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A STUDY OF ODOUR METRICS AND MODELS USING A COMPREHENSIVE MEASUREMENT CAMPAIGN DATASET

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Abstract: This paper examines the merits of odour metrics for assessing odour nuisance based on both hourly average odour concentrations and those related to sub-hourly peak odour concentrations. The most common metric for odour regulation in Europe is the 98th percentile of the hourly mean, but an increasing number of countries use metrics relating to the number of 'odour hours' in order to account for short-term peaks. An hour is categorised as an 'odour hour' if the odour levels exceed a specified threshold for a proportion (typically 10%) of the hour; the number of 'odour hours' may be calculated directly from high frequency data or estimated from hourly concentrations.

Two models have been evaluated: the advanced quasi-Gaussian ADMS plume model is able to predict 'odour hours' using a simple 'peak-to-mean' ratio as well as from a probabilistic model accounting for short-term fluctuations in concentration; the German Lagrangian particle reference model AUSTAL2000G is also able to calculate these metrics. Two datasets have been used to evaluate these models. The Baden-Württemberg Programm Lebensgrundlage Umwelt und ihre Sicherung funded an odour field campaign at a pig farm near Biberach in Germany for the purpose of generating a dataset suitable for assessing performance of dispersion models for assessing odours; this dataset has previously been reported on in the literature. A new dataset involving electronic nose odour monitoring in the vicinity of the port in Riga, Latvia, has also been studied; here, the odour is associated with the loading, unloading and storage of over five million tonnes of oil products annually. The results of the pig farm evaluation show that ADMS is suitable for modelling sub-hourly odour concentrations. Results from the port study demonstrate that ADMS and AUSTAL2000G perform comparably; further, both models predict the number of odour hours to be within a factor of three of the observed, which, when the poor source quantification and uncertainty in the measurement data is allowed for, should be considered as good performance.

Key words: *Odour, modelling, ADMS, AUSTAL2000G, monitoring*

INTRODUCTION

Odorous emissions may be regulated qualitatively or operationally (for example, by imposing large setback distances between sensitive receptors and odour sources). However, quantitative assessment is the most common regulatory approach, where measurements of odour emissions at the source are used as input to a dispersion model to determine the location and magnitude of potential odour impacts. The merits of metrics based on hourly average odour concentrations compared to those based on peak concentrations over shorter timescales is a much-discussed topic. This paper presents an evaluation of the ability of two models (ADMS, Carruthers *et al.*, 1994 and AUSTAL2000G, Janicke & Janicke, 2007) to calculate different odour metrics.

The first odour regulations in Europe were introduced in the 1970s and standards for olfactometry were developed during the 1980s. Currently, the most common metric for odour regulation in Europe is the 98th percentile of the hourly mean, but some countries use metrics relating to the number of 'odour hours' in order to account for short-term peaks. An hour is categorised as an 'odour hour' if the odour levels exceed a specified threshold for a proportion of the hour; the number of 'odour hours' may be calculated directly or derived from hourly concentrations. Other approaches have been adopted, for example Western Australia had a criterion based on the 3-minute average, although this has now been withdrawn.

Gaussian plume (e.g. ADMS, AERMOD), puff (e.g. CALPUFF) and Lagrangian (e.g. AUSTAL2000G) are the most common types of dispersion models used for odour assessments. All models are able to calculate the metrics based on the hourly mean concentration (e.g. the 98th percentile); 'peak-to-mean' ratios may be applied to hourly values to approximate the number of 'odour hours'. ADMS is able to model odour hours from the probability of exceedence of threshold values for averaging times ranging from one second up to an hour, which is calculated using its concentration fluctuations module (Dyster et al., 2001).

The models used in this intercomparison study are described below. A description of the two datasets that have been used in the study then follows. The evaluation approaches and results of the two studies are then presented, followed by some discussion.

MODELS

ADMS is an advanced quasi-Gaussian plume dispersion model that simulates a wide range of buoyant and passive releases to the atmosphere, either individually or in combination. ADMS uses two parameters to characterize the vertical structure of the atmospheric boundary layer, namely the boundary layer height and the Monin Obukhov length, and a skewed Gaussian concentration distribution to calculate dispersion under convective conditions. ADMS is used worldwide for air quality regulatory assessment and research projects, including the simulation of odour dispersion. AUSTAL2000 is a Lagrangian particle model that simulates the dispersion of air pollutants using a random walk process; it is the reference dispersion model accepted as being in compliance with the requirements of Annex 3 of the German air pollution control regulation TA Luft and the model is used internationally. AUSTAL2000G is a related model that is used for odour modelling applications.

Both ADMS and AUSTAL2000G are able to calculate time series of hourly average odour concentrations, from which the 98th percentile metric can be derived; also, peak-to mean ratios can be used to approximate the magnitude of sub-hourly concentrations. ADMS includes a fluctuations module that uses a probabilistic approach for calculating the likely distributions of sub-hourly pollutant concentrations, from which odour hours can be derived; AUSTAL2000G also calculates odour hours.

DATASETS

Two datasets are used for evaluation. The first, which is associated with an odour field campaign at a pig farm near Biberach in Germany, has previously been reported in the literature (Bachlin et al., 2002). The Baden-Württemberg Programm Lebensgrundlage Umwelt und ihre Sicherung (BWPLUS) funded a campaign for the purpose of generating a dataset suitable for assessing performance of dispersion models for assessing odours. Measurements were made not only of odour but also of the tracer gas SF_6 because the quantification of odour levels is imprecise. 14 experiments were performed and, for each experiment, 11 or 12 human 'sniffers' recorded odour intensity levels at two transects approximately 150 and 275 m downwind of the source.

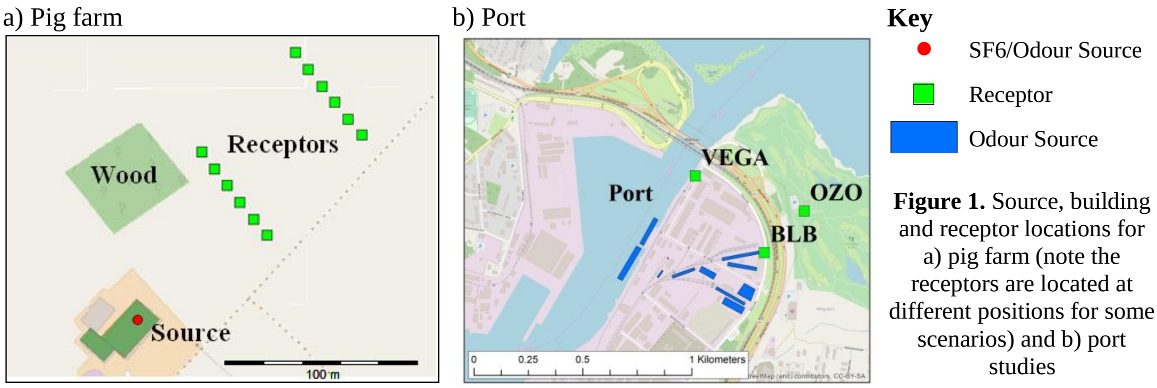

Figure 1. Source, building and receptor locations for a) pig farm (note the receptors are located at different positions for some scenarios) and b) port studies

The second dataset, which relates to the continuous monitoring of activities at the port in Riga, Latvia, where fuel-related odour emanates from loading and activity, has not previous been documented. SIA Estonian, Latvian and Lithuanian Environment (ELLE) have been using electronic noses ('RQ Box' devices manufactured by Alpha MOS equipped with PID and MOS sensors, and electrochemical cells) to continuously record 1-minute odour levels in this location, since 2017. Three e-noses ('VEGA', 'OZO' and 'BLB') have been deployed downwind of the dominant activities. Advantages of using this dataset to evaluate odour metrics include the long time series of data available, allowing the calculation of the 98th percentile metric alongside odour hours; also some complaint records are available although they are not used in the current study. The primary disadvantage of this dataset is the large uncertainty associated with the magnitude of the source term: the dominant emissions have been approximated from odour measurements of less than five representative activities at the port; and other smaller emissions have been estimated using permitting thresholds of diesel fuel use. The time-variation of emissions has not been modelled. Data for the period August-December 2017 have been used.

EVALUATION METHODOLOGY AND RESULTS

There are too few measurements recorded at the pig farm to calculate the 98th percentile of the hourly mean, but this dataset includes high temporal resolution (10 s) SF_6 and odour data that can be used to evaluate ADMS's performance in predicting sub-hourly peak concentrations; AUSTAL2000G has not been included in this part of the evaluation exercise, because it has been previously evaluated for odour modelling. The SF_6 measurements are concentration values, whereas the odour data are quantified in terms of odour intensity; the former can therefore be used to make direct comparisons of model output, whereas the latter requires an assumption regarding the relationship between odour concentration and intensity. The odour intensities ranged between one and five, but for simplicity, a value of one has been used as the threshold for odour hour calculations. Odour hours have also been calculated using a multiplier to derive the peak concentration from the mean concentration.

The e-noses deployed at the port record 1-minute odour concentration data. Hourly average concentrations can be calculated, from which the 98th percentile can be derived. An odour concentration threshold value of 5 OU_E has been used in the calculations of odour hours. Model predictions for the number of odour hours were evaluated in two ways: Firstly, a direct comparison on an hour-by-hour basis, where the observed and modelled data are fixed in space and time; this evaluation results in statistics relating to correctly and incorrectly predicted odour hours (and similarly 'non-odour' hours). Secondly, removing the time restriction results in an overall comparison of total number of odour hours; this comparison is more consistent with the 98th percentile metric for hourly averages, which does not include any temporal restrictions.

Pig farm odour field campaign

The first step in evaluating the model configuration is to compare predictions of the 10-minute SF_6 concentrations at all receptors, to ensure that the base model is representative of the field campaign. Of the 14 experiments, the results from three cases have been removed from the analysis because of quality control reasons.

Figure 2 shows a quantile-quantile plot of ADMS 5.2 modelled concentrations against observations. Two sets of ADMS results are presented – with and without buildings – because the fluctuations / odour modelling option in ADMS is not compatible with the buildings module. Figure 2 shows that the ADMS underpredicts the high concentrations by a factor of two, but gives a reasonably good prediction for the lower concentrations. This model behaviour is consistent with the model formulation of an ensemble mean plume model, which is formulated to predict average rather than peak concentrations.

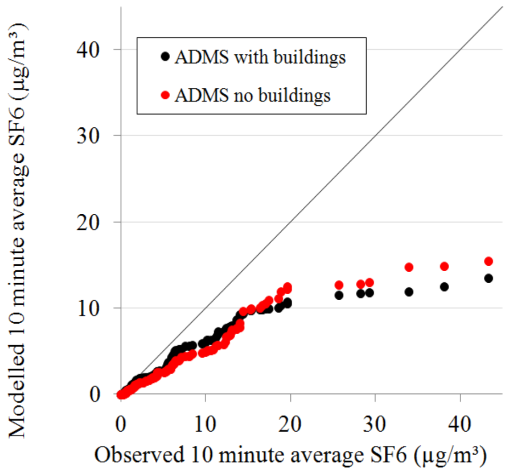

Figure 2. Quantile-quantile plot comparison of modelled and measured 10 minute average SF_6 concentrations

The next step is to use the 10 s SF_6 data records to assess how well the ADMS and AUSTAL2000G models are able to replicate short-term fluctuations. Here, the peak-to-mean concentration is a good metric to analyse because the focus moves from the evaluation of absolute concentrations (considered above) to peak values. The definition of the peak concentration is taken as the 90th percentile of the 10 s concentrations. Figure 3 shows the comparison of peak-to-mean ratios for ADMS; apart from two receptors where the fluctuations module predicts zero concentrations (which may be related to inaccuracies in the meteorological data, i.e. the plume 'misses' the receptor), the model gives a relatively good prediction of the peak-to-mean ratio, although there is a tendency for overprediction. The conclusion from the analysis of the SF_6 data is that the ADMS fluctuations module performs well in terms of calculating peak concentrations so should be suitable for use in predicting odour hours.

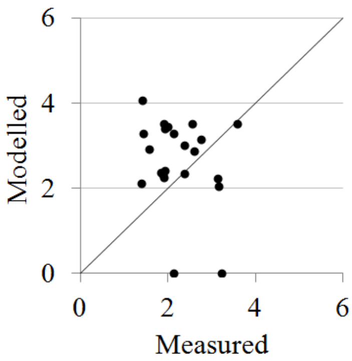

Figure 3. Scatter plots of SF_6 modelled and measured peak-to-mean ratios

The number of odour hours has been calculated by ADMS using the direct method as well as using the commonly used peak-to-mean ratio value of 4. Table 1 compares the number of correctly modelled odour and 'non-odour' hours, where the comparison fixes the values in both space and time. For this field campaign, the models perform very well, which suggests that ADMS is suitable for the calculation of the odour hour metric, either using the fluctuations modelling approach or the simple peak-to-mean ratio method. However, this good performance is related in part to the campaign configuration i.e. only cases where the wind advects from the sources to the monitor have been considered, and the meteorological conditions were generally neutral (due to parallel experiments being performed in a wind tunnel).

Table 1. Measured and ADMS modelled odour hours at the pig farm

Method	Correct odour hour	Correct non-odour hour	False odour hour	Missed odour hour
Fluctuations	79	16	24	7
Peak-to-mean	81	12	28	5

Continuous monitoring of port activities

In the following comparisons between the number of measured and modelled odour hours, results are presented separately for each of the three receptors. Figure 4 shows the comparison of the number of odour hours when results are compared taking into account the time as well as location. Both models predict similar numbers of odour hours, and neither model demonstrates particularly good performance; this is unsurprising given the poor quantification of the odour sources in terms of emissions magnitude and temporal variation and the uncertainty in the

Receptor	Mean			98th %ile		
	Obs.	ADMS	AUSTAL	Obs.	ADMS	AUSTAL
BLB	2.8	2.0	1.8	7.1	12.0	10.2
OZO	1.8	0.6	0.5	9.7	4.3	4.3
VEGA	4.5	1.1	2.0	20.2	5.4	17.0

Table 2. Observed ('Obs.') and modelled odour concentrations (µg/m³)

measurements. Results when the necessity to predict odour hours at the correct time is removed (Figure 5) improves agreement between the model and measurements; both models predict the number of odour hours to be within a factor of three of the observations. Statistics that relate to the hourly average concentrations are presented in Table 2. Mean concentrations are underpredicted by both models, but this could be an artefact of the measurement technology; the 98th percentile statistic is underpredicted at two of the three sites by both models.

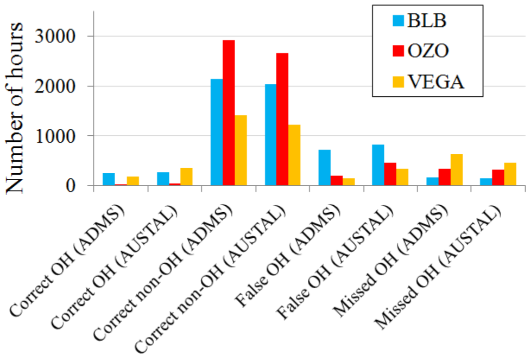

Figure 4. Measured and modelled odour hours: values fixed in time and space

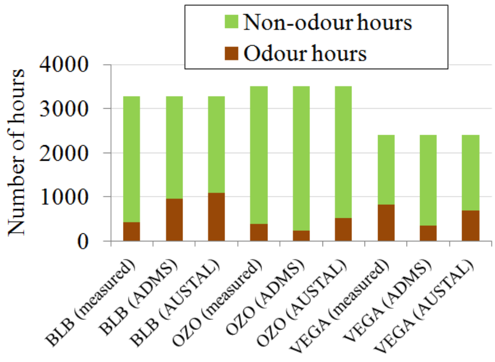

Figure 5. Measured and modelled odour hours: no temporal dependence

DISCUSSION

This paper presents some results from the evaluation of the Gaussian plume model ADMS and the Lagrangian model AUSTAL2000G in terms of the models' sub-hourly concentrations that are important for odour assessment. The results from two studies have been presented: a field campaign at a pig farm, and a continuous monitoring campaign at a port. ADMS demonstrates good performance in terms of predictions of the (more reliable) 10 s SF_6 concentrations at the pig farm. For this campaign, over 70% of odour hours are correctly predicted using both the fluctuations and peak-to-mean methods. This indicates that when sufficiently accurate source data are available, ADMS can be used to for prediction of sub-hourly concentrations i.e. odour hours. AUSTAL2000G was not included in this part of the evaluation exercise. Both ADMS and AUSTAL2000G have been evaluated for the port study. Using e-noses to detect odour is a relatively new technology that has the potential to be very useful for certain applications, particularly for long-term nuisance monitoring. ADMS and AUSTAL perform similarly when configured to represent the port, and the predicted odour hour frequencies are of the correct order of magnitude, despite the uncertainty in emissions and measurements. These preliminary results indicate that the odour hour is a statistic that can be predicted by both Gaussian plume and Lagrangian models, alongside the 98th percentile metric. Further work will involve assessing the relative merits of using a fixed peak-to-mean ratio versus a fluctuations approach to the calculation of odour hours.

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REFERENCES

Bachlin, W., A. Rühling and A. Lohmeyer, 2002: Provision of Validation Data for Odor Disposal Models – Field Measurements. FZKA-BWPLUS Research report BWE 2002.

Carruthers, D.J., Holroyd, R.J., Hunt, J.C.R., Weng, W.S., Robins, A.G., Apsley, D.D., Thompson, D.J. and Smith, F.B., 1994. UK-ADMS: A new approach to modelling dispersion in the earth's atmospheric boundary layer. *Journal of wind engineering and industrial aerodynamics*, **52**, 139-153.

Dyster, S.J., D.J. Thomson, C.A. McHugh and D.J. Carruthers, 2001: Turbulent fluctuations and their use in estimating compliance with standards and in model evaluation. *International Journal of Environment and Pollution*, **16**(1-6), 57-68.

Janicke, L., Janicke, U. 2007: Development of the dispersion model AUSTAL2000G. *Reports on Environmental Physics, Number 5, Edition 2*, Janicke Consulting, ISSN 1439-8222.