Odour monitoring by the combination of sensors and neural networks

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Abstract. The treatment of waste is always combined with odour emission and because of that annoying people near waste treatment plants. In order to recognise and evaluate those odour emissions, different methods are used. The most applied "measuring instrument" is the human nose. Different factors, e.g. Objectivity and form of the day, are difficult to assess. Therefore it is necessary to develop a measuring method, which is objective and efficient. One example is to use the combination of sensors and neural networks. With this device, called "electronic nose", it is not only possible to recognise odour but all kinds of substances, depending on the selectivities of the sensors, can be detected and monitored.

***Keywords*:** Odour control, Olfactometry, "Electronic nose", Sensors and neural network

1. INTRODUCTION

Regulations concerning odour control in Germany are very strict due to the high population density and the great number of already existing waste treatment plants. Thus, it is almost impossible to find locations for treatment plants without annoying people by odour emissions. A lot of plants are already built near residential areas and people complain about odour emissions. Especially complaints about emissions from biowaste composting plants have increased in recent times. The acceptance in the population has decreased. Therefore it is indispensable to develop systems for recognition, measurement and reduction of odours.

2. REGULATIONS AND GUIDELINES IN GERMANY

In Germany, there are a lot of VDI-Guidelines (VDI = Society of german engineers) concerning odour emissions and monitoring. One important guideline is VDI 3881 – Olfactometry. This guideline concerns with olfactometry in order to determine odourant concentration. The odourant concentration of the gas sample to be measured is determined by dilution down to the odour threshold. The odour threshold is defined as the concentration of odorous substances at threshold level which leads to an odour impression with 50 % of the defined population. The odourant concentration at the threshold is 1 OU/m³ (OU – Odour Unit) by definition. [VDI 3881]

In the guideline a lot of information about measuring procedure, sampling, determination of odour threshold are given. All this is included in a draft European odour standard by the CEN working group CEN/TC264/WG2‘Odours‘.
Also existing guidelines to control the odour pollutants:

- GIRL (Geruchsimmissions-Richtlinie) (Odour pollutants-Guideline)
  The guideline defines the threshold of odour pollutants in order to avoid interferences of odour emitting facilities with the residents.
- VDI 3940 - Determination of odour in ambient air by field inspections
  In this guideline the determination of the frequency of odour at defined places is given.

3. METHODS OF MEASURING ODOUR EMISSIONS

There are different methods of measuring odour emissions:
- Odour measurement by olfactometry and test panel
- Determination of the TOC ("total organic carbon") by FID (Flame ionisation detection)
- Gas chromatographic analysis with mass spectrometric detection
- Sensors with chemical or physical property.

3.1. Olfactometry

State of the art for the determination of odour emission is olfactometry with a test panel. Olfactometry is the controlled presentation of odourants and the registration of the sense impression of the test panel on account of the odourants. After taking a gas sample at the odourant source, the sample is diluted with neutral air in a defined ratio. This dilution is presented to the panel as a smell sample. Each sample is offered in several dilution steps. In **Figure 1**, the diagram of the olfactometric principle is given.

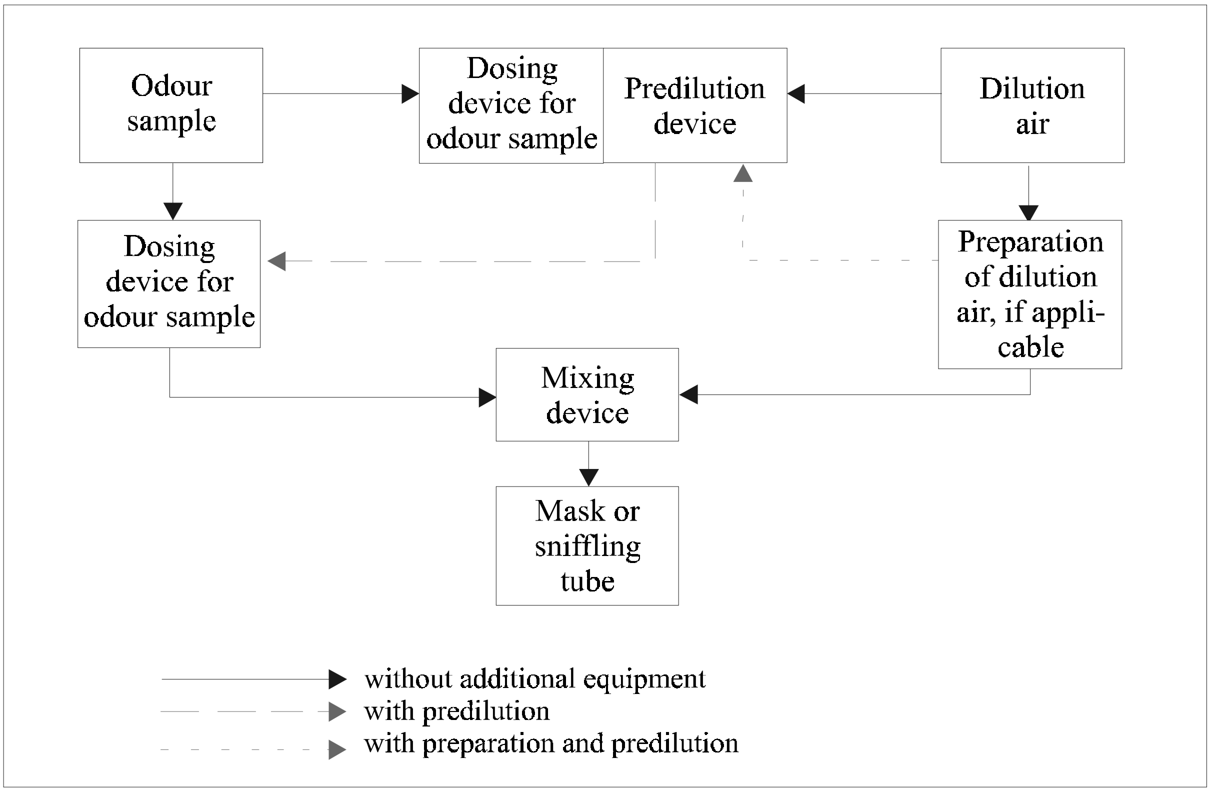

Figure 1. Diagram of the olfactometric principle (dynamic dilution) [VDI 3881]

Olfactometry is an effect related measuring method to determine the power of the human sense of smell or to determine unknown odourant concentrations with the help of the human sense of smell as the detector. The obtained odour emission refers only to the emission situation during sample taking. Since it is quite costly, olfactometry is not suitable as a continuous measuring method.

3.2. FID

Permanent control of the emission situation can be achieved by determing the TOC by FID, getting an overview of the distribution of odourant concentration over time. With FID the total content of organic substances in the samples can be determined. Because odours are basically caused by organic substances, most of the compounds contributing to the odour emission are detected by FID. Still, there can be differences between odour emission and TOC, since there is no distinction between smelling and non smelling organic compounds and inorganic compounds contributing to the odour emission like H_2S and NH_3 are not detected. In combination with olfactometry FID provides the possibility of permanent odour emission control. This was shown in tests measuring the emissions from a biofilter. In **Figure 2**, FID-measurements and the correlation with olfactometry are given.

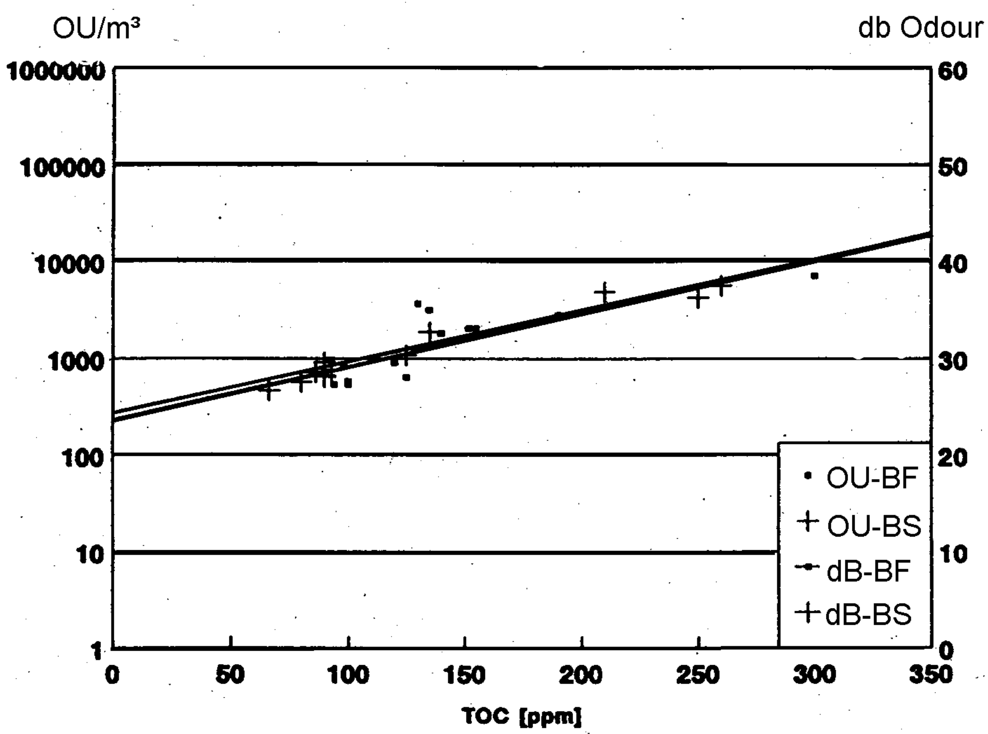

Figure 2. Correlation of FID-measurements and olfactometric odour measurements (OU/m³(OU = Odour Unit) and dB Odour (dB = dezibel)) from a biofilter (BF) and a bioscrubber (BS) [Kuchta and Ryser, 1993]

So far, it is only possible to produce a correlation of odourant concentration and TOC for one particular treatment plant. Just as it is impossible to determine a general correlation between TOC and odour emissions, especially at composting plants where the ingredients of the waste air are not constant, it is impossible to transmit the special emission situation from one treatment plant to another.

3.3. Gas chromatographic analysis

The identification of single substances requires gas chromatographic analysis with mass spectrometric detection. But due to numerous substances causing smell this method is too difficult and costly to get details about the concentration of odour or its components.

3.4. Sensor-technique

Another kind of measurement is done by chemical or physical sensors. Chemical sensors are miniature measuring tools, which collect the chemical compounds selectively and reversibly and, as a result, supply electrical signals depending on concentration. A problem of commercially available gas sensors is, that they are not selective enough to detect certain components of a mixture. In order to remediate this disadvantage, sensor arrays composed of combinations of sensors with different selectivities were developed, having different responsiveness towards the separate components of a mixture. Mostly, the sensor arrays are fitted with the same type of sensors and obtain their selectivity through varied dopings or filtermaterials.

The Institut WAR of the University of Technology, Darmstadt is testing a device called "Electronic Nose". This is a multi gas sensor device which includes a combination of gas sensor array and artificial neural networks (ANN). Metaloxide sensors are used, which get back fast to the baseline after a measurement. Because of their different surface structures and charge, they react to the separate components in the presence of oxygen in order to oxidise the volatile substances. Furthermore data processing is performed by the ANN. This means that the network is trained to identify the characteristics of odours. At present, those systems are only used in food industry, where it is possible to give detailed information about the substances which have to be recognised. But it also should be possible to identify and quantify odours and volatile compound groups from biowaste composting plants with the gas sensor arrays.

3.4.1. Training of the ANN

The same samples of odour, e.g. from a biofilter, are analysed by olfactometry and by the “Electronic Nose”. Then, the ANN is trained with these different kinds of data. This way, it is possible to calibrate the gas sensor array and to teach the ANN which ingredients of the gas mixtures correspond to odourant concentrations measured by olfactometry. This means that the data from the sensor array are defined as the access-data and the odourant concentration from the olfactometry as end-data. The ANN is trained to present the odourant concentration of a gas sample as a result (**Figure 3**).

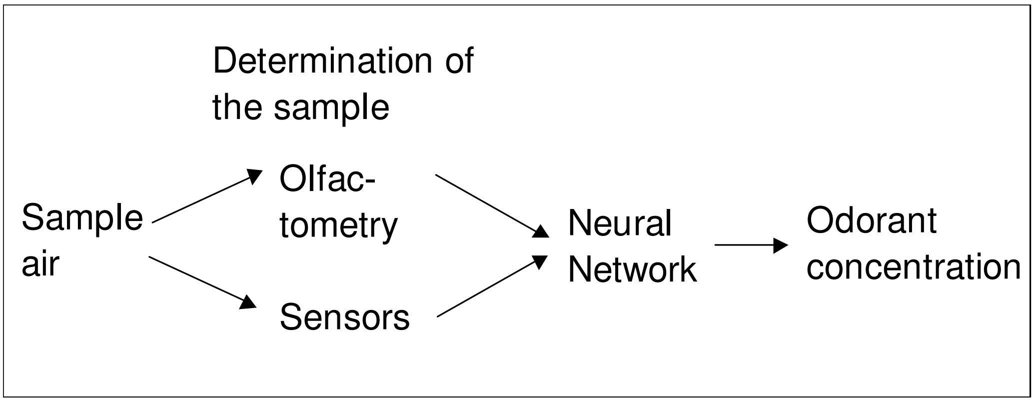

Figure 3. Training of the ANN

With the software of the device, four different algorithms are available:

- Standard Back Propagation,
- Stochastic Back Propagation,
- Quick Propagation,
- Weigend Weight Eliminator.

All the algorithms are supervised learning and the networks are being trained to perform a "black box" function. With the determination of the sensor signals as the input data, the software of the device carries out the training process automatically. The process of training the network is that of finding a set of values for the weights (representing the strength of the link between two processing elements) that make the network assign the sensor signals to their odourant concentration. The weights are adjusted in the network until the desired output is achieved.

In order to train an ANN efficiently, sufficient and reproducible data are needed. To cover the emission situation of a composting plant, a lot of samples with different kinds of odourant concentrations from 50 OU/m³ up to 100.000 OU/m³ are necessary. The varying compounds of the waste air from composting plants is strengthening the problem. For the different odourant concentrations, several data must be available, because different compounds of the waste air from the plants can cause the same odourant concentration.

With the existing data at the moment, the wide range of the odourant concentrations can nearly be covered. In order to check out the training of the ANN, 27 samples analysed by olfactometry with a range of 40 OU/m³ up to over 100.000 OU/m³ are used in one network. All of the four different training-algorithm were used and compared.
In **Figure 4**, a screenshot of the training results of a network trained with Standard Back Propagation is given.

The validity of the trained networks is then tested with known and unknown data sets in order to see if the classification is performed correctly or not. Known data means the same data with which the net is train, against this unknown data means, that the net has not being trained with them. In Table 1, the results are shown.

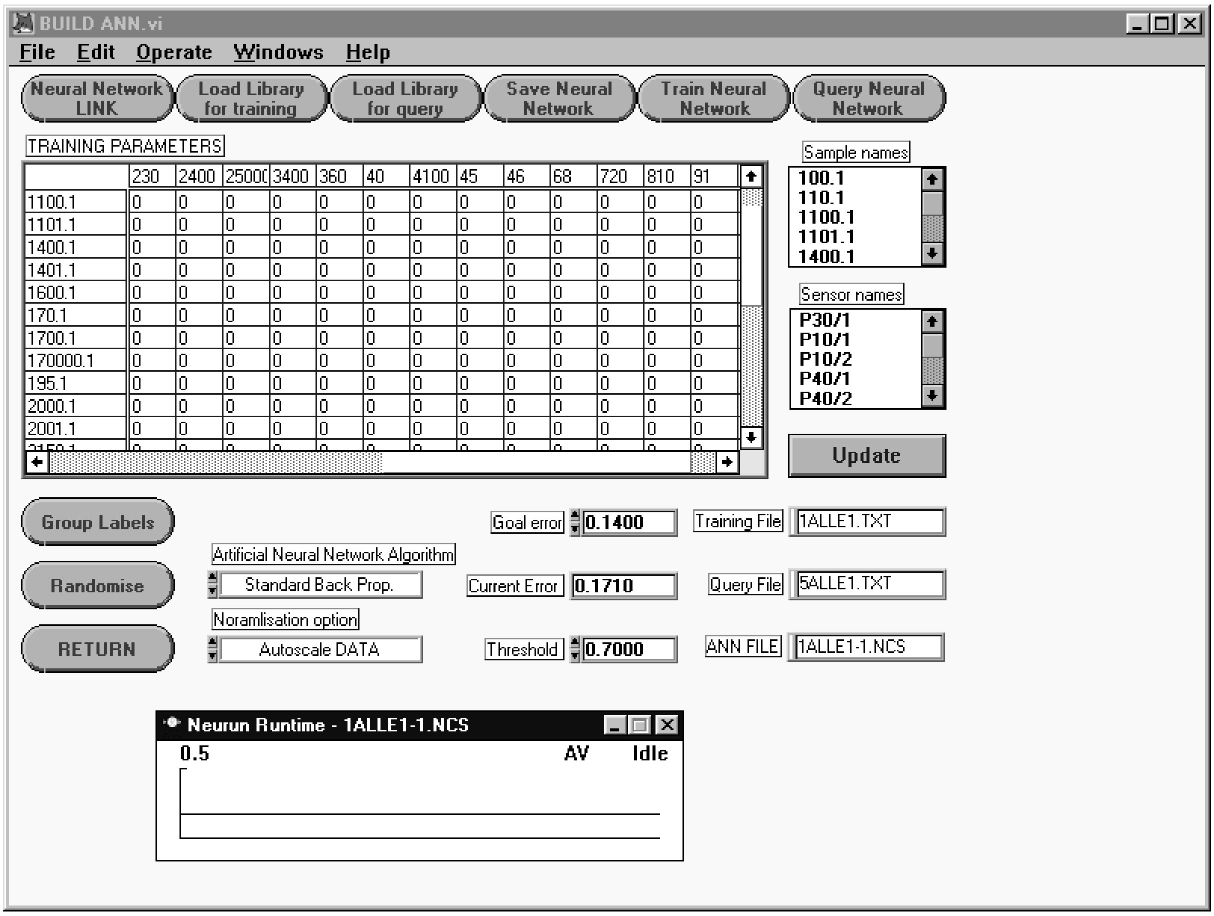

Figure 4. Screenshot of the training results of a network trained with Standard Back Propagation

Algorithm	**Current Error**	**Recognised data**		
		right [%]	wrong [%]	not recognised [%]
Standard Back Propagation	0,17	2	0	98
Quick Propagation	0,12	21	15	64
Stochastic Back Propagation	0,15	14	21	65
Weigend Weight Eliminator	0,19	0	0	100

Table 1.Results of the network training with different algorithms with data from different kinds of composting plants

Bad results referred to the last calculated errors as the current errors are shown. Even if the goal errors of the nets were high, most of the current errors have not reached them. This is a problem because only a low goal error represents a good training and therefore a better convergence of the network. With those high current errors, the convergence of the nets seems to be insufficient and produce a slight recognition as a result.

One reason for the bad recognition and bad convergence could be the origin of the data from different composting plants and different kinds of sources in each plant. After that training with data from different plants, several networks were trained with plant-specific or source-specific data. For example for the biofilter of one specific composting plant, six samples analysed by olfactometry with the range from 720 OU/m³ up to 2400 OU/m³ were used to train several neural networks with the different training algorithms. In Table 2, the current errors are given. In opposite to the training with more different kinds of data from different composting plants, the current errors were much smaller, which mean a better convergence of the networks.

Algorithm	**net number**	**current error**
Standard Back Propagation	C-1	0,01
Quick Propagation	C-2	0,1
Stochastic Back Propagation	C-3	0,01
Weigend Weight Eliminator	C-4	0,01

Table 2. Results of the network training with different algorithm and data from one composting plant

In table 3 is shown, which of the networks trained with different algorithms recognised which data. In the first column, the samples are given, the names of the samples are equivalent to their odourant concentration. In the other columns, the different nets (C-1, C-2, C-3, C-4) with their recognition of the samples are shown. The fields, underlayed with grey, show the recognition of the data with whom the net was trained.

All data, except the network C-2 trained with Quick Propagation, recognised the data with whom they were trained right. These validations to check out the validity of the network were good. The network C-2 applied several of the known data with "not recognised" (37 %). The recognition of the unknown data, that means data which were not used to train the network, seems not to depend on the kind of algorithm used for training. Unknown data sets were described with the same odourant concentration independent of the algorithm used for training, even when the described odourant concentration is not corresponding to the analysis by olfactometry.

This means that the quantity of data is not sufficient to train the ANN with the given software effectively to classify with their odourant concentration.

	C-1	C-2	C-3	C-4		C-1	C-2	C-3	C-4
Name	recognised	recognised	recognised	recognised	Name	recognised	recognised	recognised	recognised
100.1	1600	1600	810	1600	2150.1	2400	2400	2400	2400
100.2	810	1600	810	1600	2150.2	2400	2400	2400	2400
100.3	1400	1400	810	2400	2150.3	2400	2400	2400	2400
100.4	1400	1400	810	2400	2150.4	2400	810	2400	2400
100.5	2400	not recognised	810	2400	2150.5	2400	810	810	2400
110.1	2001	720	2001	2001	230.1	1400	1400	1400	720
110.2	1600	720	not recognised	2001	230.2	1400	1400	1400	1400
110.3	1600	720	not recognised	2001	230.3	1400	1400	1400	1400
110.4	1400	not recognised	not recognised	720	230.4	1400	1400	1400	1400
110.5	1400	not recognised	1400	2400	230.5	1400	1400	1400	1400
1100.1	1600	2001	1600	2001	2400.1	2400	2400	2400	2400
1100.2	1600	2001	1600	2001	2400.2	2400	2400	2400	2400
1100.3	1600	720	1600	2001	2400.3	2400	2400	2400	2400
1100.4	1600	720	1600	2001	2400.4	2400	not recognised	2400	2400
1100.5	1600	720	1600	2001	2400.5	2400	not recognised	2400	2400
1101.1	1600	720	1600	810	250000.1	810	1600	1600	810
1101.2	1600	not recognised	1600	810	250000.2	810	1600	1600	810
1101.3	1600	1600	810	2400	250000.3	810	not recognised	1600	2400
1101.4	1600	not recognised	1600	2400	250000.4	810	not recognised	1600	2400
1101.5	not recognised	not recognised	810	810	250000.5	810	not recognised	1600	2400
1400.1	1400	1400	1400	1400	3400.1	not recognised	1400	1400	2400
1400.2	1400	1400	1400	1400	3400.2	not recognised	1400	810	1400
1400.3	1400	1400	1400	1400	3400.3	not recognised	1400	810	1400
1400.4	1400	1400	1400	1400	3400.4	not recognised	1400	810	1400
1400.5	1400	1400	1400	1400	3400.5	not recognised	1400	810	1400
1401.1	1600	2001	1600	not recognised	360.1	810	1600	810	2400
1401.2	1600	2001	1600	not recognised	40.1	1400	2400	810	2400
1401.3	1600	2001	1600	not recognised	40.2	810	1400	810	2400
1401.4	1600	2001	1600	not recognised	40.3	810	not recognised	810	810
1401.5	1600	2001	1600	not recognised	40.4	810	not recognised	810	810
1600.1	1600	1600	1600	1600	4100.1	810	1600	1600	810
1600.2	1600	1600	1600	1600	4100.2	810	1600	1600	2400
1600.3	1600	1600	1600	1600	4100.3	810	1600	1600	2400
1600.4	1600	1600	1600	1600	4100.4	810	1600	810	2400
1600.5	1600	1600	1600	1600	4100.5	810	1600	810	2400
170.1	not recognised	not recognised	not recognised	810	45.1	1400	1400	1400	2400
170.2	not recognised	not recognised	not recognised	810	45.2	1400	1400	1400	2400
170.3	not recognised	not recognised	not recognised	810	45.3	1400	1400	1400	2400
170.4	not recognised	not recognised	not recognised	810	45.4	1400	1400	1400	2400
170.5	not recognised	not recognised	not recognised	810	45.5	1400	1400	1400	2400
1700.1	1400	not recognised	1400	1400	46.1	1400	2001	1600	720
1700.2	1400	not recognised	1400	1400	46.2	1400	not recognised	1400	720
1700.3	1400	1600	1400	1400	46.3	1400	1400	1400	2400
1700.4	1400	1400	1400	1400	46.4	1400	1400	1400	2400
1700.5	1400	1400	1400	1400	46.5	1400	not recognised	810	2400
170000.1	810	1600	1600	810	68.1	810	810	810	810
170000.2	810	1600	1600	2400	68.2	810	810	not recognised	810
170000.3	810	1600	1600	2400	68.3	not recognised	not recognised	not recognised	810
170000.4	810	1600	1600	2400	68.4	not recognised	not recognised	not recognised	810
170000.5	810	1600	1600	2400	68.5	not recognised	not recognised	not recognised	810
195.1	2400	2400	2400	1400	720.1	720	not recognised	720	720
195.2	2400	2400	2400	1400	720.2	720	not recognised	720	720
195.3	2400	2400	2400	1400	720.3	720	not recognised	720	720
195.4	2400	2400	2400	1600	720.4	720	720	720	720
195.5	810	810	not recognised	1600	720.5	720	720	720	720
2000.1	810	1600	1600	2400	810.1	810	not recognised	810	810
2000.2	810	1600	1600	2400	810.2	810	not recognised	810	810
2000.3	810	not recognised	not recognised	2400	810.3	810	not recognised	810	810
2000.4	810	not recognised	810	2400	810.4	810	not recognised	810	810
2000.5	810	not recognised	810	2400	810.5	810	not recognised	810	810
2001.1	2001	2001	2001	2001	91.1	2400	2400	2400	2400
2001.2	2001	not recognised	2001	2001	91.2	not recognised	not recognised	2400	720
2001.3	2001	2001	2001	2001	91.3	1400	not recognised	810	2400
2001.4	2001	2001	2001	2001	91.4	810	not recognised	810	2400
2001.5	2001	2001	2001	2001	91.5	810	not recognised	810	2400

Table 3. Determination of the odourant concentration of the networks C-1, C-2, C-3 and C-4

3.4.2. Characteristical patterns for specific parts of a composting plant

The analysis of the different fingerprints for the different odourant concentrations shows a similarity of the sensor signal of different samples. That's how it is possible to produce for determined parts of a plant or volume streams characteristical patterns. In the following figures, characteristical patterns are shown as radarplots. The signals of the twelve sensors correspond to the twelve corners of the radarplot. In **Figure 5**, the pattern of two samples of raw gas from a biowaste composting plant with a very high odourant concentration is given. Both courses are next to each other and show a defined fingerprint for raw gas.

Furthermore, in **Figure 6** two patterns of clean gas from another biowaste composting plant are shown. In the same way, a correspondence in the courses of the sensors is given.

With the characteristical patterns, the emission can be classified to determined parts of a plant. With that, process controlling is possible in order to classify the emitting parts of a plant.

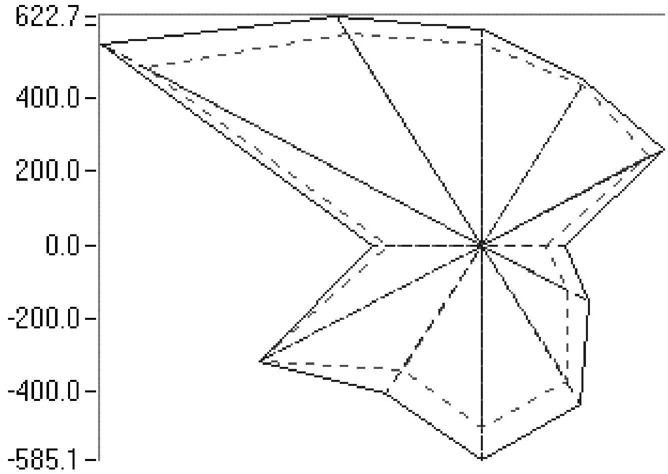

Figure 5, Radarplots of two samples of raw gas

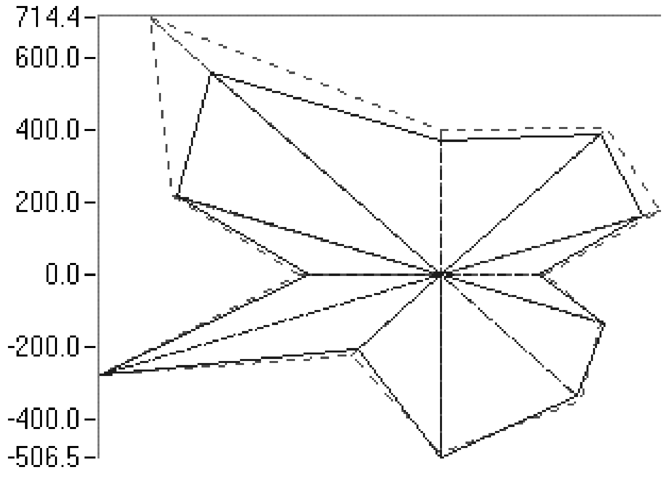

Figure 6, Radarplots of two samples of a biofilter

3.5. Advantages of the Electronic Nose in relationship to the other measurements

- Gas chromatographic analysis

This measurement is too large scaled and costly and not suitable for continuous measuring.

- FID

Measuring with FID is not very selective and characterised through the low sensitivity. The disadvantage of FID is that only the carbon-compounds are detected in opposite to the Electronic Nose, which is able to detect different substances depending on the sensors.

- Olfactometry

The great disadvantage of the olfactometry is the dependence on the sense of smell of human beings. It depends on the form of the day of the test panel and because of that it is not as objective as an Electronic Nose, which is not influenced by emotions. Another problem is the selection of the test panel. In order to get an average distribution, the persons in the panel should smell „normally“, not very good and not too bad. The training of the ANN with the data from olfactometry is only as good as the test panel smells during the measurements.

4. CONCLUSIONS

At the time, olfactometry is state of the art for odour determination in Germany, but it can not be used as a continuous measuring method. The proposed approach is to combine the results of olfactometry with a gas sensor array in order to train an ANN, getting a system for on-line odour detection as an alternative to the human nose for routine analysis.

One problem is the varying composition of an odour mixture from waste treatment plants, which can cause the same odourant concentration in olfactometry. Especially at a composting plant, with the frequently changing ambient air, it is difficult to produce a correlation between odourant concentration and the signals of the sensor array by training the ANN.

At the time, it is possible to get characteristical patterns for different parts of composting plants. For these parts a good similarity between the samples are shown. With the used ANN software, a sufficient training of networks can not be achieved. An optimisation of the networks with different algorithm should happen, recognising and evaluating the similarity between the samples.

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Gefördert mit Mitteln der Deutschen Bundesstiftung Umwelt –
Sponsored by Deutsche Bundesstiftung Umwelt