbance may go unnoticed.

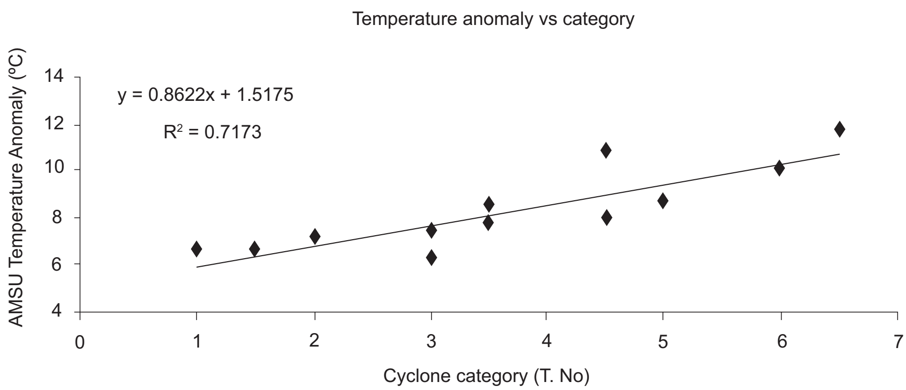


Fig. 7. AMSU-MBT anomaly with cyclone intensity.

In order to avert the ‘gap’ in sounding retrievals and to keep continuity, more number of polar orbiting satellites are needed to have a close watch for the analysis of tropical disturbances. With the launch of INSAT-3D geostationary satellite, which will be having sounder payload, it is hoped that the temporal resolution as well the ‘data gap’ problem would be solved.

4. Concluding remarks

In this study, two different schemes, NN approach and the physical retrieval method used in IAPP, have been briefly described. The RMS errors of the retrieved profiles from the NN are compared with IAPP. The results indicate that the trained network can obtain much better accuracy in the training region and a comparable accuracy in other regions. Although the iterative physical retrieval procedure in IAPP, can give sometimes substantial improvement, in most of the times it is unable to yield all the low-level atmospheric information contained in the low-level and window channel measurements. However, the NN can easily and effectively include these measurements specifically at the low levels and about the 200-hPa. The RMS errors of NN are found to be less than 3 ºC at the surface, 0.9 to 2.2 ºC between 700-300 hPa and less than 2 ºC between 300-200 hPa. Finally, the NN based AMSU-MBT anomaly near the center of the cyclone has been used for the study of super cyclone Gonu. It has been found that the single AMSU-MBT anomaly at 200 hPa can be an indicator of the intensity of tropical cyclone. This study has also briefly highlighted the unique feature of single AMSU channel for analyzing the strength of warm anomaly which can be particularly valuable during the period of intense cyclone.

Based on the performance of the above studies, we conclude that the NN retrieval scheme could show great promise for use in operational retrievals of temperature profiles from the NOAA (K, L, M, and N) satellites measurement over Indian region. With the availability of various space based data from geostationary (INSAT-3D) and polar orbiting satellites (Megha-Tropiques) over the Indian region, in the near future an improvement in the quality of vertical profile data at the input to the model is expected to improve the accuracy of weather forecast. Further work is in progress to construct a more robust and specialized network to generalize the retrieval for all seasons.

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References

Aires F., A. Chedin, N. A. Scott and W. B. Rossow, 2002. A regularized neural net approach for retrieval of atmospheric and surface temperature with the IASI instrument. *J. Appl. Meteor*. **41**, 144-159.

Bhatia R. C., P. N. Khanna, K. Prasad and Y. V. Rama Rao, 1999. A preliminary study of the impact of NOAA soundings retrievals on a limited area model (LAM) forecasts, *Vayumandal* **29**, 147-149.

Brueske Kurt F., C. S.Velden and S. Christopher, 2003. Satellite-based tropical cyclone intensity estimation using the NOAA-KLM series advanced microwave sounding unit (AMSU). *Mon. Wea. Rev*. **131**, 687-697.

Butler C. T., R. V. Z. Meredith and A. P. Stogryn, 1996. Retrieving atmospheric temperature parameters from DMSP SSM/T-1 data with a neural network. *J. Geophys. Res*. **101**, 7075-7083.

Hagan M. T. and M. B. Menhaj, 1994. Training feedforward networks with the Marquardt algorithm. *IEEE T Neural Network* **5**, 989-993.

Hannon S., L. L. Strow and W. W. McMillan, 1996. Atmospheric infrared fast transmittance models: A comparison of two approaches. Proc. SPIE-Int. Soc. Opt. Eng. **2830**, 94-105.

Hawkins H. F. and D. T. Rubsam, 1968. Hurrican Hilda, 1964. II. Structure and budgets of the hurricane on October 1, 1964. *Mon. Wea. Rev.* **96**, 617-636.

Hsieh W. W. and B. Tang, 1998. Applying neural network models to prediction and data analysis in meteorology and oceanography. *B. Amer. Meteorol. Soc.* **79**, 1855-1870.

Khanna P. N. and R. R. Kelker, 1993. Temperature sounding of the atmosphere over Indian region using satellite data. Mausam **44**, 167-174.

Kidder S. Q., M. D. Goldberg, R. M. Zehr, M. DeMaria, J. F. W. Purdom, C. S. Velden, N. C. Grody and S. J. Kusselson, 2000. Satellite analysis of tropical cyclones using the Advanced Microwave Sounding Unit (AMSU). *B. Am. Meteorol. Soc.* **81**, 1241-1259.

Klaes D. and R. Schraidt, 1999. The European ATOVS and AVHRR processing package (AAPP). Tech. Proc.10th Int. ATOVS Study Conf. Boulder USA, January 27 to February 2, 288-294.

Kuligowski R. J. and A. P. Barros, 2001. Combined IR-microwave satellite retrieval of temperature and dewpoint profiles using artificial neural networks. *J. Appl. Meteorol*. **40**, 2051-2067.

Lavanant L., P. Brunel, G. Rochard and T. Labrot, 1999. NOAA-15 sounding profiles retrieved with the ICI scheme. ITSC No.10.

Li J., W. W. Wolf, W. P. Menzel, W. J. Zhang, H. L. Huang, and T. H. Achtor, 2000. Global sounding of the atmosphere from ATOVS measurement: The algorithm and validation. *J. Appl. Meteorol*. **39**, 1248-1268.

Mo T., 1999. AMSU-A antenna pattern corrections. *IEEE T Geosci. Remote* **37**, 103-112.

Motteler H. E., S. L. Larrabee, L. McMillin and J. A. Gualtieri, 1995. Comparison of neural networks and regression-based methods for temperature retrievals. *Appl. Optics* **34**, 5390-5397.

Nath S., A. K. Mitra and S. K. Roy Bhomwik, 2008. Improving the quality of INSAT derived quantitative precipitation estimates using an neural network method. *Geofizika* **25**, 41-51.

Rigone J. L. and A. P. Stogryn, 1977. Data processing for the DMSP microwave radiometer system. Proc. Eleventh International Symposium on Remote Sensing of the Environment, University of Michigan Press. Ann Arbor, MI, USA, 1599-1608.

Rosenkranz P. W., 2001. Retrieval of temperature and moisture profiles from AMSU-A and AMSU-B measurements. IEEE Trans. *Geosci. Remote Sen.* **39**, 2429-2435.

Rumelhart D. E., G. E. Hinton and R. J. Williams, 1986. Learning internal representation by error propagation. In: *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*. (D. E. Rumelhart and J. L. McClelland, Eds.). Massachusetts Institute of Technology Press. MA. USA, 318-362.

Shi L., 2001. Retrieval of atmospheric temperature profiles from AMSU-A measurement using a neural network approach. *J. Atmos. Oceanic Technol.* **18**, 340-347.

Singh D., R. C. Bhatia, S. K. Srivastav and B. Singh, 2003. An experiment of the ICI3 scheme for retrieving atmospheric parameters over the Indian region using AMSU data from NOAA-16 satellite. *Mausam* **54**, 107-110.

Stogryn A. P., C. T. Butler and T. J. Bartolac, 1994. Ocean surface wind retrievals from special sensor microwave imager data w ith neural networks. *J. Geophys. Res*. **90**, 981-984.

Velden C. S., B. M. Goodman and R. T. Merrill, 1991. Western North Pacific tropical cyclone intensity estimation from NOAA polar-orbiting satellite microwave data. *Mon. Wea. Rev.* **119**, 159-168.

Yang C. C., S. O. Prasher and G. R. Mehuys, 1997. An artificial neural network to estimate soil temperature. *Can. J. Soil Sci.* **77**, 421-429.

Zhigang Y., Ch. Hongbin and L. Longfu, 2005. Retrieving atmospheric temperature profiles from AMSU-A data with neural networks. *Adv. Atmos. Sci*. **22**, 606-616.