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Adaptive neuro fuzzy inference system for profiling of the atmosphere

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Abstract

Retrieval of accurate profiles of temperature and water vapor is important for the study of atmospheric convection. However, it is challenging because of the uncertainties associated with direct measurement of atmospheric parameters during convection events using radiosonde and retrieval of remote-sensed observations from satellites. Recent developments in computational techniques motivated the use of adaptive techniques in the retrieval algorithms. In this work, we have used the Adaptive Neuro Fuzzy Inference System (ANFIS) to retrieve profiles of temperature and humidity over tropical station Gadanki (13.5° N, 79.2° E), India. The observations of brightness temperatures recorded by Radiometrics Multichannel Microwave Radiometer MP3000 for the period of June–September 2011 are used to model profiles of atmospheric parameters up to 10 km. The ultimate goal of this work is to use the ANFIS forecast model to retrieve atmospheric profiles accurately during the wet season of the Indian monsoon (JJAS) season and during heavy rainfall associated with tropical convections. The comparison analysis of the ANFIS model retrieval of temperature and relative humidity (RH) profiles with GPS-radiosonde observations and profiles retrieved using the Artificial Neural Network (ANN) algorithm indicates that errors in the ANFIS model are less even in the wet season, and retrievals using ANFIS are more reliable, making this technique the standard. The Pearson product movement correlation coefficient (r) between retrieved and observed profiles is more than 99 % for temperature profiles for both techniques and therefore both techniques are successful in the retrieval of temperature profiles. However, in the case of RH the retrieval using ANFIS is found to be better. The comparison of mean absolute error (MAE), root mean square error (RMSE) and symmetric mean absolute percentage error (SMAPE) of retrieved temperature and RH profiles using ANN and ANFIS also indicates that profiles retrieved using ANFIS are significantly better compared to the ANN technique. The error analysis of profiles concludes that retrieved profiles using ANFIS techniques have improved the retrievals substantially; however, retrieval of RH by both techniques (ANN and ANFIS) has limited success.

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1 Introduction

Atmospheric convection plays an important role in the energy circulation of the atmosphere by transporting heat, momentum and moisture from the boundary layer to the free atmosphere. The vertical transport of these fluxes (heat, momentum and moisture) determines the evolution of multi-scale convective phenomena such as thunderstorms, tornadoes, etc. The temporal scale of these phenomena range from a few minutes to hours and are associated with disastrous effects having socio-economic importance. Therefore, a continuous monitoring of profiles of the atmosphere is important for their study. Conventionally, they are observed using radiosonde (GPS-sonde, hereafter referred to as radiosonde) measurements. However, it is difficult to study the evolution of convection using them due to the limited availability of these observations, as operationally two radiosonde launches are scheduled at 00:00 and 12:00 UTC every day. Also, it is very expensive to launch radiosonde operationally at regular intervals of one hour. Therefore it is difficult to monitor the convective systems that evolve during the interval between these launches. Moreover, the network of radiosonde observations is spatially coarse and many times convection may not occur in the way radiosonde is flying. Furthermore, updrafts and downdrafts occurring during the convection cause either drift or burst of rubber balloons attached to radiosonde equipment. On the other hand, spaced based measurements of vertical profiles of the atmosphere using radio and microwave RADARS/radiometers on low earth orbiting/sun-synchronous/geostationary satellites are useful for identifying the convections, their movement and evolution. However, their re-visit time/frequency of the observations and limited retrieval skill in the lower portion of the atmosphere do not allow investigation of the genesis and evolution of the convection in most of the cases.

In this situation, multichannel microwave radiometers (MWR) have evolved as a powerful tool for monitoring the genesis and evolution of the convection over a site. An MWR is a device that measures the vertical profiles of temperature, humidity and cloud liquid water content. The MWR enables continuous monitoring of the thermodynamic

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conditions of the atmosphere. Generally, it is a passive radiometer, continuously monitoring brightness temperatures at various wavelengths in the microwave regions of electromagnetic spectra. Many nonlinear statistical/evolutionary algorithms are being developed to retrieve the profiles of the atmosphere using MWR. Artificial neural networks (ANNs) are one of them, which are widely used for different types of infrared and microwave sounding instruments.

At the National Atmospheric Research Laboratory, Gadanki (13.5° N, 79.2° E), India, MWR (MP3000-A manufactured by M/S Radiometrics, USA) is installed to study diurnal variation of convection and rainfall for which understanding of the genesis and further evolution of convection is very important. MWR is associated with the software (VIZMet-B) enabled ANN retrieval algorithm for retrieving the profiles of temperature, relative humidity, liquid water content and vapor density. Figure 1 shows the evolution of thunderstorms observed continuously (temporal resolution of temperature and relative humidity (RH) profiles: 4 min) by this MWR on 28 May 2013. The observed profiles of equivalent potential temperatures indicate preconditioning of the vertical column of the atmosphere to be conducive to the occurrence of thunderstorms about 3–4 h prior to their actual occurrence (Fig. 1a). The profile of relative humidity indicates the horizontal advection of moisture in a layer between 800 and 600 mb and uplifting of moisture about 4 h prior to the occurrence of thunderstorms. This radiometer was used by many investigators for scientific research because of its utility and capacity to generate high-frequency profiles with reasonable accuracy. The ANN used in this MWR is useful to train vertical profiles observed at sites using radiosonde observations, microwave radiances and vertical distribution of weighting functions. Catherine Gaffard and Tim Hewison in their trial report on the radiometer MP3000 state that the RMSE in the temperature profiles increases rapidly from 0.5 K at the surface to 1.5 K at 1 km and more slowly to 1.8 K at 5 km. According to Cimini et al. (2006a, b), temperature and humidity retrieval accuracy is best near the surface and degrades with height, and also above 3 km the retrieval accuracy and resolution degrade rapidly for all techniques. These studies used the observations reported without rain, because the MWR cannot make any useful atmospheric observations during anything more than moderate rains. Thus, the major limitation of MWR is its performance degradation under heavy precipitation conditions. Nevertheless, this instrument is believed to play an important role in investigating the thermodynamic condition of convection; however, the reliability and the performance can be enhanced by using better retrieval algorithms.

Recent developments in the retrieval algorithms and computational techniques are adaptive and devise a model (Gaffard and Hewison, 2003) that improves the performance and accuracy of radiometer retrievals. ANFIS is a nonlinear computational intelligent system that adapts itself by forming rules to survive with changing environment and uncertainty. The Fuzzy Inference System (FIS) incorporates human knowledge and performs inference and decision-making, and achieves better prediction than conventional statistical methods (Jang et al., 2007). ANFIS can be employed to model and predict a chaotic time series to yield a remarkable result in numerous practical applications (Jang, 1993). ANFIS tunes a Sugeno-type interface system and generates a single output of a weighted linear combination of the consequents (Jang et al., 2007). Therefore, such methods are useful for retrieving atmospheric profiles based on the passive microwave remote-sensed brightness temperatures at different frequencies observed by MWR.

In the present work, we have developed an ANFIS model-based retrieval of atmospheric parameters using MWR observations at NARL, India. The objective of this algorithm development is to improve the accuracy of the retrieval of temperature and humidity profiles of MWR, especially over the lower atmosphere. The high-frequency and accurate measurement of these profiles is very important for understanding mesoscale processes and physical mechanisms involved in the preconditioning and triggering of small-scale convections such as thunderstorms, tornadoes, etc., and also for understanding their evolution. There are very limited efforts to understand it, especially over the tropical region, because of the unavailability of high-frequency observations over this region, even though it is very important to understand it to improve the understanding about global energy transport. In this work, the high-frequency, i.e., 4 min

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observations each of brightness temperatures of 10 microwave channels for the period of June 2011 to September 2011 are used to train the ANFIS model and to retrieve vertical profiles of temperature and relative humidity. The details of the data and method are described in Sect. 2. The experimental results are discussed in Sect. 3 and conclusions obtained from this work are presented in Sect. 4.

2 Data

In this work, we have developed an ANFIS model based on the observations of MWR installed at NARL, Gadanki. This MWR uses 36 channels in the microwave frequency range of 20–200 GHz (22 in the K band and 14 in the V band). This MWR provides data with a vertical resolution of 50 m to 500 m, 100 m from 500 m to 2 km and 250 m from 2 km to 10 km. For this study, we have used the zenith observations from 10 microwave channels, viz. 22.234, 22.500, 23.034, 23.834, 25.000, 26.234, 28.000, 30.000, 57.964 and 58.800 GHz to retrieve profiles of atmospheric temperature and relative humidity. These channels are selected based on their sensitivity to the occurrence of thunderstorms over the study site. The period of the observations used in this work is from June 2011 to September 2011. From available observations, 80 % of observations are used for training of ANFIS and 20 % of observations are used for the validation of the ANFIS model. For the training of the ANFIS system, we have used temperature and relative humidity observed by co-located GPS radiosonde (Meisei, Japan make, RS-01GII measurements usually available almost every day at 12:00 UT (LT = UT + 05:30 h) at NARL Gadanki for the same period of the training data set. We have retrieved these atmospheric parameters for every 1 km up to 10 km and validated them with GPS radiosonde observations for the validation period. Note that the Meisei radiosonde uses the temperature (relative humidity) sensors made with the thermistor (carbon humidity sensor) that measures the temperature (relative humidity) in the range of –90 to +40 °C (0–100 %) with an accuracy of 0.20 to 0.50 °C (2–5 %) (Basha and Ratnam, 2007).

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3 Method

3.1 ANFIS

ANFIS is a hybrid learning procedure that constructs an input–output mapping based on fuzzy if-then rules with an appropriate member functions to generate the stipulated input–output pairs (Jang, 1993). ANFIS exploits the machine learning potential of ANN and much valued logic of fuzzy systems in a single framework. The fuzzy logic is used for classification of the input data set in different classes and forms the input to an artificial neural network. Then ANN is used to predict the output based on the training data sets. Thus fuzzy logic controls the way of processing data by its classification to minimize the error in the neural network prediction (Tahmaseb and Hezarkhani, 2010). In recent decades the ANFIS system has been used for many applications such as turning tool-failure detection (Lo, 2002), quantitative structure activity relationship (Buyukbingol et al., 2007), drought forecasting (Bacanli et al., 2008), sea level prediction (Lin and Chang, 2008), greed estimation (Tahmaseb and Hezarkhani, 2010), etc. ANFIS caters to the need of complex real-world problems, which requires intelligent systems that combine knowledge, techniques and methodologies from various sources.

In this work, the ANFIS models create the fuzzy inference system based on the 10 predictors (brightness temperatures of 10 channels observed by MWR as mentioned above) and predict the temperature and humidity. Most of the rule-based prediction models need a few rules to predict. Since the number of predictors (10) is large, it may produce many dispiriting ANFIS structures. To avoid this, subtractive fuzzy clustering has been used to build the fuzzy rules. This helped in reducing the number of rules, automatically determining the number of clusters by assuming each data point as a potential cluster center and creates clusters based on the density (Chiu, 1994). The ANFIS model structure used in this work is shown in Fig. 2 and described in the next section.

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3.2 ANFIS model structure

In this work, to profile the vertical distribution of temperature and relative humidity, a separate ANFIS model is developed for each level, starting from 1 km to 10 km with a vertical resolution of 1 km. Each ANFIS model in this work uses type −3 architecture (Fig. 2) based on fuzzy set if–then rules proposed by Takagi and Sugeno (1983). It comprises of five layers, viz. the input layer, input membership functions, rules, output membership functions and output. Layer 0 of this model passes the input to all membership functions by using observed brightness temperature at 10 different microwave frequencies at each height level as mentioned earlier. Layer 1 is known as the fuzzification layer, in which the input values of brightness temperatures (x) are normalized with a maximum equal to 1 and a minimum equal to 0. This layer uses a bell-shaped Gaussian function for normalization. This process is termed fuzzification and each node i associates with the membership function O_i^1.

$$O_i^1 = \mu A_i(x) \tag{1}$$

where x is the input, A_i are the linguistic labels associated with the membership function and μA_i is a Gaussian function written as

$$\mu A_i(x) = \exp\left\{-\left(\frac{x-b_i}{a_i}\right)^2\right\}, \tag{2}$$

where $\{a_i, b_i\}$ are model parameters determined quantitatively and responsible for variation in the shape of input membership functions.

Layer 2 multiplies input signals and sends products out. The node in layer 2 is the product of the degrees to which the inputs satisfy the membership functions and is found by

$$w_i = \mu A_i(x) X \mu B_i(y), \quad i = 1,2. \tag{3}$$

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Layer 3 is the normalization layer in which the ratio of each rule's firing strength is calculated with respect to the sum of the firing strengths of all the rules.

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{4}$$

The output of each node in layer 4 (the defuzzification layer) is the weighted consequent value, and it is calculated by

$$O_i^4 = \bar{w}_i f_i = w_i(p_i x + q_i y + r_i), \tag{5}$$

where $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5 is the summation layer and its output is the sum of all the outputs of layer 4.

$$\sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{6}$$

As the number of predictors is more in this analysis, many dispiriting ANFIS structures may be produced (most rule-based prediction models need a small number of rules to predict). To avoid this, subtractive fuzzy clustering has been used to build the fuzzy rules. This helps in reducing the number of rules and automatically determining the number of clusters (Chiu, 1994).

3.3 Fitness of the ANFIS Model

The fitness of the model is examined by calculating r, MAE, RMSE, and SMAPE. r is a measure of linear correlation and useful for finding the correlation of retrieved profiles and radiosonde observations. Therefore we have calculated r between ANFIS/ANN-retrieved profiles and radiosonde observations using the formula

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mentioned below.

$$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(f_i - \bar{f})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(f_i - \bar{f})^2}}, \tag{7}$$

where f_i is the observed value and y_i is the retrieved value, either ANFIS or ANN.

MAE is useful for understanding how close the retrived profiles are from radiosonde measurements. MAE is calculated for each level using the following formula:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|e_i|, \tag{8}$$

where e_i are the residuals and n represent the total number of observations. The residuals e_i are obtained by $e_i = |f_i - y_i|$.

RMSE is useful for estimating the differences between retrieval and actual observations by radiosonde. RMSE estimate the residual between observed and retrieved atmospheric profiles for each level. The values of the RMSE are calculated from the formula given below.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}e_i^2} \tag{9}$$

SMAPE is useful for estimating the direction of bias in the retrieval of atmospheric profiles from radiosonde observations. The values of SMAPE are calculated using the following formula.

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$$\mathrm{SMAPE} = \frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} (f_i + y_i)} \tag{10}$$

The MSE, RMSE and SMAPE are used to verify the ANFIS models during the training phase as well as by using independent validation data sets. The results based on this analysis are discussed in the next section.

4 Results and discussions

4.1 ANFIS training phase

The temperature and humidity profiles retrieved from the ANFIS models for the training period are compared with the profile derived from GPS radiosonde observations. Figure 3 shows the RMSE profile of retrieved temperature and relative humidity profiles during the training period. It is observed from the figure that, during the training period, the values of the RMSE of the temperature and relative humidity profiles are less than 0.01 °C for all heights. The decrease in RMSE values both in RH and temperature retrieval are observed at heights 2, 4 and 8 km for temperature retrieval. Similarly for the RH profile there is a decrease in the RMSE values at 2, 6 and 9 km during the training period. This is attributed to a relatively higher frequency of observations available over these heights that enabled better learning of the ANFIS algorithm. However, it is implied from Fig. 3 that during the training phase the ANFIS model shows a very good fit to radiosonde observations. Therefore it is worth testing this model using an independent data set that is not considered for the training. We have selected days for testing ANFIS retrieval from different months of the monsoon season, as shown in Fig. 4.

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4.2 Correlation between retrieved and radiosonde profiles

The values of r calculated for the dates selected for the testing of retrieved profiles are shown in Fig. 4a and b. The r values for the temperature retrieval are more than 0.99 for both algorithms. It indicates that these algorithms are successful in retrieving temperature profiles. It is also noted from the figure (Fig. 4a) that the performance of ANFIS for temperature retrieval is slightly better compared to the ANN algorithm. Therefore it may be stated that the retrieval of temperature profiles using ANFIS is more reliable and can be used for the investigation of the physical mechanism associated with the tropical convective systems. However, the retrieval of RH is also very important for investigating different micro-physical processes responsible for the convection. Figure 4b shows the values of r for RH retrieval. As the spatial variablility of RH is comparatively more than that of temperature, it is difficult to correlate the RH-retrieved profiles with those observed with radiosonde measurements. This is mainly because radiosonde drifts due to heavy wind and may not measure the atmospheric parameters over the region zenith of the MWR. Even so the values of r are more than 60 % for about 18 (9) cases out of 29 cases for the ANFIS (ANN) algorithm, i.e., about 62 % (31) of the cases. For the rest of the cases the values of r are less than 60 %. In the case of ANN (ANFIS) retrieval of RH it is found that 4 (1) case(s) out of 29 cases are negatively correlated with the radiosonde measurements. Thus we found that the retrieval of RH using ANFIS is comparatively better than that of ANN. However, we believe that a detailed investigation is required to be carried out to understand and improve the correlation between RH profiles of radiosonde and retrieved profiles, especially in the cloudy atmosphere or convectively efficient environment. This requires us to understand the environmental dependence of the brightness temperatures measured by the radiometer. The adaptive virtue of the ANFIS model makes it suitable for further improvement of this model with the above-mentioned considerations.

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4.3 Error analysis of retrieved temperature profiles

Figure 5a–d shows the mean vertical profiles obtained by radiosonde profiles and retrieved from the ANFIS and ANN techniques. As mentioned in the previous section, it is seen from Fig. 5a that the mean (29 hypothesis testing days) observed and retrieved profiles overlap and have relatively far fewer errors. The RMSE for the verification data set is less than 0.7 °C up to 2 km and shows a slight increase to 1 °C to 2.3 °C at higher heights (Fig. 5b). The average error is 1.08 °C. The profile of the RMSE shows a warm bias in the retrieved values of temperatures using the ANFIS model. However, ANFIS shows relatively better performance as compared to the ANN algorithm, as is evident from this figure. The MSE for the test data set follows the qualitative trend of the RMSE, but is slightly less in magnitude. The behavior of SMAPE (Fig. 5d) suggests that ANFIS considers relatively more variation of temperature to compared to the ANN algorithm and has a positive bias below 6 km and a negative bias between 6 and 9 km.

Venkat Ratnam et al. (2013) have compared GPS radiosonde profiles with retrieved profiles using the Artificial Neural Network algorithm available with MWR (ANN-MWR). Their results showed that the warm (cold) bias between radiosonde and MWR in temperature is clearly observed below (above) 3–4 km, depending upon the time. Madhulatha et al. (2013) have studied the mean profiles for temperature and vapor density and the difference between temperature and vapor density along with standard deviations derived from ANN-MWR and GPS radiosonde for the period June through December 2011. They found a very close agreement in temperature profiles between MWR and GPS radiosonde. Their results show differences in retrieved profiles, with an ANN-MWR cold bias of about 2 °C up to 4 km and a warm bias of about 2 °C above 4 km. As seen from Fig. 5b, the ANFIS method is successful in reducing this bias, with an average RMSE of 1.08.

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4.4 Error analysis of retrieved humidity profiles

Figure 6a–d shows the mean profile of retrieved relative humidity using the ANFIS/ANN models and observed profiles. The figure shows that, qualitatively, the profile retrieved using the ANFIS model is better compared to that using the ANN model. It is seen from Fig. 6b that the RMSE of retrieved relative humidity averaged over the training data set is less than 0.01 % throughout the profile. However, the values of RMSE of the testing data set for the ANFIS model vary significantly with respect to height from 5–20 %. At 1 km the value of the RMSE is 4.87 %, at 2 km it is 6.19 %, and it gradually increases towards higher heights up to a maximum of 23.89 % at 8 km. It is seen from Fig. 6b that ANFIS shows better performance than ANN in retrieving relative humidity. The variation of MSE more or less coincides with the behavior of RMSE. The behavior of SMAPE with height shows that the ANFIS model considers more variability compared to the ANN models but has more negative bias at higher heights. The study by Venkat Ratnam et al. (2013) also indicated a large wet (dry) bias of 6–8 $\mathrm{g\,kg^{-1}}$ in the specific humidity below (above, except around 5–6 km) 2–3 km between the radiosonde and the ANN algorithm.

5 Conclusions

In this work we have presented a formulation of the ANFIS model for the retrieval of atmospheric profile of temperature and humidity using brightness temperatures observed at different microwave frequencies mentioned above by MWR. In this work we found that ANFIS is more suitable for retrieving vertical profiles of the atmosphere by observing the power received on the ground due to different emissions at different microwave frequencies. Our results indicated that the performance of the ANFIS model is better than the ANN back propagation algorithm in retrieving the profile of both temperature and RH. The retrieved temperature profiles are relatively closer to the observations by radiosonde. However, an improvement is needed in the retrieval of relative humidity to reduce relatively large errors at higher heights. For this purpose, a detailed investigation is required to be carried out to understand the behavior of the brightness temperatures, weighting functions of MWR and retrieval of vertical profiles using the ANFIS method, especially during complex environmental conditions, to develop a robust tool for the study of the physical mechanisms associated with small-scale convections.

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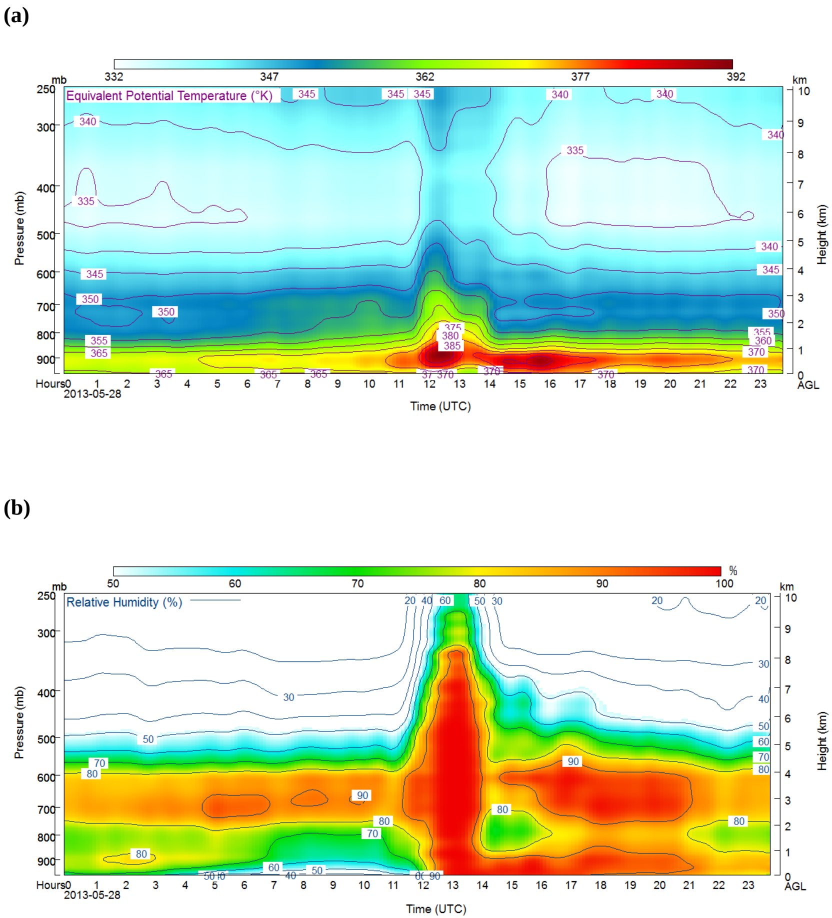

Fig. 1. Composite of vertical profiles of equivalent potential temperature **(a)** and relative humidity **(b)** retrieved during the convection event on 28 May 2013 over NARL Gadanki using MWR (ANN algorithm). The time resolution of these profiles is 4 min.

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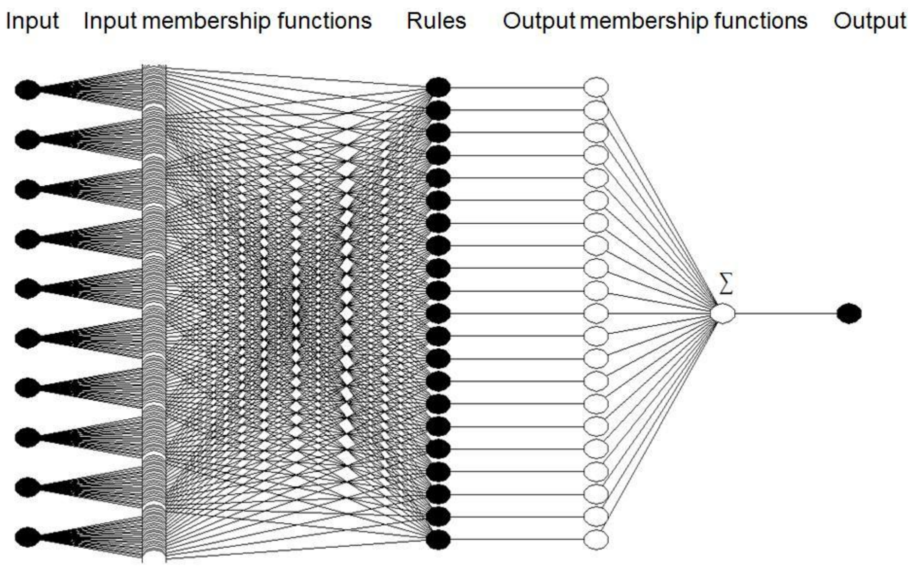

Fig. 2. Structure of the ANFIS model.

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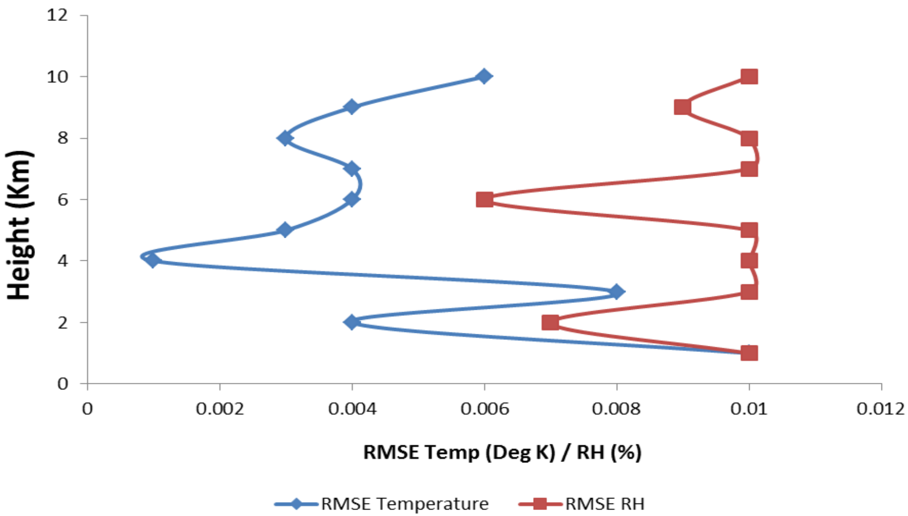

Fig. 3. Profiles of RMSE for temperature and relative humidity retrieved from ANFIS models with respect to radiosonde observations during the training phase.

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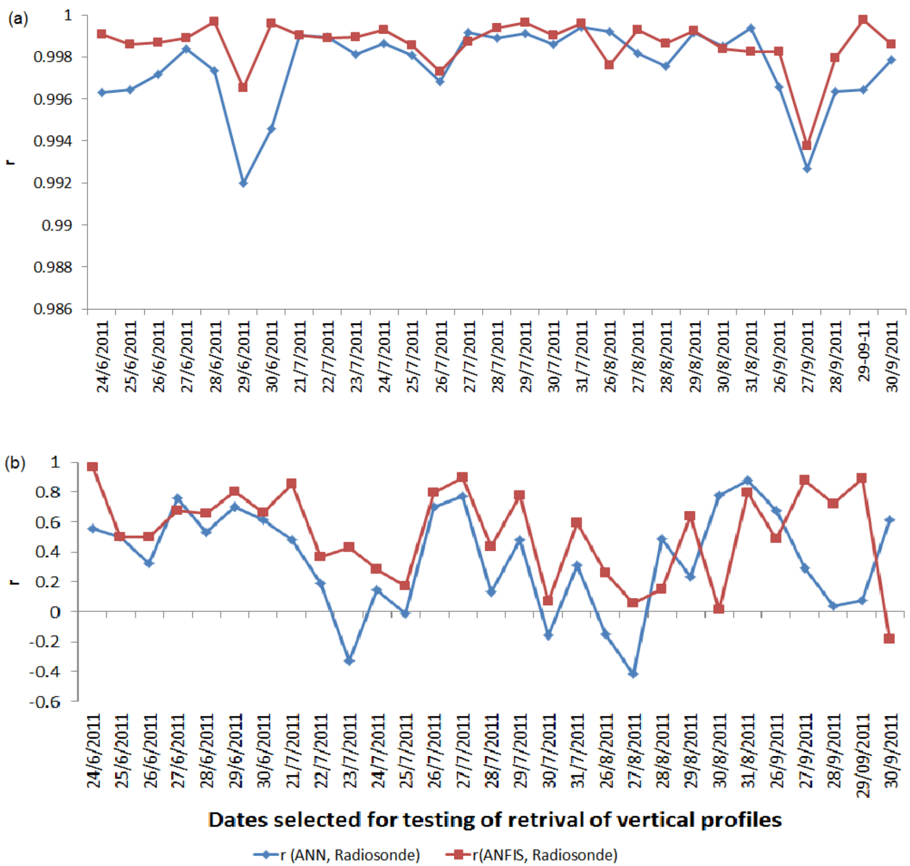

Fig. 4. Pearson product movement correlation coefficient (r) between radiosonde temperature **(a)** and humidity **(b)** profiles and retrieved profiles using ANN and ANFIS.

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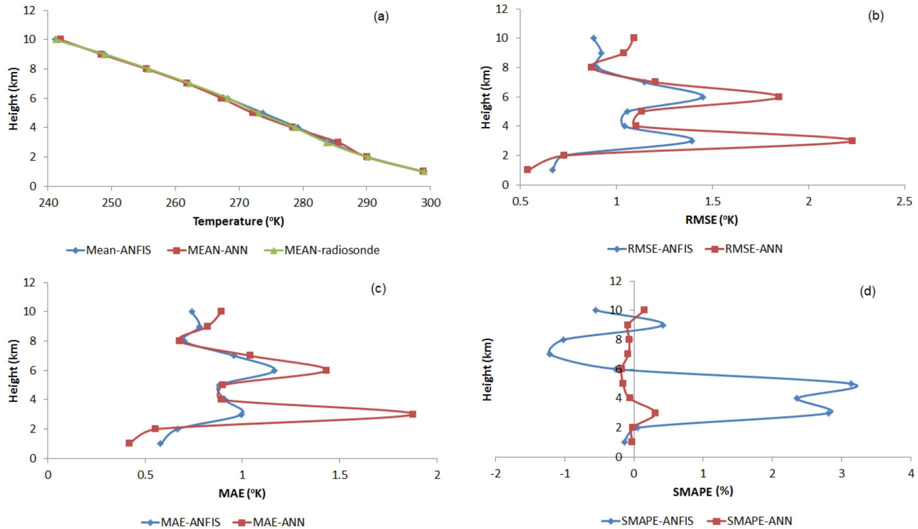

Fig. 5. Comparison of vertical profiles of **(a)** temperatures from radiosonde and profiles retrieved from ANN and ANFIS, and **(b)** RMSE, **(c)** MAE and **(d)** SMAPE retrieved from ANN and ANFIS with respect to temperature profiles from radiosonde observations.

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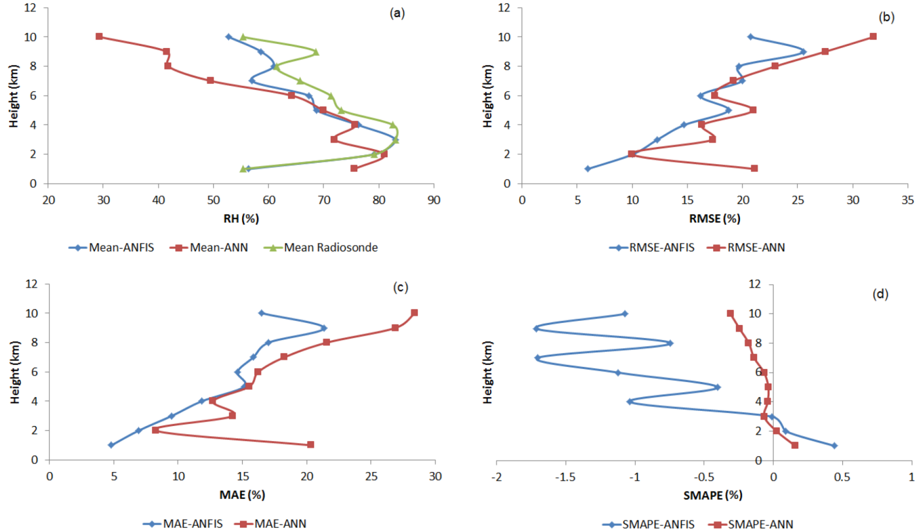

Fig. 6. Comparison of vertical profiles of **(a)** RH from radiosonde and profiles retrieved from ANN and ANFIS, and **(b)** RMSE, **(c)** MAE, and **(d)** SMAPE retrieved from ANN and ANFIS with respect to RH profiles from radiosonde observations.

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