Odour from municipal solid waste (MSW) landfills: A study on the analysis of perception

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Abstract

The objective of this work was to develop a relationship between odour intensity and odour concentration by using data collected from various sensitive areas of the municipal solid waste (MSW) landfill site. A number of well-known psychophysical models (e.g., Weber–Fechner law, Steven’s power law, Beidler’s and Laffort’s models) have been discussed that can successfully relate the perceived intensity with the odour concentration. Respective parameters for each of the models were estimated by the nonlinear Levenburg–Marquardt parameter estimation method. The overall performance of the model was tested statistically against sets of data from the olfactometry analysis. The model based on the Weber–Fechner law was ranked 1 in case of five out of nine samples and it has been found more representative of the less intense odour samples. The model based on Laffort’s equation has represented the intensity–concentration relationship better with extremely low uncertainties on both parameters $k_1$ and $k_2$ for comparatively more intense odour samples. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Odour; Perception; Olfactometry; MSW landfills; Parameter estimation

1. Introduction

Odours from landfill wastes comprise complex mixtures of a large number of volatile compounds. Odour concentration is a measure of the detectability of the odour as assessed by a panel of people. Odour intensity (ASTM, 1991) is defined as the perceived magnitude of a stimulus. Odour intensity and offensiveness are subjective measures of the strength and unpleasantness of an odour as assessed by a panel of people. Odours of equal concentration will not necessarily be of equal perceived intensity or offensiveness. Although the intensity can be perceived directly without any knowledge of the odour concentration, it is necessary when used in conjunction with dispersion modelling, in terms of comparing the resultant odour concentrations at the receptors (locations of potential complaints), as obtained from the dispersion analysis, with those obtained by reducing the intensity scales of the odour complaints to odour concentration levels. The idea could also be utilised by legislators to establish minimum separation distances between the landfill site and zones of potential complaints based on objective criteria.

In this paper, the main focus will be given to the selection of various psychophysical models and estimation of their parameters with suitable techniques. Afterwards, the models will be evaluated with statistical analysis.

The results will be discussed afterwards, with nine samples taken from various locations within a municipal solid waste (MSW) landfill site. There will be an attempt to rank the models according to their performance and one or two model(s) will be selected as the basis for community nuisance analysis. One of these psychophysical models, already discriminated on the basis of its performance, will be used to convert the intensity scales reported by the community sniffers to odour concentration (ou/m$^3$), which may be used to validate the results from dispersion analysis.

1.1. Psychophysical functions

In order to describe the mathematical relationship between perceived odour intensity and concentration, various questions need to be addressed. It is doubtful whether
one type of mathematical function could describe the growth of intensity for all types of odours or odour mixtures. Stevens (1957) proposed that the growth of sensation $\psi$ on all prothetic continua is a power function of stimulus magnitude $\phi$, i.e., $\psi = k\phi^b$ ($k$ is a constant). This relationship, also well known as the psychophysical power law, has now been verified for various sensory continua (Stevens, 1960; Ekman and Sjoberg, 1965). The important parameter of the above equation is $\beta$, the growth parameter. Its size varies from one sensory continuum to another. Several scientists have showed that the olfactory sensation grows as a power function of concentration (Jones, 1958; Reese and Stevens, 1960; Cain, 1969, 1970; Berglund et al., 1971). The form of the function might be approximately the same for all odorants, $\beta$ varies from one odorant to the other.

Fechner proposed that the magnitude of sensation is linearly related to the logarithm of stimulus magnitude. Katz and Talbert (Cain and Moskowitz, 1974) found that psychophysical functions for most substances were in accord with the logarithmic relation and they tested it for about 55 odorants.

It has been investigated by several researchers that the functional relation between response magnitude and concentration obtained via neurophysiological recording would have the same form as that obtained from psychophysical decisions. Beidler (Stone and Oliver, 1966) proposed a fundamental taste equation to account for the growth of neurophysiological responses from taste receptors and from the chorda tympani nerve of various species. Beidler’s equation is

$$r = \frac{RK\phi}{1 + K\phi}$$  \hspace{1cm} (1)

where $\phi$ is concentration, $r$ is the neural response, $K$ is the equilibrium constant and $R$ is a constant that reflects the maximum neural response from a particular type of olfactory receptor (Eq. (1)). An equation of this form has been found to describe the growth of the receptor potential in a number of other sensory systems (Lipetz, 1971), like the olfactory one. Laffort (Cain and Moskowitz, 1974) suggested that the fundamental taste equation may be modified to describe psychophysical functions for odour intensity. Laffort’s modification (Eq. (2)) is

$$\psi = \left(\frac{\phi}{1 + \phi\psi_{\text{max}}^{-1/\beta}}\right)^\beta$$ \hspace{1cm} (2)

Like other power laws, both Beidler’s and Laffort’s expressions imply that, at high end of the perceived sensation, equal ratio increments would cause smaller increments in sensation. The main aim of this paper will be the selection of these psychophysical models and estimation of their parameters with suitable techniques. Afterwards, the models will be evaluated with statistical analysis.

2. Methodology

The development of methods will include

- Measurement of odour concentration and intensity,
- Selection of the psychophysical models and estimation of the respective parameters,
- Evaluation of the models with statistical analysis.

Odour intensity and threshold odour concentration were measured simultaneously by using a dynamic dilution forced-choice olfactometer. Several experiments were carried out and data of odour intensity and threshold odour concentration were obtained.

2.1. Measurement of odour concentration and intensity

2.1.1. Odour sampling

Samples of odour emissions were collected from the knock-out-pots (KOPs) and from the waste surface. The KOPs and gas well heads had conveniently fixed gas sampling ports, a sampling tube was connected to this and the gas sample sucked from the port into a Nalophan odour bag, contained in a barrel, using the lung principle. Duplicate samples were taken from each well or KOP. W28H and W1H are samples of gas from horizontal wells. Samples from waste surfaces, freshly tipped and those 1-day-old, were collected using a Lindwall hood. With this equipment, a controlled flow of air is passed over the surface. The flexible air inlet hose is positioned at least 10 m upwind of the sampling area, the air passes through the fan and then through an activated charcoal filter to eliminate the odour of the inlet air. The hood covers 1.5 m$^2$ and the air velocity is of the order of 0.1 m/s. At each sampling position, duplicate samples of inlet and outlet air were taken over a period of about 10 min immediately after the fan was started.

2.1.2. Olfactometry

This is an objective method of expressing the strength, concentration or intensity, etc., of an odour. The method used determines how many times a sample must be diluted with odour-free air to be at the threshold of detection by 50% of the panel. The number of required dilutions defines the odour concentration in odour units per cubic meter (ou/m$^3$). These tests are carried out inside an odour-free, clean laboratory with trained and selected panelists.

In this study, odour concentration was measured using an “Olfactomat” dynamic dilution olfactometer (Project Research, Amsterdam). A sample was presented to an odour panel using the forced-choice method. Six dilutions of each sample, differing from each other by a factor of two, were presented to the panelists three times. Dilutions were made using odour-free air supplied by a compressor fitted with carbon filters and an air dryer. The olfactometer has two sniffing ports, one containing the diluted sample air and the other odour-free air. For each presentation, panelists
indicated via a keyboard which port delivered the odorous air. In order to put greater confidence on the panelists’ responses, they were also asked to indicate whether their choice was a “guess” (as it would have to be if the odour presented was below their personal threshold level), whether they had an “inking” that their choice was correct (when the odour was close to the threshold level) or whether they were “certain” that their choice was correct. The mean threshold value for each sample was calculated using Dravniek’s method (Cheremisinoff and Young, 1975).

2.1.3. Odour intensity
The assessment of odour intensity indicates the effect of differing odour dilutions on the likely smell sensation for an individual. Measurements of intensity are determined by the “sniffing” panel using a subjective scale (usually 0–6) from no odour to extremely strong. Depending upon odour type and selection of the panel, high confidence levels can be achieved from these qualitative judgements. Odour intensity was measured using a category estimation technique. Following the determination of odour concentration, ranges of suprathreshold dilutions were presented in random order. The panelists were required to indicate their perception of intensity at each dilution. Mean intensity scores were obtained at each dilution presented to the panel. The concentration of the odour at each dilution was calculated as the sample concentration divided by the dilution factor. A sensitivity matrix was derived for the four models for each of the odour concentrations, ranges of suprathreshold dilutions were presented in random order. The panelists were required to indicate their perception of intensity at each dilution. Mean intensity scores were obtained at each dilution presented to the panel. The concentration of the odour at each dilution was calculated as the sample concentration divided by the dilution factor.

2.2. Model selection and estimation of model parameters
Various psychophysical functions were chosen to demonstrate the relationship between perceived intensity and odour concentration for the samples drawn from the landfill site.

Model 1: This is based on the Weber–Fechner law, which states that equal ratio changes in olfactory sensation differences correspond to equal changes in the stimulus magnitude.

\[ I = k_1 \log C + k_2 \quad (3) \]

where \( I \) stands for a perceived intensity, \( C \) stands for the corresponding threshold odour concentration and \( k_1 \) and \( k_2 \) are constants (Eq. (3)).

Model 2: This is based on Steven’s psychophysical power law and implies that equal ratio changes in sensation magnitude correspond to equal changes in the stimulus magnitude.

\[ I = k_1 C^{k_2} \quad (4) \]

where \( k_1 \) is a constant of proportionality and \( k_2 \) depends on the type of odorant (Eq. (4); Stevens, 1960).

Model 3: Beidler’s model relates the response magnitude with concentration as follows (Eq. (5)):

\[ I = \frac{k_1 k_2 C}{1 + k_2 C} \quad (5) \]

Model 4: Based on Laffort’s expression, this model can be described as in Eq. (6):

\[ I = \left( \frac{C}{1 + k_2 C} \right)^{k_1} \quad (6) \]

2.3. Parameter estimation method
The nonlinear Levenburg–Marquardt parameter estimation method (Beck and Arnold, 1977; Press et al., 1992) was used to obtain the parameters in each of the four models. In this method, we usually define a merit function \( \chi^2 \) and determine the best-fit parameters by its minimization. The parameters are iteratively adjusted, due to nonlinear dependencies, to minimize \( \chi^2 \) in order to achieve a global minimum. We start with a set of trial values for the parameters to be estimated, which are gradually improved, and the procedure is then repeated until \( \chi^2 \) effectively stops decreasing. A sensitivity matrix was derived for the four models for the odour intensity function with respect to the parameters \( k_1 \) and \( k_2 \).

The sensitivity matrix can be written as (see Eqs. (7)–(10)):

For Model 1:

\[ \frac{\partial I}{\partial k_1} = \log C \]

\[ \frac{\partial I}{\partial k_2} = 1.0 \quad (7) \]

For Model 2:

\[ \frac{\partial I}{\partial k_1} = C^{k_2} \]

\[ \frac{\partial I}{\partial k_2} = k_1 C^{k_2} \log C \quad (8) \]

For Model 3:

\[ \frac{\partial I}{\partial k_1} = \frac{k_2 C}{(1 + k_2 C)} \]

\[ \frac{\partial I}{\partial k_2} = \frac{k_1 C}{(1 + k_2 C)^2} \quad (9) \]

For Model 4:

\[ \frac{\partial I}{\partial k_1} = \left( \frac{C}{1 + k_2 C} \right)^{k_1} \log \left( \frac{C}{1 + k_2 C} \right) \]

\[ \frac{\partial I}{\partial k_2} = -k_1 \left( \frac{C}{1 + k_2 C} \right)^{(k_1 + 1)} \quad (10) \]
2.4. Evaluation of the four models (Neter et al., 1983)

Inference about the nonlinear regression parameters require the evaluation of the following statistical parameters:

1. The minimized \( \chi^2 \) function, \( \chi^2 \), which is the least-squares measure of fit (the smallest \( \chi^2 \) gives the best model). The \( \chi^2 \) minimization is a useful means for estimating parameters even if the measurement errors are not normally distributed.

2. The uncertainties associated with the estimate of each parameter, formally termed as the standard error \( s \). These are the square root of the error term covariance matrix \( C_{ij} \) of the fit. The closer this value is to zero, the better the fit.

When the method used to estimate the parameters is \( \chi^2 \) minimization, there is a natural choice for the shape of the confidence intervals. If the confidence level and the degrees of freedom are known, the confidence interval \( \partial a \) for each of the fitted parameters can be computed as

\[
\partial a_1 \cong \pm \sqrt{\Delta \chi^2 / C_{ii}}
\]  

where \( \Delta \chi^2 \) are given in tables as functions of confidence levels and degrees of freedom \( (\nu) \). This relation is approximate and holds good when:

- The fit is good.
- The error terms (noise) in the nonlinear regression model are normally distributed and
- The sample size is large.

### Table 1
Sampling details

<table>
<thead>
<tr>
<th>Date</th>
<th>Source of sample</th>
<th>Sample index</th>
<th>Collection time</th>
<th>Odour concentration (geometric mean; ou/m³)</th>
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<td>KOPs</td>
<td>KOP W (3)</td>
<td>13:00</td>
<td>801,920</td>
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<td>Horizontal wells</td>
<td>W28H (1)</td>
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<td>1,155,019</td>
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<td>13:10</td>
<td>1355</td>
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<td>Waste surfaces</td>
<td>Filling (3)</td>
<td>11:05</td>
<td>937</td>
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<td>Waste surfaces</td>
<td>Day 3 1a outlet</td>
<td>12:17–12:22</td>
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<td>24/11/97</td>
<td>Waste surfaces</td>
<td>Day 3 3b outlet</td>
<td>12:54–12:57</td>
<td>142</td>
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</table>

* Samples collected by cover sheet method.
* Samples collected using Lindvall hood.

### Table 2
Odour intensities \( (I) \) and corresponding odour concentrations \( (C_i) \)

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<th>Step</th>
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<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tr>
<td>KOP C (2)</td>
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<td>( C_i )</td>
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</table>

\( C_i \) has the unit of ou/m³ and \( D_i \) and \( I \) are dimensionless.
2.5. Estimation of the noise

We know that (Eq. (12))

\[
\chi^2 = \frac{\sum (y - \bar{y})^2}{\sigma^2}, \quad \Rightarrow \chi^2 \approx \frac{1}{\sigma^2}
\]  

(12)

Hence, estimate of \( \sigma^2 \) is important in all model fitting technique that use \( \chi^2 \) estimates.

![Fig. 1. Comparison of the measured data with models for the KOP W3.](image-url)
In order to estimate the standard deviation of odour intensity measurement data (reported both as an integer category and a fraction in case of odour intensity measurement and reported only as an integer in the community survey reports), we assume that (see Eqs. (13)–(15))

\[
E(\sigma^2) = \int \rho(x)(x - \bar{x})^2 \, dx / \int \rho(x) \, dx
\]  

\[\Rightarrow E(\sigma^2) = \int (x - \bar{x})^2 \, dx \]  

\[\Rightarrow E(\sigma^2) = \frac{x^3}{3} \bigg|_{-\bar{x}}^{1/2} = \frac{1}{12} \]  

When the sample size is large, the Gaussian distribution can be approximated as a Poisson’s and the mean is approximately equal to the variance. Thus,

\[E(\sigma^2) \approx \sigma^2\]

Thus, the value of \(\sigma\) is \(1/\sqrt{12} = 0.288\). Now, each reported intensity level was an arithmetic mean of number of reported data, each of which was an integer. The actual noise (population) was

\[\text{noise} = \frac{\sigma}{\sqrt{n}}\]

When \(n = 4\), \(\sigma = 0.144\) and \(n = 6\), \(\sigma = 0.1175\).

3. Results and discussion

Table 1 shows the mean odour concentration of various odour samples from the MSW landfill site. Table 2 gives the details of the olfactometry analysis carried out for finding out the perceived odour intensities of various dilutions of the samples when presented to the trained panelists. Parameter estimation results are given in Table 3 where the uncertainties and confidence intervals of each parameter are presented for each of the four models (as described before) for various samples. Models are ranked according to their performance in the nonlinear least-squares fit and rated with their respective values of \(\chi^2\) (see Table 3). Table 4 gives the ranges of residual intensities (defined as residual intensi-
ty = predicted intensity – measured intensity) with respect to the four models tested.

Fig. 1 gives the example of how the measured odour intensity varies with the odour concentration for the odour sampled from the KOP W3 with respect to each of the four models. The performance of Model 1 was best with a rank of 1 out of 4 based on the estimate of minimum $\chi^2$ ($\chi^2 = 8.4$) and quite low values of uncertainties on $k_1$ (0.05) and $k_2$ (0.03). The corresponding 95% confidence intervals were worked out with a $\chi^2$ estimate for each of the parameters. The widths of the interval with regard to both model parameters look quite narrow (see Table 3). In Fig. 2, residual intensities are plotted against measured odour concentration. It did not show serious departures from the model assumptions with the residuals ranging from $0.5$ to $+0.4$. Models 3 and 4 had a similar regression trend with the residuals ranging from $-0.5$ to $+0.4$ (Model 3) and from $-0.5$ to $0.5$ (Model 4). However, both of them showed much higher values of $\chi^2$ than Model 1. Model 2 had the largest value of $\chi^2$ (19.9) and was preferentially discarded. Thus, it was found that Model 1 (based on the Weber–Fechner law) and the corresponding regression function could be accepted for the intensity analysis of the odour sample from KOP W3. Similarly, for another sample from the KOP C, again, Model 1 did best (see Table 3).

The next set of samples tested were from the filling areas of freshly tipped wastes. In case of these samples, also, Model 1 performed well (see Table 3). In these cases, lowest value of $\chi^2$ and corresponding low uncertainties on the estimated parameters were found on Model 1 ($\chi^2 = 1.31$ for Filling 1b, see Fig. 3; $\chi^2 = 0.58$ for Day 3 2b sample, see Fig. 5). In Fig. 4, the residuals ranged from $-0.19$ to $+0.13$ for Model 1, while in Fig. 6, the range was from $-0.14$ to $+0.15$. The trend was similar for Filling 3. The levels of odour and the corresponding intensities for the samples from freshly tipped wastes could be best related with Model 1.

The samples taken from various horizontal wells showed a slightly different trend, and in this case, Model 4 (based on Laffort’s model) performed best, predicting the lowest values of $\chi^2$. However, the estimated $\chi^2$ values of Model 3 (based on Beidler’s equation) were very near to those estimated by Model 4. For the sample W1H1 (Fig. 7), Model 3 had a $\chi^2$ value of 2.2 with uncertainties estimated on $k_1$ and $k_2$ being 0.002 and 0.001, respectively, and a precise and narrower confidence interval as well (see Table 3). On the other hand, Model 4 had a lower $\chi^2$ value of 1.76, though the uncertainty on $k_1$ was 8.3 and the corresponding confidence interval was wider. Fig. 8 gives the residual intensities for all the models for the sample W1H1. It could be inferred that Models 3 and 4 both correlate the intensity with odour concentration equally capable for samples from the horizontal wells. Table 5 gives a picture of the overall performance of all the models based on the goodness of fit.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
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It should be noted that the assumptions behind Eq. (11) were not quite applicable in case of our study since the sample size was restricted by the number of dilution levels of the PREC (Project Research) olfactometer (ranging from 1 to 14) used for all the experiments. A more rigorous set of validation experiments was not possible with the resources available, although these initial results are quite encouraging.

4. Conclusion

The analysis of perception of odour samples from a MSW landfill site was done using various well-known psychophysical models and respective parameters for each of the models were estimated and the overall performance of the model was tested against sets of data from the olfactometry analysis.

- It could be concluded that for odour samples from various KOPs and areas of freshly tipped wastes of the landfill site, Model 1 (based on the Weber–Fechner law), could demonstrate the intensity–concentration relationship best. In the above analysis, Model 1 (based on Weber–Fechner law) was ranked 1 in case of five out of nine samples and it has been found more representative of the less intense odour samples.

- The Weber–Fechner law performed better than Power Law since the scaling technique used was category estimation and not magnitude estimation.

- Model 4 (based on Laffort’s equation) could correlate the intensity with odour concentration very well for samples from the horizontal wells. Laffort’s equation has specifically represented the intensity–concentration relationship better for comparatively more intense odour samples.

- In case of the particular samples analysed, it has been found that frequency of intensity scales reported have been mostly in the lower range (refer to Table 6). Hence, the performance of Model 1 could be tested with much more data in comparison to Model 4.

- Depending on the nature of the odour sample and its range of intensity levels, each of Model 1 or 4 could be selected to find out the concentration of odour at a particular receptor location and the dispersion modelling results could be validated.

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References