Fuzzy weather forecast in forecasting pollution concentrations

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In this paper we want to analyse fuzzy weather forecasts, which are computed in our system and used to forecast pollution concentrations. The system works on real data: weather forecasts, meteorological situations and pollution concentrations. We compare defuzzification of the fuzzy weather forecast with weather forecast from Institute of Meteorology and Water Management. This comprehensive analysis allows us to investigate the effectiveness of forecasting pollution concentrations, putting the dependence between particular attributes describing the weather forecast in order and proving the legitimacy of the applicable fuzzy numbers in air pollution forecasting.
Model is created for data, which is measured and forecast in Poland. By reason of this data our model is tested in real sets of data and effects are received in active system.

Keywords: Fuzzy system models, Fuzzy numbers, Fuzzy matrix, Fuzzy weather forecast, Air pollution forecasting

1. Introduction

Weather forecasting is increasingly perfected in subsequent centuries. In recent years many prediction approaches, such as statistical [1], fuzzy [2; 3], neural networks [4; 5], neuro-fuzzy predictor [6] have emerged. Using numerical short-term weather prediction, research into the forecasting of air pollution concentrations began [7; 8]. This task is very difficult because apart from the information about meteorological conditions, the emission of air pollution depends first of all on the immission. Fuzzy logic [9; 10; 11] is an established methodology that is widely used in model systems in which variables are continuous, imprecise, or ambiguous. Use of this method is known in many mathematical forecasting models. It is usually used when the information transferred to the model is imprecise or incomplete [12; 13]. Many everyday phenomena of an ambiguous, continuous and imprecise nature may be effectively described using this theory.

The main problem is with the knowledge. We do not have precise knowledge about the weather in the future. We only have numerical forecasting, i.e. conditions which may announce many similar meteorological situations.

The result of a working Air Pollution Forecasting Model (APFM) is a forecast of air pollution concentration, among others PM10 for the next day. It is a specially chosen pollution because PM10 has a huge influence on human life [14; 15].

In each stage we use meteorological data with a mathematical apparatus [16; 17]. In particular in

APFM we use the weather forecasts derived from the Consortium for Small Scale Modelling (COSMO) model based on the Local-Model (LM) of Deutscher Wetter Dienst (DWD).

Objects appearing in the paper are vectors and matrices. In vector space $\mathbb{R}^d$ for vectors we use (1) as the distance between objects.

$$d_k^d(x,y) = \left(\sum_{i=1}^{d} |x_i - y_i|^k\right)^{\frac{1}{k}}, x, y \in \mathbb{R}^d,\ k > 0\,. \tag{1}$$

For $k \geqslant 1$, $k \in \mathbb{N}$ the function (1) is metric.

The distance between matrix objects is composition of vector objects. For terms distance between matrices we use (2).

$$d_{k_1 k_2}^{n\times m}(A,B) = d_{k_1}^{n}([d_{k_2}^{m}(a_{i\cdot}, b_{i\cdot})], \mathbf{0}_n),\ \text{ for } A = [a_{ij}], B = [b_{ij}], A, B \in \mathbb{R}^{n\times m}\,, \tag{2}$$

where $\mathbf{0}_n$ is a zero vector and $a_{i\cdot}$, $b_{i\cdot}$ are i-th rows in matrices A and B.

In the first instance we introduce a term, time horizon set T, in which the forecast will be calculated. $T = \{t = i\cdot\Delta t : i = 0,\ldots,n_T\}$, $\Delta t > 0$, where Δt means a time step (usually $\Delta t = 1$ hour).
We will identify the term from set T with 0 hour UTC. We assume that for each term from T we have values of d_f parameters of a numerical weather forecast (e.g. temperature, sea level pressure, wind direction and speed, cloud cover — high, medium, low). For the term weather forecast we will understand a matrix $F \in \mathbb{R}^{(n_T+1)\times d_f}$. Moreover, we assume that we possess the data from days from many years in every term $t \in T$. Every term t describes the state of the atmosphere with the aid of the d_s parameters measured near the surface (e.g. temperature, wind direction) and the value of concentrations whose size we are forecasting. The set of meteorological data for each subsequent term $t \in T$ defines the meteorological situation. The meteorological situation will be represented by a matrix $S \in \mathbb{R}^{(n_T+1)\times d_s}$. The aerosanitary situation is the number of sequences of concentrations in $t \in T$ terms, so it is a time series belonging to $\mathbb{R}^{n_T+1}$. In order for the model to function properly it is essential to have all the historical data. Let us denote the set of weather forecasts as WF, the set of meteorological situations as MS, the set of pollution concentrations as AS.

In the first stage, because of the huge data range, we start from $min - max$ normalisation for every weather forecast in every column separately. Let us define:
$f^* \in WF$ — a chosen weather forecast for which we are calculating the forecast of pollution concentrations.
$k = k_1 = k_2$ — first parameter used to control APFM system, it decides about dispersion between elements from set WF. Θ — a set of real numbers representing distances between every normalised weather forecast from WF and f^* so $\Theta = \{\omega_1,\ldots,\omega_q\}, q = |WF| - 1$, where $\omega_i = d_k^{(n_T+1)\times d_f}(f_i, f^*)$ and $f_i \in WF$. $|A|$ means cardinality of set A.
Fractional distance — distance (1) for $k_1, k_2 \in (0,1)$.

In the next step we define second parameter ε. Parameter ε decides about the cardinality of similar elements from set WF. ε is decided in (3).

$$\forall_{i=1,\ldots,q}\ \omega_i < \varepsilon, \tag{3}$$

where $\omega_i \in \Theta$ for $i \in \{1,\ldots q\}$, i is the number of an element. The result of the first stage is set ε–$WF(f^*)$.

In the second stage, in connection with results from the first stage, we create subset ε–$MS^F \subset MS$. Every weather forecast is related with meteorological situation with date. Therefore for ε–MS^F we consider pairs $(f,s), f \in WF, s \in MS$. Then, we set parameters describing the meteorological situations and the time horizon. After review of the chosen meteorological situations, we get a sequence of values:

$$\forall_{t\in T}\forall_{i=1,\ldots,d_s}(\xi_{t,i}^{(1)},\ldots,\xi_{t,i}^{(m)}),$$

where

$$m = |\varepsilon\text{–}MS^F|\,. \tag{4}$$

We modify this sequence into a fuzzy number using a special form of the fuzzy number given by (5). For each attribute i and in each hour $t \in T$ we have individual fuzzy number. This fuzzy number is approximate to the Gaussian function. The fuzzy number (5) was chosen based on our own calculations and based on paper [18].

$$\mu_{i,t}(x) = \begin{cases} \exp(\frac{-(x-m_{1_{i,t}})^2}{2\cdot\sigma^2_{1_{i,t}}}) & \text{if } x \le m_{1_{i,t}}\,, \\ 1 & \text{if } x \in (m_{1_{i,t}}, m_{2_{i,t}})\,, \\ \exp(\frac{-(x-m_{2_{i,t}})^2}{2\cdot\sigma^2_{2_{i,t}}}) & \text{if } x \ge m_{2_{i,t}}\,, \end{cases} \tag{5}$$

where $m_{1_{i,t}} \le m_{2_{i,t}}, \sigma_{1_{i,t}} > 0, \sigma_{2_{i,t}} > 0$ for $m_{1_{i,t}}, m_{2_{i,t}}, \sigma_{1_{i,t}}, \sigma_{2_{i,t}} \in \mathbb{R}$, for each attribute i in each hour $t \in T$. An individual fuzzy weather forecast consists of a time series (5). We receive fuzzy weather forecast (6) — equivalent to the real weather.

$$\phi^* = [\mu_{i,t}] \text{ for } 1 \leqslant i \leqslant d_s, t \in T \tag{6}$$

where i is a number of attribute and t is an hour. ϕ^* is a function for which we determine membership matrix composed from fuzzy numbers. $\phi^*_{it} : \mathbb{R}^{d_s} \to [0,1]$. In ϕ^* we can take property values. We receive $\phi^*(s) = [\mu_{it}(s_{it})]$ which is membership matrix, $s \in \mathbb{R}^{(n_T+1)\times d_s}$. A time series is a sequence of the regularly sampled quantities of an observed system.

Fuzzy weather forecast needs to be able to clearly and precisely define the quality of a weather forecast and assign meteorological situation relative to a fuzzy weather forecast [13]. The assignment of a coefficient quality of a weather forecast is the point of entrance for the exact determination of the individual influence of an attribute on forecasting pollution concentrations in the future.

In the third stage we review all meteorological situation $s \in MS \subset \mathbb{R}^{(n_T+1)\times d_s}$. Then, for every meteorological situation s we calculate $\phi^*(s)$ and number $\varrho(s) = |\phi^*(s)|$ using formula (7).

$$|\phi^*(s)| = d_k^{n_T+1}([d_k^{d_s}(\phi^*_{\cdot t}(s_{\cdot t}), \mathbf{1}_{d_s})]_{t\in T}, \mathbf{0}_{n_T+1}),\ s \in MS,\ k \in [0,1]\,, \tag{7}$$

Let us fix $\eta \in [0,1]$ and determine a set $\eta\text{–}MS \subset MS$ that $|\eta\text{–}MS| = r$, where $\varrho(s) < \eta$ for $s \in \eta\text{–}MS$. For subset $\eta\text{–}MS$ we consider pairs $(s,p), p \in AS$. Then we fix the weight of the meteorological situations using following formula $w(s) = 1 - \varrho(s), s \in \eta\text{–}MS$. In the fourth stage we choose r time series from set AS, where $r = |\eta\text{–}MS| > 1$. Afterwards, for every chosen time series we get a function $p^{(j)} : T \to \mathbb{R}^+_0, j = 1,\ldots,r$ with weight $w^{(j)} \in \mathbb{R}$, representing pollution concentrations. For each $t \in T$ we create a sequence $(p^{(1)}(t),\ldots,p^{(r)}(t))$.

Then we take these sequences and we carry out an aggregation process to obtain one time series. We have used for example method $\alpha\beta$-aggregation (9). This and another the methods are described in details in paper [17]. We base these methods on the well-known methods: (8).

$$\forall_{t\in T} u_{a,t} = \frac{\sum_{i=1}^r w^{(i)} p^{(i)}(t)}{\sum_{i=1}^r w^{(i)}}\,, \forall_{t\in T} u_{m,t} = \max_{i=1,\ldots,r}\{p^{(i)}(t)\}\,. \tag{8}$$

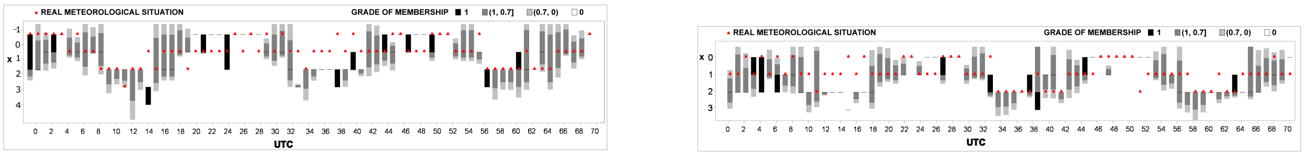
where a means average aggregation, m means maximum aggregation.

Let us denote for each $t \in T$ the following time series $u_{a,t}$ and $u_{m,t}$ as a time series received from methods (8) and $u_{r,t}$ as a time series received from the actual researched data. For $l \approx \frac{n_T}{4}$ we determine two numbers based on knowledge about actual aerosanitary situation. We forecast pollution concentrations having partial knowledge, that is real number l of pollution concentrations. We execute some calculations on time series and we get parameters α, β from the second function (9). When we determine the optimal value of the parameters α, β for (9) we receive formulas (10), (11).

$$h(\alpha,\beta) = \sum_{t=0}^{l} (\alpha u_{a,t} + \beta u_{m,t} - u_{r,t})^2\,. \tag{9}$$

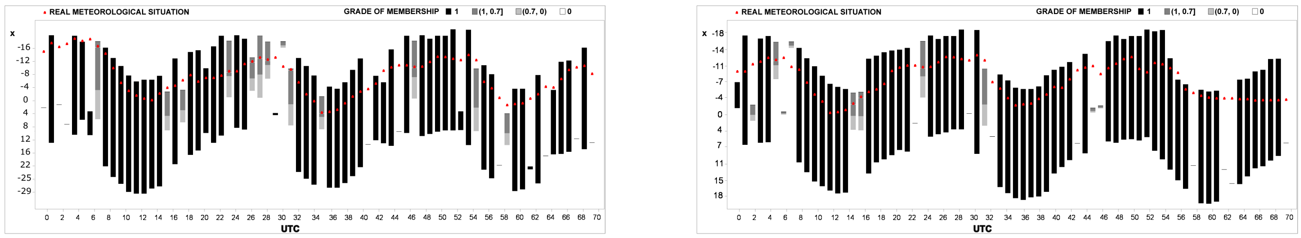
where

$$\alpha = \frac{\sum_{t=0}^l u_{a,t}u_{r,t} \sum_{t=0}^l u^2_{m,t} - \sum_{t=0}^l u_{m,t}u_{r,t} \sum_{t=0}^l u_{a,t}u_{m,t}}{\sum_{t=0}^l u^2_{m,t} \sum_{t=0}^l u^2_{a,t} - (\sum_{t=0}^l u_{m,t}u_{a,t})^2}\,, \tag{10}$$



(a) (b)

Fig. 1. Fuzzy weather forecast for wind speed attribute on a) 9 January 2006 b) 10 January 2006.



(a) (b)

Fig. 2. Fuzzy weather forecast for temperature attribute on a) 9 January 2006 b) 10 January 2006.

if $\sum_{t=0}^{l} u_{m,t}^2 \sum_{t=0}^{l} u_{a,t}^2 - (\sum_{t=0}^{l} u_{m,t}u_{a,t})^2 \neq 0$.

$$\beta = \frac{\sum_{t=0}^{l} u_{m,t}u_{r,t} \sum_{t=0}^{l} u_{a,t}^2 - \sum_{t=0}^{l} u_{m,t}u_{a,t} \sum_{t=0}^{l} u_{a,t}u_{r,t}}{\sum_{t=0}^{l} u_{m,t}^2 \sum_{t=0}^{l} u_{a,t}^2 - (\sum_{t=0}^{l} u_{m,t}u_{a,t})^2}, \tag{11}$$

if $\sum_{t=0}^{l} u_{m,t}^2 \sum_{t=0}^{l} u_{a,t}^2 - (\sum_{t=0}^{l} u_{m,t}u_{a,t})^2 \neq 0$.

From (9) we receive parameters α, β given by (10) and (11).

Then using method (9) and having knowledge about collateral information i.e. first ten hours real pollution concentrations in the day we being forecast, we can calculate for each $t \in T$ the final time series $u_{f,t}$.

2. Characteristics of fuzzy weather forecast

A fuzzy weather forecast ϕ^* is determined for each attribute i individually and is evenly distributed on each hour $t \in T$. It is valued on the basis of data similarity and proper weights of classification. We researched the behaviour of the fuzzy weather forecasts using different sets of forecast data. This is necessary because we have weather forecasts from a short period of time (only six years). Therefore, continuous work in a COSMO LM model weather forecast [19], [20] is not heterogeneous for finding the period of a weather forecast which is the best estimate of real meteorological situations. In Figs 1, 2, 3 fuzzy weather forecasts are shown along with real meteorological situations. The fuzziness is a good measure with which to mark the quality of a weather forecast both its elements and the whole weather forecast because fuzziness characterises the scattering of real data around the prognosis.

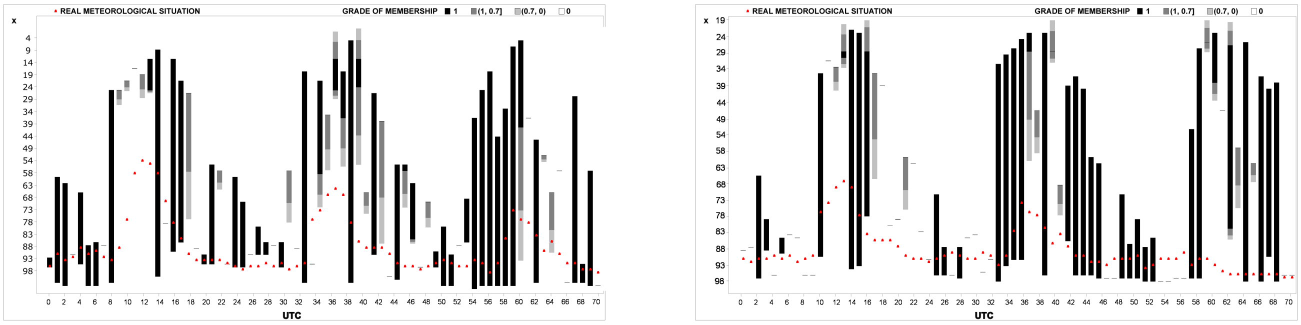
3. Features to estimate the quality of a fuzzy weather forecast

The first feature is research volume for all attributes i in each hour $t \in T$. We receive the first number $F^{i,t}$

$$F^{i,t} = \int_{-\infty}^{\infty} \mu_{i,t}(x)\mathrm{d}x = \frac{\sqrt{2\Pi}}{2}(\sigma_{1_{i,t}} + \sigma_{2_{i,t}}) + m_{2_{i,t}} - m_{1_{i,t}}, \tag{12}$$

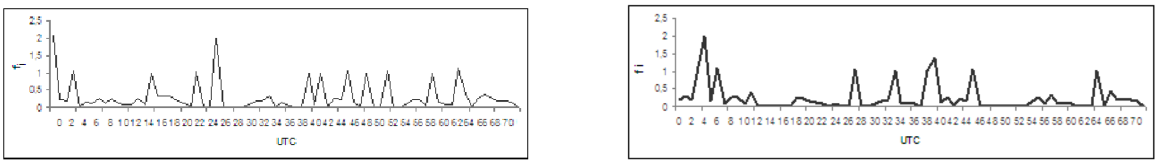
where $i \in \{1, \ldots, d_s\}, t \in \{0, \ldots, n_T\}, \sigma_{1_{i,t}}, \sigma_{2_{i,t}}, m_{1_{i,t}}, m_{2_{i,t}} \in \mathbb{R}^{(n_T+1)\times d_s}$.

Let us define $f_i(t) = F^{i,t}$ for each $t \in T$. In Figs 4, 5, 6 we see the functions $f_i(t)$ for all $t \in T$ and for the chosen attributes i are shown using real meteorological situations: wind speed, temperature and humidity.



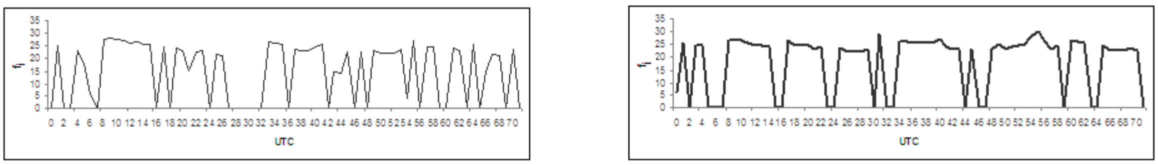
(a) (b)

Fig. 3. Fuzzy weather forecast for humidity attribute on a) 9 January 2006 b) 10 January 2006.



(a) (b)

Fig. 4. f_i for wind speed attribute on a) 9 January 2006 b) 10 January 2006.



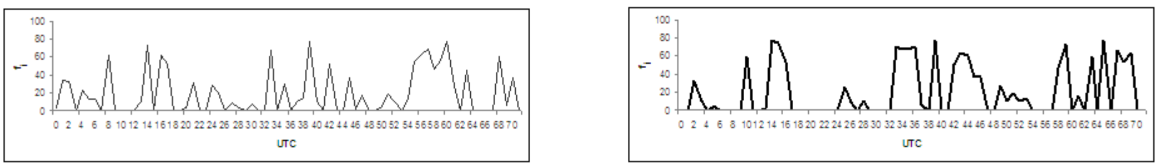
(a) (b)

Fig. 5. f_i for temperature on a) 9 January 2006 b) 10 January 2006.

In Fig. 7 fuzzy weather forecast is shown for all attributes.

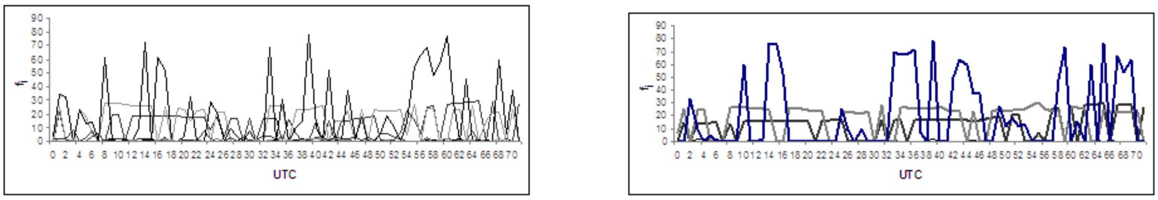
The second feature is researching the quality of a fuzzy weather forecast by comparing it to a real meteorological situation. In this way we keep an attribute characterised by a grade of membership for each hour. In Figs 8, 9 grades of membership for wind speed, temperature and humidity are shown.

In Figs 1, 2, 3 the fuzzy weather forecasts are clearly and explicitly shown and it can be seen that the fuzzy weather forecast has a little fuzziness when the grade of membership is large. By analysing other examples, a fairly significant dependence between small fuzziness and membership can be observed, a reverse correlation between them, because if the fuzziness is greater then the checkness of the pollution concentrations forecasting is minor.



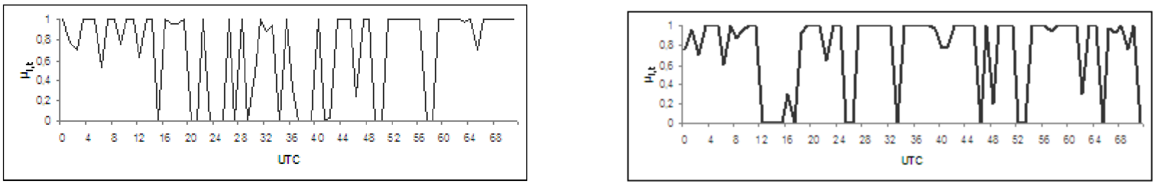
(a) (b)

Fig. 6. f_i for humidity attribute on a) 9 January 2006 b) 10 January 2006.



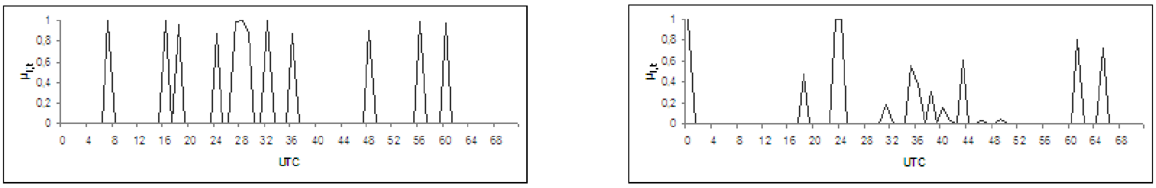
(a) (b)

Fig. 7. f_i for all attributes on a) 9 January 2006 b) 10 January 2006.



(a) (b)

Fig. 8. The grade of membership $\mu_{i,t}$ for wind speed attribute and $T = 72$ on a) 9 January 2006 b) 10 January 2006.



(a) (b)

Fig. 9. The grade of membership $\mu_{i,t}$ for a) temperature attribute b) humidity attribute and $T = 72$ on 9 January 2006.

4. Verifiability of the weather forecast

Taking into account that the key to the pollution concentration forecasting is reliable information coming from the weather forecast we need to separate the forecasts which we think that are fulfiled from the forecasts that have not fulfil. To make this we will use fuzzy weather forecast, weather forecasts and meteorological situations. Let us introduce following defuzzyfication method for $\mu_{i,t}(x)$:

$$\overline{\phi_{i,t}} = \frac{\int\limits_{-\infty}^{\infty} \mu_{i,t}(x)\cdot x \,\mathrm{d}x}{\int\limits_{-\infty}^{\infty} \mu_{i,t}(x) \,\mathrm{d}x} = \frac{\frac{1}{2}(m_{2_{i,t}}^2 - m_{1_{i,t}}^2) + \sigma_{2_{i,t}}^2 - \sigma_{1_{i,t}}^2 + \frac{\sqrt{2\pi}}{2}(m_{1_{i,t}}\sigma_{1_{i,t}} + m_{2_{i,t}}\sigma_{2_{i,t}})}{F^{i,t}} \tag{13}$$

Fuzzy weather forecast $f_{i,t}$ is defuzzyficated according to equation (13), we obtain a real value for every hour $t \in T$ and for every attribute i. The verification of the weather forecast is based on similarity of the data:

(1) value of the attributes describing the weather forecast to the values of the meteorological situations attributes
(2) $\overline{\phi_{i,t}}$ to the value of the attributes describing the weather forecast
(3) $\overline{\phi_{i,t}}$ to the value of the meteorological situations attributes

Table 1. Results of the tests for the temperature attribute.

Date	M_{f_i,s_i}	$M_{\phi_{i,t},f_i}$	$M_{\phi_{i,t},s_i}$
1 January 2006	0.363	0.562	0.082
5 January 2006	0.525	0.424	0.125

Table 2. Results of the tests for the wind speed attribute.

Date	M_{f_i,s_i}	$M_{\phi_{i,t},f_i}$	$M_{\phi_{i,t},s_i}$
1 January 2006	0.069	0.076	0.018
5 January 2006	0.133	0.172	0.046
10 January 2006	0.053	0.050	0.066

We use Mean Absolute Error [22] to estimate the verifiability of the weather forecast. For each attribute i the Mean Absolute Error between fuzzy weather forecast and weather forecasts is given by:

$$M_{\phi_{i,t},f_i} = \frac{1}{n_T+1}\sum_{t=0}^{n_T} |\overline{\phi_{i,t}} - f_i| \tag{14}$$

where $f \in WF$ and $|x|$ is the absolute value of x.

Analogous is with the differences between meteorological situations and fuzzy weather forecast. We denote the Mean Absolute Error in this case as $M_{\phi_{i,t},s_i}$, $s \in MS$ and for the differences between meteorological situations and weather forecasts we use the notation M_{f_i,s_i}, $s \in MS, f \in WF$ for the Mean Absolute Error.

In Tabs. 1, 2 we have the obtained average differences between the weather forecast attributes and real situations, weather forecast and $\overline{\phi_{i,t}}$, real situations and $\overline{\phi_{i,t}}$.

At first we can see in Tab 1 that for greater fuzzines differences between weather forecasts and meteorological situations, between fuzzy weather forecast and weather forecast are greater than between meteorological situations and fuzzy weather forecast. At second we see possibility to improve the weather forecast. Analogous is with the wind speed attribute in Tab 2, however small fuziness give us minor possibility to improve the weather forecast.

5. Conclusion

Computations were performed for weather forecasts in 2003-2007, meteorological situations in 1997-2007 and pollution concentrations in 1998-2007 with $\Delta t = 1$. We have $d_f = 28$ attributes describing weather forecasts, while the number of meteorological situations was equal to $d_s = 9$. Attributes describing meteorological situations were chosen based on investigations by [21]. The effect of the suggested method for the prediction of a weather forecast was introduced for data from COSMO LM model, but the same method can be used for different weather forecasts based on numerical models. The condition which has to be met is to have real meteorological data.

In the paper we have introduced the analysis of the fuzzy weather forecast, with specification of the method which allows us to improve the calculated weather forecast.

In Figs. 1, 2, 3 is shown fuzzy weather forecast and in Figs 8, 9 particular grades of membership. The performed experiments have shown that if the fuzzines is smaller than the membership to the real situations is bigger.

In Tabs 1, 2 we see that for $\overline{\phi_{i,t}}$ and real situation we have the smallest difference between obtained attributes, what allows us to improve the quality of the weather forecast.

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