

Re-calculation of the odour emission of a thermal treatment plant for waste by using a Monte-Carlo based model

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The assessment of the impact of ambient odour concentrations in the vicinity of a plant can only be done if the odour emission is known. Based on the measurements of ambient concentrations of seven substances (butyl acetate, benzene, ethyl acetate, toluene, m/p-xylene, o-xylene and α -pinene) and meteorological parameters, the emission mass flow of a thermal treatment plant for waste was calculated by inverse dispersion modelling. The odour emission was calculated from the odour concentration thresholds of these substances. The emission data are available however only for the wind directions for which the measuring station is leeward of the plant. Using a Monte-Carlo model, the dataset was completed also for wind directions for which no ambient concentration measurements were available. In a statistical analysis the following main predictors, describing the strength of the emission for all substances, are identified: time of the day, day of the week, ambient air temperature und wind velocity. Additionally the intermittence factor is used to describe the emission scenario. Due to the stochastic character of the emissions, a model for each substance was developed, which is based on the Monte-Carlo methodology to generate time series of the emission. For the model evaluation the emission data based on the measurements were compared with the synthetic emission data of the Monte-Carlo model. After calibrating the Monte-Carlo model, the expected values and the variances are in good agreement with the empirical data.

1. Introduction

The availability of reliable emission data is the crucial point to apply dispersion models.

The characterisation of a thermal treatment plant for waste in Southern Austria with unknown emissions was derived by using long term measurements of the ambient concentrations of several species leeward of the plant. Based on these measurements and the meteorological data the emission is re-calculated by an inverse dispersion model (Schaubberger et al., 2008). Using this method, the calculation of the emission is possible only in cases when the measuring site is leeward of the pollution source. This means that in the majority of the time no emission data are available. There are many other

reasons why emission data can be incomplete (e.g. only short measuring campaigns can be financed, failure of the measuring device, changes in the process flow).

In this paper we present a method which is developed to assess the odour emission of a thermal treatment plant for waste over the entire year to calculate the annoyance potential in the vicinity of the pollution source. The odour emission is calculated on the basis of seven species which are identified to have a high odour relevance because of a low odour threshold concentration.

The model is based on the Monte-Carlo technique that involves using random numbers and probabilities to solve problems. This method is often used when the model is complex, nonlinear, or involves more than just a couple of uncertain parameters.

2. Material and Methods

2.1 Monte-Carlo model

Due to the statistical structure of the emission flow we use a two step Monte-Carlo model. For each half hour value two even distributed random numbers RN_1 and RN_2 are used. The first stochastic process, using the first random number RN_1 , decides on the intermittence factor which describes if an emission value is generated or if the emission value is set to zero.

The second stochastic process, using the second random number RN_2 , will generate a value according to the log-normal distribution. The evenly distributed random number RN_2 is inverted to a random number, distributed according to an arbitrary distribution function. If $F(x)$ is a distribution function of a random variable x and p is the probability of the realisation in the interval $[0; 1]$, then the quantile function F^{-1} , as an inverse function of the distribution function F , is defined as

$$F^{-1}(p) = \inf \{x \in \mathbb{R} \mid F(x) \leq p\} \quad (1)$$

If RN is an even distributed random number in the interval $[0;1]$

$$RN \in E \text{ then} \quad (2)$$

$$x = F^{-1}(RN)$$

is a random variable, distributed according to the selected distribution function F . As an example, the random number $RN = 0.60$, for a normal distribution $F = N(\mu, \sigma^2)$ with the two parameters expected value (arithmetic mean value) $\mu = 2$ and variance $\sigma^2 = 2$, the p -quantile ($p = RN$) with the quantile function gives $F^{-1}(RN) = 2.506$.

The statistical analysis of the emission E shows a good agreement with the log-normal distribution Λ

$$E \sim \mathbf{L}(\mu, \sigma^2) \quad (3)$$

with the mean value μ and the standard deviation σ .

As estimators for these two parameters of the cumulative distribution function the mean value MW_{log} and the standard deviation SD_{log} of the logarithmically transformed emission mass flow E are used.

2.2 Emission data

The thermal treatment plant is situated in an Austrian basin in the South of the main Alpine chain, in the province of Carinthia in the South of Austria. The plant is approved for commercial and industrial hazard waste. The waste, predominantly solid and paste-like, is shredded and conditioned to ensure a constant calorific value. This mix of materials is burned in one of two different thermal treatment devices (rotary and fluidised-bed furnace). The exhaust air is conditioned by dry flue gas cleaning, scrubber, catalytic NO removal and activated charcoal filter.

The measuring station is in the East-Northeast of the plant in a distance of about 950 m. At this station, the ambient concentrations and the meteorological parameters are measured. For this thermal treatment plant the emission mass flow E of seven substances and the correspondent odour emission is determined by an inverse dispersion model (Schauberger et al., 2008). Using this method, E is only derived for these half hour values for which ambient concentration measurements are available. This is the case, if the wind direction is directed from the source towards the measuring site. For all other half hour values, no information about the emission is available.

3. Results

3.1 Model parameters

For the development of the Monte-Carlo model, the internal structure of the pollution source has to be analysed. The goal of the data analysis is the determination of predictors which describe the data set in an appropriate way. Depending on the character of the pollution source, two groups can be identified. The first group of parameters describes the influence of the meteorological situation. The wind velocity is used to characterise the natural ventilation of the buildings due to the wind pressure. The forced stripping of volatile solvents is taken into account via the air temperature.

The regression analysis for a 1½ year time series of these two meteorological parameters shows a high regression coefficient both for the logarithmically transformed values of the emission of the seven species (mg/s) and the two odour emission flows,, significant for all species and odour on the 1%-level. Therefore these exponential

functions were used to describe the influence of the two parameters on the emission flow E .

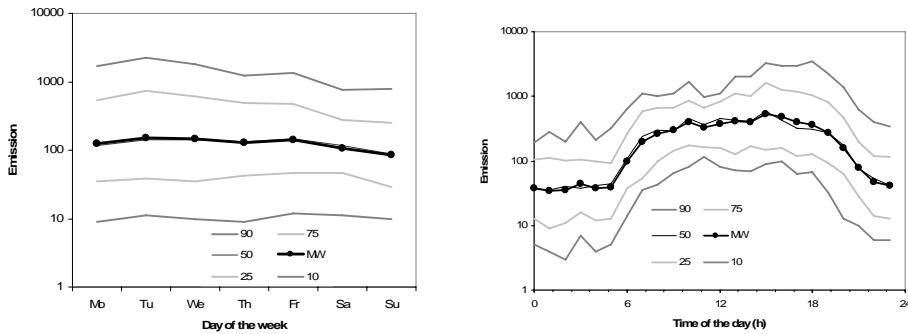


Fig. 1: Influence of the day of the week (left) and time of the day (right) on the emission mass flow E (mg/s) for ethyl acetate (Quantiles Q : 0.90- Q , 0.75- Q , 0.50- Q (median), 0.25- Q and 0.10- Q) and mean value MW .

The second group of parameters describes the process flow of the plant (shredding, conditioning and storing). The process flow is expected to depend on two parameters: day of the week and time of the day.

In Fig. 1, the two parameters which describe the process flow are exemplified for ethyl acetate, the species which has the strongest contribution to the odour emission of all measured substances (Schauberger et al., 2008).

All four predictors are used to describe the internal structure of the data set. Based on the two meteorological parameters air temperature and wind velocity, a 3 x 3 matrix is defined. The limits of the matrix are defined by the 0.33 and 0.67 percentile of the time series of the two parameters (6.6°C and 15.1°C as well as 0.4 m/s and 1.4 m/s). Therefore each element of the matrix contains the same number of half-hour mean values. For each element the mean value and the standard deviation of the log-normal distribution is determined.

An important parameter to describe the time series of ambient concentration measurements is the intermittence factor IF (Chatwin and Sullivan, 1989). This factor describes the fraction of values above a certain threshold. In many cases this threshold is assumed to be 0 or taken as the detection limit of the measurement device. For the intermittence factor, the diurnal variation for working days and for the weekend is taken into account. Further on, the influence of the process flow is included by the relative diurnal variation of the mean values and the standard deviation for all days of the week.

The flow diagram of the Monte-Carlo model is shown in Fig. 2.

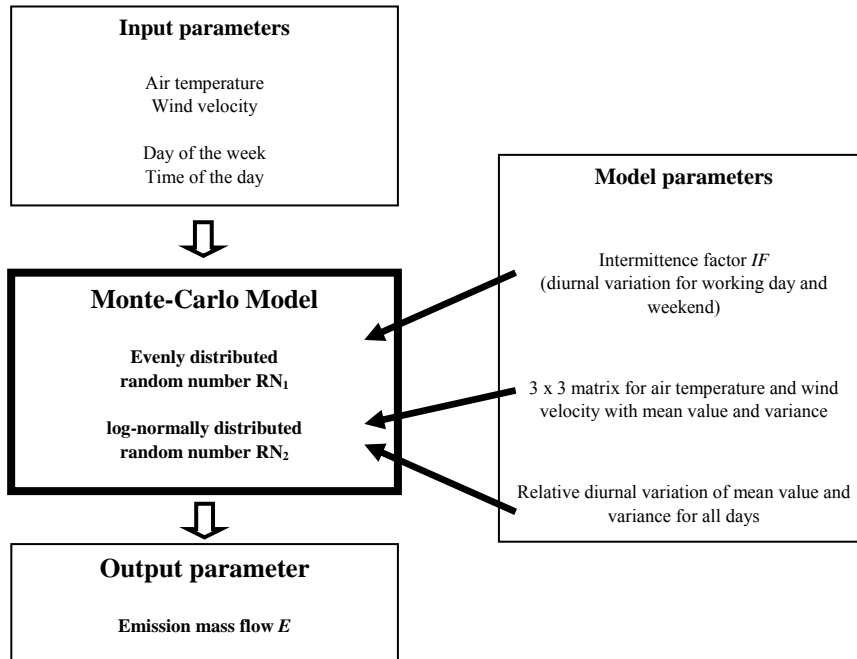


Fig. 2: Structure of the Monte-Carlo model

3.2 Validation of the modelled emission data

Emission data are determined only for those half-hour values when the site of the ambient concentration measurements is the leeward of the pollution source. This is the case for a wind sector between 235 and 265°; only wind directions from this sector are used.

In Tab. 1 the result of the Monte-Carlo model is compared with the empirical emission data, calculated by the inverse dispersion model (Schauberger et al., 2008). The stratification of the dataset to describe the influence of the process parameters (time of the day and day of the week) and the meteorological parameters (air temperature and wind velocity) cannot be separated into disjunkt subsets. Therefore the sum of the variances of the subsets is greater than the variance of the entire dataset. To fit the synthetic model data, a calibration factor was introduced. As cost function of the adjustment, the root mean square error was used.

Using the two calibration factors f_{MW} und f_{SD} , the log-normal distribution of the Monte-Carlo model (defined by the mean value MW_{MC} and the standard deviation SD_{MC}) is transformed to the calibrated distribution. Mean value and standard deviation are corrected by $MW_{syn} = f_{MW} MW_{MC}$ and $SD_{syn} = f_{SD} SD_{MC}$, respectively. The emission E_{syn} is distributed according to a log-normal distribution $E_{syn} \sim \Lambda(MW_{syn}, SD_{syn})$.

The calibration factor for the mean value f_{MW} lies between 1.010 for odour (OD_{mean}) and 1.046 (α -pinene). As a result of this calibration, the relative deviation of the mean value lies between 6.5 and -5.0%. The deviation of the intermittence factor is below 2%.

Tab. 1: Comparison of the emission data based on the ambient concentration measurements (E_{meas}) and the synthetic dataset, calculated by the Monte-Carlo model (E_{syn})

	Species								
	Butyl	Benz	Ethyl	Tol	mp-X	o-X	α -Pin	OD _{max}	OD _{mean}
Measurements									
E_{meas}									
MW_{meas}	2.091	1.779	2.101	2.214	1.960	1.617	1.995	3.952	2.314
SD_{meas}	0.823	0.741	0.815	0.758	0.757	0.751	0.733	0.852	0.866
IF_{meas}	0.615	0.859	0.693	0.875	0.797	0.618	0.519	1.000	1.000
Model E_{syn} (calibrated)									
MW_{syn}	2.062	1.787	2.082	2.235	1.963	1.614	1.999	3.949	2.307
SD_{syn}	0.843	0.741	0.826	0.757	0.754	0.752	0.731	0.851	0.862
IF_{syn}	0.601	0.854	0.677	0.870	0.786	0.607	0.509	1.000	1.000
Calibration factor									
f_{MW}	1.036	1.018	1.022	1.025	1.014	1.021	1.046	1.013	1.010
f_{SD}	0.582	0.692	0.612	0.699	0.683	0.697	0.721	0.698	0.761
Model performance									
MW^* rel deviation.(%)	6.5	-1.9	4.3	-5.0	-0.7	0.7	-0.9	0.6	1.6
IF deviation (%)	1.40	0.50	1.60	0.50	1.10	1.10	1.00	-	-

(Butyl butyl acetate; Benz benzene; Ethyl ethyl acetate; Tol Toluene; mp-X m/p-Xylene; o-X o-Xylene; α -Pin α -pinene; OD_{max} maximum odour emission, calculated by the minimum odour threshold, OD_{mean} mean odour emission, calculated by the mean odour threshold)

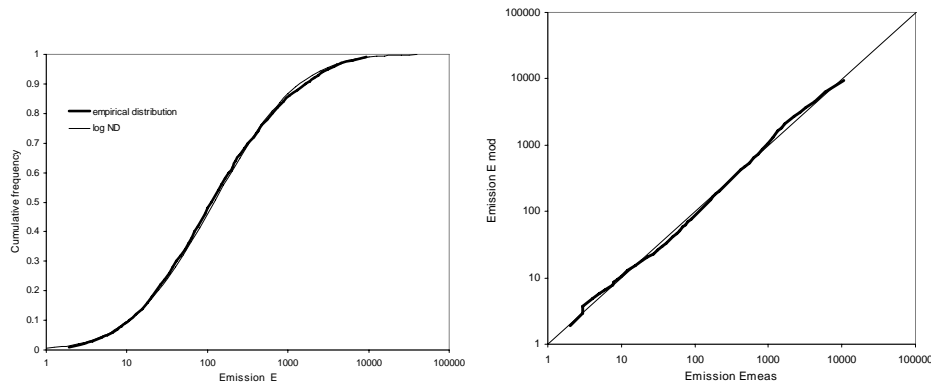


Fig. 3: Comparison of the synthetic emission data E_{mod} , calculated by the Monte-Carlo model, with empirical emission data E_{meas} , calculated by the inverse dispersion model for ethyl acetate, the most important species for the odour emission. CDF (left), qq-plot (right)

In Fig. 3, the cumulative distribution function CDF of the empirical data and the synthetic emission data are presented exemplarily for ethyl acetate, the most important species for odour (Schauberger et al., 2008). A good agreement is achieved.

The regression analysis of the modelled data for the two meteorological parameters air temperature and wind direction shows a stronger relationship compared to the empirical data. The correlation coefficient is about 20 to 50% higher for air temperature and about 17 to 50% higher for the wind direction. This over-estimation of the influence of the meteorological parameters on the emission is caused by the fact that for the Monte-Carlo model, only these two parameters are included. Other effects are neglected.

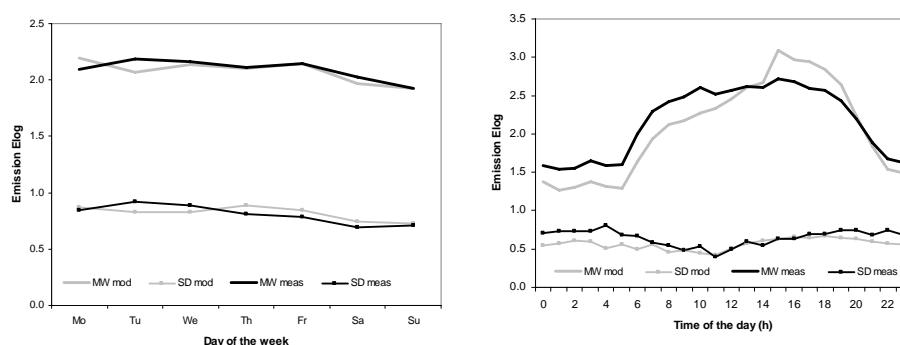


Fig. 4: Comparison of the time course of the synthetic emission data (modelled data), calculated by the Monte-Carlo model and the empirical emission data (measured data), calculated by the inverse dispersion model for butyl acetate (a) day of the week, (b) time of the day (mean value MW and standard deviation SD)

4. Discussion

Reliable emission data are crucial for the application of dispersion models. In many cases the pollution source is characterised by a constant value for the emission mass flow. The use of only one (mean) value can lead to an underestimation of the impact of the ambient concentration, calculated by a dispersion model. This error depends on the observed impact of the ambient concentration. In many cases, the health impact is described by a non-linear dose response function (Hilderman and Wilson, 1999). Especially health related phenomena show such a relationship with the ambient concentration C which can be described by a power function C^n with an exponent n in the range between 1.0 and 3.5. Some chemicals show an exponent between 2.0 and 3.0 for the toxicity and fatalities. Only if the exponent $n = 1$, then high concentrations are no longer relevant and therefore the only variable determining toxicity is the mean concentration. However, if $n > 1$, then the use of a constant emission mass flow concentration will underestimate the impact of the substances. The health effects of toxic gases are described in detail by Hilderman (1997).

An example for such impact criteria with a non-linear relationship is odour. Odour annoyance is evaluated by the exceedance of the ambient concentration above a certain threshold (eg 1 OU/m³) and related to the exceedance probability. A second aspect for odour is the non-linear relationship between odour concentration and the perceived odour intensity, described by the Weber-Fechner law or Steven's power law, respectively (Sarkar and Hobbs, 2002).

The pollution source can be described as a dynamic system. The features of such a system cannot be described in a direct way because the emissions are seldom known in detail. These hidden conditions can be determined by the set of emission data derived from inverse dispersion modelling (Schauberger et al., 2008). For the thermal treatment plant two sets of predictors are determined: first, the environmental parameters air temperature and wind velocity, which parametrise the release of the emitted substances; secondly the two parameters day of the week and time of the day, which describe the modulation of the emission by the changing process flow of the plant.

The goal of such an assessment is an extensive description of the dynamic system. Based on the recovered predictors, a Monte-Carlo simulation of the emission flow is developed. The goal of this method is the prediction of the macroscopic state of the emission source due to the simulation of microscopic interdependency. In our case these are the environmental and the process-related interactions which describe the variance of the emission source.

After calibrating the synthetic emission data of the Monte-Carlo model, the expected values and the variances of the seven substances and the two odour emissions are in good agreement with the empirical data.

5. References

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