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EVALUATION OF MODELS FOR THE DEW POINT TEMPERATURE DETERMINATION

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Key words: dew point temperature, relative humidity, model, artificial neural networks.

Abstract

The accuracy of the available from the literature models for the dew point temperature determination was compared. The proposal of the modelling using artificial neural networks was also given. The experimental data were taken from the psychrometric tables. The accuracies of the models were measured using the mean bias error MBE, root mean square error RMSE, correlation coefficient R, and reduced chi-square χ^2. Model M3, especially with constants A=237, B=7.5, gave the best results in determining the dew point temperature (MBE: -0.0229 – 0.0038 K, RMSE: 0.1259 – 0.1286 K, R=0.9999, χ^2: 0.0159 – 0.0166 K^2). Model M1 with constants A=243.5, B=17.67 and A=243.3, B=17.269 can be also considered as appropriate (MBE=-0.0062 and -0.0078 K, RMSE=0.1277 and 0.1261 K, R=0.9999, χ^2=0.0163 and 0.0159 K^2). Proposed ANN model gave the good results in determining the dew point temperature (MBE=-0.0038 K, RMSE=0.1373 K, R=0.9999, χ^2=0.0189 K^2).

Symbols

A, B, C, D – odel coefficients,
c – number of constants,
e – partial pressure of water vapour [Pa],
e_s – partial saturation pressure of water vapour [Pa],
n – number of observations,
L – enthalpy of vaporization [J · kg^{-1}],
R_w – gas constant for water vapour [J · kg^{-1} · K^{-1}],
RH – relative humidity, decimal,
RH$_{\%}$ – relative humidity [%],
t – temperature [°C],
T – temperature [K],
$_FT$ – temperature [F],

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Subscript
DP – dew point,
m – measured value,
p – predicted value.

Introduction

The relative humidity and dew point temperature are widely used indicators of the amount of moisture in air (LAWRENCE 2005).

The dew point temperature can be defined as the temperature at which the partial vapour pressure of water in moist air would be sufficient to saturate the air. It can be therefore stated that the partial vapour pressure is equal to the partial saturation vapour pressure at the dew point temperature (WOOD 1970). In other words, the dew point temperature is that at which water vapour starts to condense out of the air or the temperature at which air becomes completely saturated. The following conclusion can be drawn from this definition: if the air relative humidity is low, the dew point temperature is below the air temperature but if, however, the air relative humidity is high, the dew point temperature is close to the air temperature (BROOKER et al. 1992).

Relative humidity RH is the ratio of the mole fraction of water vapour in a given volume of moist air to the mole fraction of water vapour in the same volume of saturated moist air at the same temperature and pressure. For the ideal gas mixtures assumed in this paper the equivalent definition of relative humidity can be formulated in the following way: RH is the ratio of the partial pressure e of water vapour in moist air to the partial saturation pressure of water vapour e_s at the temperature of the air (WOOD 1970, WILHELM 1976).

Knowledge of the psychrometric properties of an air-water vapour mixture, among them dew point temperature and relative humidity, is fundamental to the design environmental control system for plants, crops, animals, and human beings. Psychrometric properties of the moist air are useful in plant materials drying and storage, and in heating, ventilating, air-conditioning, meteorology (SINGH et al. 2002, LOPES et al. 2009).

Dew point temperature is preferred by meteorologists over relative humidity as an indicator of human comfort (BOHREN, ALBRECHT 1998). Dew point temperature is useful in the designing of traditional evaporative coolers, and it is the theoretical minimum temperature achieved by modern indirect evaporative coolers (LAWRENCE 2005, ZHAO et al. 2008, RIANGVILAIKUL KUMAR 2010a, 2010b). Dew point temperature coupled with wet-bulb temperature can be applied to determine air temperature, allowing producers to respond to potential frosts that may damage crops (SNYDER, DE

MELO-ABREU 2005). The knowledge of dew point temperature is indispensable for estimating the height convection cloud base. This height has a very important meaning for glider pilots (SALWIŃSKI 2002). If a glass barriers in building are cooled below the dew point, the air in contact with these surfaces will become saturated and dew will form on the surfaces what causes problems for the building users (GERYŁO 2008).

Nowadays, the modelling of different processes is a very important task. The principle of modelling is based on having a set of mathematical equations that can adequately describe the operation (EFREMOV 2013, GOLISZ et al. 2013, KALETA et al. 2013). Many agronomical, ecological, hydrological, and climatological models require dew point temperature as an input to estimate evapotranspiration (HUBBARD et al. 2003). In literature there are equations which represent the dew point temperature as a function of the temperature and relative humidity or as a function of partial saturation pressure of water vapour. However, different values of models coefficients were given and no the comparison of these models accuracy.

An artificial neural network (ANN) is an information processing system, which learns from input/output data to determine the relationships between input/output data, and is used in pattern recognition, classification, etc. Unlike other modelling techniques such as differential equations and regression equations, an ANN can handle more than two variables to predict two or more outputs. The regression equations or statistical models are subject to assumptions and cautions inherent in the analyses. ANNs have attracted researchers in many disciplines of science and engineering, since they are capable of correlating large and complex data sets. ANNs are used for their learning or adapting ability, and they do not need much knowledge of underlying relationships between their input and output variables. The network learns from the input and data itself, repeatedly. It also can approximate any continuous or discontinuous linear or nonlinear function. Therefore such networks are very useful for modelling some not-well-understood processes as reported by MITTAL (1996).

The psychrometric chart reflects the relationships between thermodynamic properties of moist air. If the relationships can be learned by an ANN with valid thermodynamic properties of air, then the trained ANN can be used as a database of air properties for real-time calculations, simply by multiplying input and weight matrices. An ANN offers an efficient means of analysing process data to obtain relationships descriptive of various process trends (MITTAL, ZHANG 2003).

SREEKANTH et al. (1998) made a first attempt to predict psychrometric parameters using NN. Neural network models were developed for the each of the three main variables: dry bulb temperature, wet-bulb temperature and relative humidity, as a function of the other two variables. Models were also developed for the prediction of the dew point temperature using the dry bulb and wet bulb temperatures, and for the saturation vapor pressure as a function of the dry bulb temperature. The prediction accuracy of the neural network models were found to be very good, with errors less than 4%. Relative errors were as high as 0.18% ± 0.17% for predicting dew point temperature. MITTAL and ZHANG (2003) used ANN to predict dew point temperature, wet bulb temperature, enthalpy, humidity ratio, specific volume as a function of dry wet bulb temperature and relative humidity with relative error <5%. For ANN training, validation and testing SREEKANTH et al. (1998) and MITTAL and ZHANG (2003) used data taken from models of dew point temperature. SHROFF and DABHI (2013a,b) used Gene Expression Programming for modelling of dew point.

Many authors used intelligent models to predict daily dew point temperature. Dew point temperature has been estimated and analysed for trends dew point temperature prediction. The overall goal of the research was to develop ANN models for predicting hourly dew point temperatures. Specific objectives were to identify the important weather-related inputs that affect dew point temperature prediction, to determine the preferred values of the ANN parameters, and to determine the preferred duration of prior data for each lead time.

SHIRI et. al (2014) assessed the capability of two different artificial neural network (ANN) models and gene expression programming (GEP) technique for estimate daily dew point temperature in two weather stations in Korea (8 years of daily records of air temperature, wind speed, relative humidity, atmospheric pressure, incoming solar radiation and dew point temperature). Authors noted that the GEP model surpasses ANN in estimating daily dew point temperature values. AMIRMOJAHEDI et al. (2016) used method by hybridizing the extreme learning machine (ELM) with wavelet transform (WT) algorithm to predict daily dew point temperature. Daily climate data of an Iranian station placed in the south costal of the country were utilized as a case study. Average air temperature, relative humidity and atmospheric pressure, were considered as input elements. Based upon the achieved results it was conclusively proved that the hybrid ELM-WT approach favourably outperforms other examined techniques. SHANK et al. (2008) utilized ANN technique for prediction of dew point temperature from 1 to 12 h ahead based upon the previous weather data sets. They used measured data of 20 stations in Georgia State in USA for developing general models to predict dew point temperature in the whole Georgia State. HUBBARD et al. (2003) developed a regression model for estimating the daily average dew point temperature, using the daily mean, minimum, and maximum air temperature as inputs.

Their research used 14 year of data for six cities in the USA. Their regression equation based on multiple cities was more accurate than the regression equations for each of the individual cities, with a mean absolute error (MAE) of 2.2°C for the most accurate regression equation. This study's estimations were useful for determining the values for missing historical weather data, but did not allow the prediction of future values. ZOUNEMAT-KERMANI (2012) evaluated the capability of multi linear regression (MLR) and Levenberg–Marquardt (LM) feed-forward neural network for estimation of hourly dew point temperature in Ontario (Canada). It was found that LM–NN model provide further accuracy compared to the MLR model. NADIG et al. (2013) developed combined air and dew point temperatures models using ANN technique to provide an enhancement in the predictions of both temperatures. Their results demonstrated that the combined method decline the predictions error. KIM et al. (2015) utilized two soft computing techniques for estimation of daily dew point temperature in California, USA. By providing comparisons with a conventional regression model, they found that developed soft computing models are more precise in estimating daily dew point temperature. MOHAMMADI et al. (2016) applied adaptive neuro fuzzy inference system (ANFIS) to select the most influential parameters for prediction of daily dew point temperature. They analysed the influence of eight different parameters on dew point temperature prediction in two cities of Iran. Their results showed that, despite climate difference between the selected studied areas, for both cities water vapour pressure was the most relevant parameter while relative humidity was the least relevant parameter. They concluded that using more than two input parameters couldn't be proper and advisable. JALAL et al. (2014) estimated of daily dew point temperature using genetic programming and neural networks approaches.

The objective of this study was the comparison of the accuracy of the available from the literature models for the dew point temperature determination and the proposal of the modelling using artificial neural networks.

Materials and Methods

The models used to determine the dew point temperature are shown in Table 1. The accuracy of the models under consideration was checked using data (about 8000) taken from psychrometric tables (ROJECKI 1959). Statistical parameters of the used data are shown in Table 2.

Table 1

Models for the determination of dew point temperature

Model no.	Model equation	Model coefficients	References
M1	$t_{DP}\,(t,\mathrm{RH}) = \dfrac{A\left(\ln(\mathrm{RH}) + \dfrac{Bt}{A+t}\right)}{B - \ln(\mathrm{RH}) - \dfrac{Bt}{A+t}}$	A=241.2; B=17.5043	Own working out after: https://pl.wikipedia.org/wiki/Temperatura_punktu_rosy
		A=243.5; B=17.67	Own working out after: http://www.srh.noaa.gov/images/epz/wxcalc/rhTdFromWetBulb.pdf http://www.emc.ncep.noaa.gov/gmb/yzhu/imp/i201204/NAEFS_Science_Documentation.pdf
		A=237.7; B=17.27	Own working out after: SIMONS 2008
		A=237.3; B=17.269	Own working out after: GERYŁO (2008), WEISS (1977)
		A=243.04; B=17.625	LAWRENCE (2005)
M2	$t_{DP}\,(t,\mathrm{RH}) = \dfrac{A\left(\ln(\mathrm{RH}) + \dfrac{Bt}{C+t}\right)}{B - \ln(\mathrm{RH}) - \dfrac{Bt}{C+t}}$	A=237; B=17.27; C=237.3	Own working out after: holmes.iigw.pl/??mbodzion/dydaktyka/hydro/pliki/wilgotnosc.pdf
		A=237.7; B=17.67; C=243.5	Own working out after: http://www.srh.noaa.gov/images/epz/wxcalc/rhTdFromWetBulb.pdf
M3	$t_{DP}\,(t,\mathrm{RH}) = \dfrac{A\left(\log(\mathrm{RH}) + \dfrac{Bt}{A+t}\right)}{B - \log(\mathrm{RH}) - \dfrac{Bt}{A+t}}$	A=237; B=7.5	Own working out after: SALWIŃSKI (2002)
		A=237.3; B=7.5	Own working out after: http://web.mit.edu/weather/info/Frequently_Asked_Questions-temp-dewpoint; http://www.srh.noaa.gov/images/epz/wxcalc/wetBulbTdFromRh.pdf
		A=237.7; B=7.5	Own working out after: http://www.crh.noaa.gov/Image/epz/wxcalc/wetBulbTdFromRh.pdf
M4	$t_{DP}(t,\mathrm{RH})=(\mathrm{RH})^{1/8}(112+0.9t)+0.1t-112$		http://www.ajdesigner.com/phphumidity/dewpoint_equation_dewpoint_temperature.php
M5	$t_{DP} = t - \left(\dfrac{100 - \mathrm{RH}_{\%}}{5}\right)$, for $\mathrm{RH}_{\%}>50\%$		LAWRENCE (2005)
M6	$T_{DP} = T\left(1 - \dfrac{T\ln(\mathrm{RH})}{\dfrac{L}{R_w}}\right)^{-1}$	R_w=461.5 J · kg^{-1} · K	LAWRENCE (2005)

cont. table 1

Model no.	Model equation	Model coefficients	References
M7	$t_{DP} = (0.198 + 0.0017t)\ RH_{\%} +$ $- 0.84t - 19.2$ for $40 \leq RH_{\%} \leq 100\%$; $0<t<30°C$		SARGENT (1980), LAWRENCE (2005)
M8	$t_{DP} = t - A + B \cdot RH_{\%}$	$A=17.9$; $B=0.18$ for $65 \leq RH_{\%} \leq 100\%$ $A=22.5$; $B=0.25$ for $45 \leq RH_{\%} \leq 65\%$	SARGENT (1980), LAWRENCE (2005)
M9	$t_{DP} = t - \left(\frac{100 - RH_{\%}}{5}\right)\left(\frac{T}{300}\right) -$ $- 0.00135(RH_{\%} - 84)^2 + 0.35$ for $40 \leq RH_{\%} \leq 100\%$; $0<t<30°C$		LAWRENCE (2005)
M10	$RH = \left(\frac{173 - 0.1_F T + {}_F T_{DP}}{173 + 0.9_F T}\right)^8$		BOSEN (1958)
M11	$t_{DP} = A\ B\ \ln(e) + C(\ln(e))^2$ where: a) $\ln(e_s) = -\frac{7511.52}{T} + 89.63121 +$ $+ 0.23998970\ T - 1.1654551 \cdot$ $\cdot 10^{-5}T^2 \cdot 1.2810336 \cdot 10^{-8}T^3 +$ $+ 2.0998405 \cdot 10^{-11}T^4 - 12.15079\ln(T)$ b) $e_s = 0.61078\exp\left(\frac{17.269382t}{237.30 + t}\right)$	$A=6.983$; $B=14.38$; $C=1.079$ for $0 \leq t \leq 50°C$	WILHELM (1976), WEISS (1977)
M12	$t_{DP} = A + B\ln(e) + C(\ln(e))^2 +$ $+ D(\ln(e))^3 + De^{0.1984}$ $\ln(e) = -5.8002 \cdot 10^3/T - 55163 -$ $- 4.864 \cdot {}^{-2}T + 4.1765 \cdot 10^{-5}$ $T - 1.4452 \cdot 10^{-8}\ T + 6.546{*}\ln(T)$	$A=6.09$; $B=12.608$; $C=0.4959$ for $t_{DP} \leq 0°C$ $A=6.54$; $B=14.526$; $C=0.7389$; $D=0.09486$; $E=0.4569$ for $0<t_{DP} \leq 93°C$	ASHRAE (1993), MITTAL, ZHANG (2003)

Table 2

Statistical parameters of the used data

Parameter	Unit	Statistical parameters					
		mean	maximum	minimum	standard deviation	coefficient of variation	skewness coefficient
t	°C	22.5	37	0	10.1	0.45	-0.44
$RH_{\%}$	%	55.4	100	14	24.4	0.44	0.13
t_{DP}	°C	11.6	37	-20	11.7	1.02	-0.15

ANN modelling was carried out with Matlab 7.0. The dew point temperature was predicted with feedforward multilayer perceptron artificial neural networks. In this study 8000 cases were chosen for our experiments. Chosen cases were randomly divided into the following sets: for training 5,600 samples (consisted of ≈70% cases), for validation 1,200 samples (≈15% cases) and for testing 1,200 samples (≈15% cases). Inputs (t_{DP} and $RH_{\%}$) were normalized to obtain values in range 0–1. The values of dry bulb temperatures and relative humidity were normalized by dividing them by 37 and 100 respectively. The values of dew point temperatures (output) were divided by 37.

The goodness of fit of the tested models and ANN to the data taken from psychrometric tables was evaluated with the mean bias error MBE:

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(x_{i,p} - x_{i,m}) \tag{1}$$

the root mean square error RMSE:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{i,p} - x_{i,m})^2} \tag{2}$$

the correlation coefficient R:

$$R = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x_{i,p}) \cdot \sum_{i=1}^{n}(x_i - x_{i,m})}{\sqrt{\sum_{i=1}^{n}(x_i - x_{i,p})^2 \cdot \sum_{i=1}^{n}(x_i - x_{i,m})^2}}} \tag{3}$$

and reduced chi-square χ^2:

$$\chi^2 = \frac{\sum_{i=1}^{n} (x_{i,m} - x_{i,p})^2}{n - c} \tag{4}$$

The higher the R value, and lower the MBE, RMSE, and χ^2 values confirm the better the goodness of fit (KALETA, GÓRNICKI 2010).

Results and Discussion

Models of dew point temperature

The results of statistical analysis undertaken on the considered models are given in Table 3. The statistical analysis results shown that model M3 best determining the dew point temperature. The values of statistical parameters from this model (for different model coefficients) were following: MBE=-0.0229 – 0.0038 K, RMSE=0.1259 – 0.1286 K, R=0.9999, χ^2=0.0159 – 0.0166 K^2. The values of all statistical parameters from this model with constants A=237, B=7.5 were the smallest (MBE=0.0038 K, RMSE=0.1259 K, R=0.9999, χ^2=0.0159 K^2).

Model M1 can be also considered as appropriate (MBE=-0.0225 – -0.0062 K, RMSE=0.1261 – 0.1286 K, R=0.9999, χ^2=0.0159 – 0.0165 K^2). For model M1 with constants

A=243.3, B=17.269 the root mean square error and chi-square were the smallest (0.1261 K and 0.0159 K^2 respectively) and with constants A=243.5, B=17.67 mean bias error was the smallest (MBE=-0.0062 K). The values of all statistical parameters from model M1 with constants A=237.7, B=17.27 were the worst.

Model M2 only with constants A=237, B=17.27, C=237.3 gave good results (MBE=-0.0218 K, RMSE=0.1218 K, R=0.9999, χ^2=0.0166 K^2) and was not much better than Models M4 and M10. The values of statistical parameters for Models M4 and M10 were following: MBE: -0.0239 and -0.0331 K, RMSE: 0.1466 and 0.1488 K, R=0.9999, χ^2: 0.0215 and 0.0222 K^2, respectively.

Some models to determine dew point temperature gave good results, but can be only used in a narrow range of t and $RH_{\%}$. The values of statistical parameters from model M9 were the small: MBE=0.0098 K, RMSE=0.1502 K, R=0.9999, χ^2=0.0226 K^2. This model can be used to determine dew point

Table 3

Comparison of results of statistical analyses on the modelling of dew point temperature

Model no.	Model coefficients	MBE, K	RMSE, K	R, –	χ^2, K^2
M1	A=241.2; B=17.5043	-0.0167	0.1280	0.9999	0.0164
	A=243.5; B=17.67	-0.0062	0.1277	0.9999	0.0163
	A=237.7; B=17.27	-0.0225	0.1286	0.9999	0.0165
	A=237.3; B=17.269	-0.0078	0.1261	0.9999	0.0159
	A=243.04; B=17.625	-0.0152	0.1286	0.9999	0.0165
M2	A=237; B=17.27; C=237.3	-0.0218	0.1288	0.9999	0.0166
	A=237.7; B=17.67; C=243.5	-0.2827	0.4085	0.9999	0.1669
M3	A=237; B=7.5	0.0038	0.1259	0.9999	0.0159
	A=237.3; B=7.5	-0.0076	0.1261	0.9999	0.0159
	A=237.7; B=7.5	-0.0229	0.1286	0.9999	0.0166
M4		-0.0239	0.1466	0.9999	0.0215
M5*		0.0606	0.5944	0.9988	0.3534
M6		-0.0809	0.2016	0.9999	0.0406
M7*		0.0779	0.4400	09987	0.1937
M8*	A=17.9; B=0.18	0.1825	0.4065	0.9996	0.1654
	A=22.5; B=0.25	0.8329	1.1375	0.9994	1.2954
M9*		0.0098	0.1502	0.9999	0.0226
M10		-0.0331	0.1488	0.9999	0.0222
M11a	A=6.983; B=14.38; C=1.079	0.0760	0.2664	0.9998	0.0710
M11b		0.0774	0.2677	0.9998	0.0717
M12*	A=6.09; B=12.608; C=0.4959	-0.6578	0.8255	0.9995	0.6830
	A=6.54; B=14.526; C=0.7389; D=0.09486; E=0.4569	-0.0271	0.5255	0.9999	0.2764
M13 (ANN)		-0.0038	0.1373	0.9999	0.0189

* Limited range of data

temperature only for 40≤RH$_{\%}$≤100% and 0<t<30. Model M5 (for RH$_{\%}$>50%) was easy to use and fairly accurate, values of statistical parameters were following: MBE=0.0606 K, RMSE=0.5944 K, R=0.9988, χ^2=0.3534 K^2.

Models M8 (for 45≤RH$_{\%}$≤65%; with constants A=22.5, B=0.25) and M12 (for t_{DP}≤0°C) can not be recommended for the determination of dew point temperature, because their MBE, RMSE, and χ^2 values were found too high (MBE: 0.8329 and -0.6578 K, RMSE: 1.1375 and 0.8255 K, χ^2: 1.2954 and 0.6830 K^2, respectively).

Artificial neural network

Determination of the best ANN topology for predicting a desire response is a very critical stage. Generally, the trial–and–error approach is used. A large number of different topologies have been constructed, trained and tested. NAZGHELICHI et al. (2011) and AGHBASHLO et al. (2011) reported that one hidden layer ANN with sigmoid transfer function is normally appropriate to provide an accurate prediction and can be the first choice for any practical feed-forward network design. A sigmoid function is a widely used non-linear activation function whose output is between 0 and 1 and is defined as:

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{5}$$

In addition, more hidden layers may cause overfitting and the model cannot adapt to new inputs as reported by OMID et al. (2009).

The number of hidden nodes in a network is critical to network performance. Too many nodes can lead the system toward memorizing the patterns in the data. Too few nodes can lead to underfitting as informed by ERB (1993). Recently, many researchers successfully used response surface methodology and genetic algorithm to solve this problem (NAZGHELICHI et al. 2011, NOURBAKHSHA et al. 2014, WINICZENKO et al. 2016).

In this study, different activation functions (tansig, logsig and linear) and number of neurons varied from 2–6 were used to obtain the optimal architecture of the network. Finally, the simulation results shows that a MLP ANN with one hidden layer, 3 nodes in the hidden layer and sigmoid activation function is found to have the best performance.

The optimal architecture of the ANN was constructed as 2–3–1 NN and activation functions in hidden layer and output layer were respectively "logsig" and "purelin". Schematic of three layer neural network is shown in Figure 1.

The network was trained with Levenberg-Marquardt backpropagation algorithm (trainlm) (see Fig. 2). The algorithm stopped, when the validation error increased for six iterations, which occurred at iteration 482. LM is often the fastest available back-propagation algorithm and highly recommended as the first choice supervised algorithm, although it requires more memory than other algorithms as informed by KHALAJ et al. (2013). In our study LMBP method was used because of mean-squared error (MSE) values for LM method were lower compared with those Bayesian regulation in the training stages, the LM method was preferred in the modelling of the experimental data.

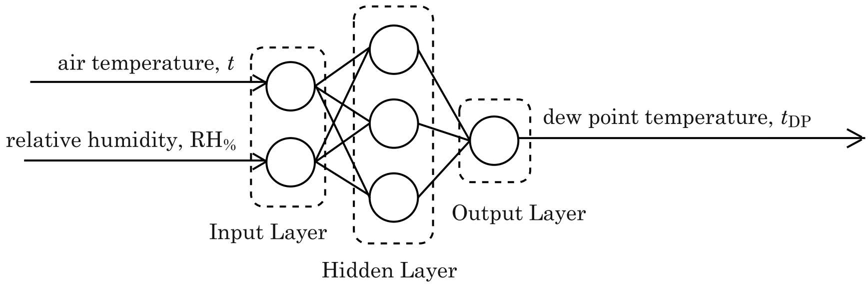

Fig. 1. Neural network architecture

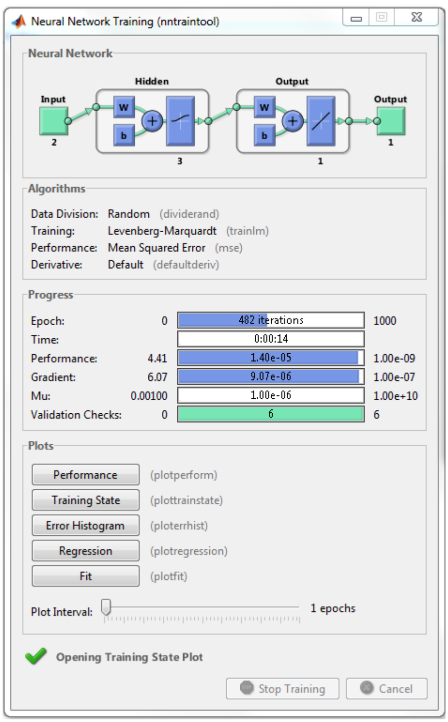

Fig. 2. Neural network training window

The mean square error changes at the epochs shown in Figure 3. As can be seen from the graph, the best validation performance $1.3429 \cdot 10^{-5}$ has occurred at epoch 476. Therefore, the final mean square error is small. Moreover, the test set error and the validation set error have similar characteristics. Additionally, no significant overfitting has occurred, where the best validation performance occurs.

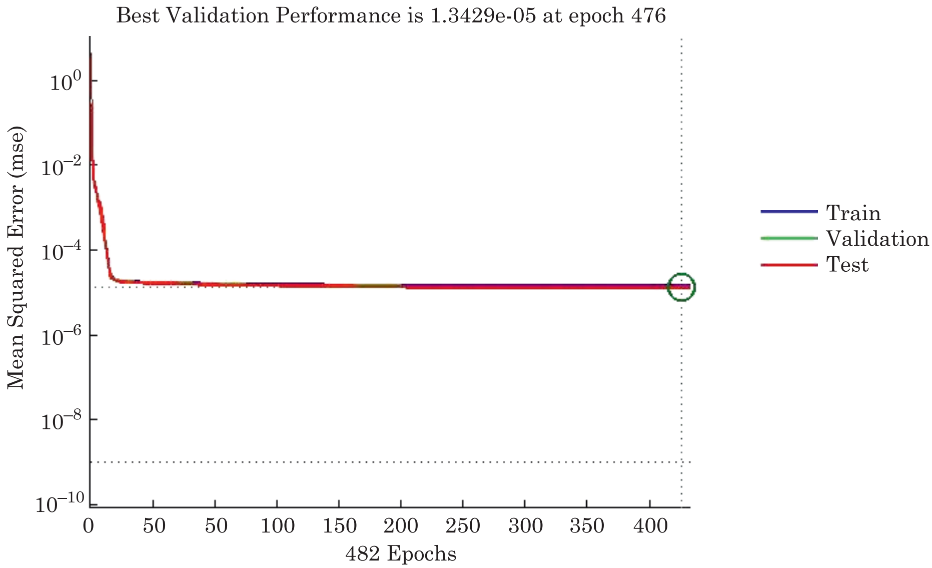

Fig. 3. Performance goal of neural network

Linear regression analyses were performed to compute the correlation coefficient R between the experimental and predicted values (see Fig. 4). As can be seen from the graphs, the output tracks the targets very well both for training (Fig. 4*a*),validation (Fig. 4*b*), and testing (Fig. 4*c*), respectively. In addition, the R-value is over 0.99 for the total response (Fig. 4*d*).

To determine the dew point temperature t_{DP} was derived from the ANN (model M13):

$$t_{DP} = -5.2686 \cdot F_1 + 11.5088 \cdot F_2 - 5.2164 \cdot F_3 - 6.3302 \tag{6}$$

where $F_{(i=1,2,3)}$ can be calculated using:

$$F_i = \frac{1}{1 + \exp^{-W_i}} \tag{7}$$

and W_1–W_3 can be determined as follows:

$$W_i = D_{1i} \cdot t + D_{2i} \cdot \mathrm{RH} + D_{3i} \tag{8}$$

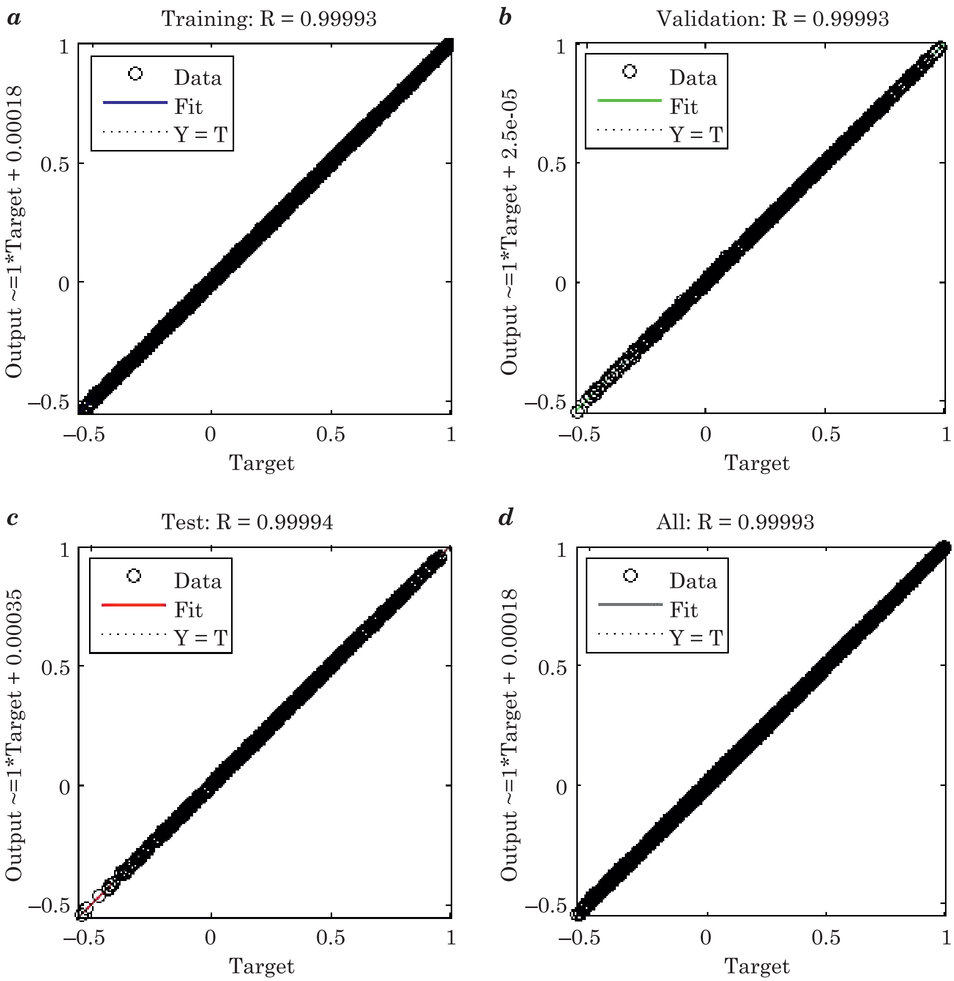

Fig. 4. A linear regression graph for observed and predicted values of dew point temperature: *a* – training, *b* – validation, *c* – testing, *d* - all samples

Weights: D_{1i}, D_{2i} and bias D_{3i} in Eq. (8) are given in Table 4 for algorithm with three neurons.

Presented ANN (consists of Eqs. (6) – (8) and Table 3) can be easy to use model. The model M13 (ANN) gave good results in determining the dew point temperature. The values of statistical parameters from ANN model (Tab. 2) were following: MBE=0.0038 K, RMSE=0.1373 K, R=0.9999, χ^2=0.0189 K^2. Those parameters were little worse than for model M3 with constants A=237, B=7.5.

Table 4

Weights and biases between input layer and hidden layer

No.	Weight		Bias
i	D_{1i}	D_{2i}	D_{3i}
1	0.4894	0.4559	-1.3690
2	0.2403	-4.1578	-2.8064
3	0.4680	-0.1209	1.1178

Conclusions

It turned out from the investigations that model M3, especially with constants A=237, B=7.5, gave the best results in determining the dew point temperature. Model M1, especially with constants A=243.3, B=17.269 and A=243.5, B=17.67 can be also considered as appropriate. Model M9 can be used to determine dew point temperature, but only for $40 \leq RH_{\%} \leq 100\%$ and $0<t<30$.

Proposed model M13 (ANN) gave good results in determining the dew point temperature. The ANN have 2 input (t and RH%) hidden layer (3 neurons) and 1 output – t_{DP}, activation functions in hidden layer and output layer were "logsig" and "purelin" respectively.

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