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Assessment of batch bioreactor odour nuisance using an e-nose

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ABSTRACT

The method of assessing a smell nuisance of the SBR laboratory bioreactor using a calibrated gas sensor array (e-nose) is described in the article. The SBR bioreactor is used to remove organic carbon and nutrients and can contribute to the emission of smell nuisance compounds. Two measurement devices were used as an information source regarding the presence of smell nuisance gases: an array consisting of 8 MOS-type gas sensors and a dynamic olfactometer. The research covered the stage of a normal bioreactor performance and simulation of the aeration system failure. With the gas sensor array, a static response has been recorded for air samples above the surface of treated wastewater. The dynamic olfactometer Ecoma TO-7 was simultaneously used in order to measure odour concentration with the "yes–no" method, according to EN-13725:2007. Comparative analyses were carried out with artificial neural networks in the statistical program. The research conducted indicates that normal bioreactor performance is related to a low smell nuisance. However, in the case of the failure during the activation of the aeration system, there occurs significant emission of smell nuisance compounds and an increase in odour concentration to 995,606 ou_E/m^3. The correlation coefficient R between real odour concentration and the estimated value using the e-nose system exceeds 0.9, in the range of 1E5–1E6 ou_E/m^3. The obtained results indicate that the gas sensor array can be used for assessment of the smell nuisance in the vicinity of SBR reactors during their normal performance as well in the case of the failure.

Keywords: SBR bioreactor; Wastewater treatment; Smell nuisance; E-nose; Dynamic olfactometer

1. Introduction

Wastewater treatment plants (WWTP) can be regarded as one of the major nuisance sources of air pollution [1]. Each process of sewage treatment, especially associated with anaerobic conditions, emits smell active compounds. Air pollution sources in WWTP can generally be assigned to 2 groups: (i) places with a high flow rate, large surface, e.g.

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retention or mixing tanks and (ii) places where new odorous components are created. Predominantly, these include inlets of the raw sewage and the places connected with sludge treatment [2]. Questionnaire surveys conducted in 100 WWTP in Germany among technical personnel confirmed that the main sources of air pollution are connected with inlet works, primary sedimentation tanks and sewage treatment works [3,4]. The odour concentration at sewage inlets and mechanical treatment installations amounts to 30–1,000 ou/m^3 (odour unit), biological treatment 5–120 ou/m^3 and sludge treatment 100–1,000,000 ou/m^3 [5].

In some countries, the acceptable level of odour concentration of annoyance gas sources is regulated for a specified averaging period. From European countries, there ought to be mentioned UK 5 ou/m^3, the Netherlands 0.5 ou/m^3 (1 h) and Denmark 0.6–1.2 ou/m^3 (1 h) and 5–10 ou/m^3 (1 min) [6]. In Poland, there are still no official regulations concerning odour emissions. For the measurements of odour concentration, a dynamic olfactometry methodology is used, which is currently the only technique providing information on the real nature of odour nuisance perceived by human organisms. Measurements are performed by sensory panel members selected according to EN-13725. Although olfactometric results are loaded with errors associated with subjectivity of assessors, reliable results can be obtained by applying due procedures of sampling and measurements. Accredited laboratories specialized in assessment of the level of nuisance gas emission from miscellaneous facilities, e.g. WWTP, landfills, etc. are currently developing in Poland. Dynamic olfactometry will be irreplaceable for a long time, but it has one essential drawback: measurements cannot be performed continuously, e.g. in the *online* mode. Here, techniques calibrated with dynamic olfactometry should be implemented, for instance, standard gas detectors, gas chromatography, or e-nose systems.

Each measurement technique of odour nuisances has some advantages and disadvantages. Sewage is the source of many volatile organic compounds, and any apparatus may be used to perform full assessment, especially of their synergistic influence on odour concentration [7]. Polluted air usually contains sulphur compounds, organic acids, aldehydes and ketones. The level of concentration of particular compounds such as hydrogen sulphide may be a good indicator of the air smell nuisance [2]. Research conducted by Qu et al. [8] in the vicinity of swine manure sources proved that hydrogen sulphide correlates with odour concentration ($R^2 = 0.51$), but no significant relationships were found for ammonia. Gostelow and Parsons [9] analysed relations between odour concentration c_{od} and the concentration of sulphide hydrogen c_{H2S} from 17 WWTP and obtained an equation $c_{od} = 38{,}902 \cdot c_{H2S}^{0.6371}$ in the range of 100–1,000,000 ou/m^3, with a determination coefficient $R^2 = 0.69$. Research carried out at the University of Hertfordshire UK in 10 WWTP revealed no clear relationships between the concentration of hydrogen sulphide and TON (*Threshold Odour Number*) in the range 125–781,066 ou/m^3 [10].

Similarly, the signal from the PID detector (*Photoionization Detector*) can be correlated with odour concentration. Hobbs et al. [7] obtained correlations $R^2 = 0.984$ and 0.978 for pig and chicken slurry, respectively, in the range 0–10,000 ou/m^3.

Gas chromatography is a professional technique, which allows for qualitative and quantitative assessment of polluted air. One of these techniques is GC–MS–O (Gas Chromatography–Mass Spectrometry–Olfactometry), which facilitates detection of the most odorous compounds in the sample, not necessarily with the highest concentration. It allows for further assessment of odour concentration on the basis of chemical analysis. The factor that limits GC is the high cost of the measuring apparatus and measurements. Therefore, measurements with an array consisting of many low selective gas sensors are more popular. The full-fledged device with a signal processing analysis and interpretation systems is called an e-nose. The e-nose has proved to be a useful measuring device in food industry [11,12], medicine [13,14], environmental monitoring [15], agriculture and forestry [16,17] and even in building constructions [18] or car industry [19].

E-nose has an advantage over olfactometry due to its repeatability and low cost of measurements. Besides, the sensors have a better resolution and facilitate the measurement of hazardous pollutions. It can give results in odour concentration ou$_E$/m^3 unit only after calibration with olfactometry. Uncertainty of measurements is an inherent feature of such a calibrated method, as it is impossible to establish a more accurate method than the reference technique [20]. Additionally, the device cannot provide any information regarding the hedonic tone of the sample [21].

E-nose has been used for continuous monitoring of sewage. The purpose of these attempts was to detect accidental pollutants or illegal inflows of hazardous substances to a sanitation system. Considering the large amount of polluting compounds, the system with many low selective gas sensors is suitable to detect such incidents. The prototype system was installed in a WWTP in Cranfield University. Continuous monitoring facilitated instantaneous detection and the initial identification of pollutants that appeared in the sewer [22,23]. In another research, classification of odours according to the place of generation in the WWTP was successfully accomplished. Additionally, MOS (metal oxide semiconductor) sensors proved to be more precise than CP (conducting polymer) sensors [24].

Classification of odours was conducted by Onkal-Engin et al. [25] for treatment plants of municipal and industrial sewage of light industry. A total of 144 samples for measurements from the inlet works, sedimentation tanks, bioreactors and outflow were collected. To analyse a neural network with 12 inputs, 2 hidden layers both with 12 neurons were used. The investigations revealed a high correlation of odour class prediction (0.99). For more information see Table 1.

Sensors working in a harsh environment are exposed to permanent poisoning by chemical compounds, which leads to a long-term and irreversible signal drift and deterioration of the sensor characteristics. Due to this fact, gas sensor arrays should be examined with a calibration gas. Research conducted by Romain and Nicolas [26] on long-term stability of MOS sensors shows a significant drift of the output occurring after 7 years of operation. A longer time of sensor operation can be ensured by shortening the time of sensor exposition to pollutants. A short time of sampling (few minutes) alternating with sensor purging with clean air seems to be a very good solution.

2. Materials and methods

The SBR (sequence batch reactor) is a suitable facility for measurements with the gas sensor array—this also applies to chemical as well as biological reactors that are used for wastewater treatment. The SBR reactor allows for the reduction of the concentration of organic compounds and biogenes (especially N, P, S) during the active phase of treatment comprising mixing and aeration. In aerobic conditions, pollutants are transformed to CO_2, H_2O and oxidized inorganic P, S and N compounds, which is followed by removal of organic compounds and oxygen bound in nitrates. Methane is generated in anaerobic conditions by a specific group of microorganisms. All processes of treatment are performed in one volume in a proper sequence and, hence, only one measurement device can be used for monitoring. In the classical WWTP working in the flow mode, the measurements should be conducted in a few places to collect comparable data.

The SBR reactor used in the experiment was working as a laboratory-scale device, and treated sewage with activated sludge in a 12 h operating cycle. The 9 h continuous mixing started from the second hour of the cycle. Simultaneously with mixing, aeration was activated for 2.5 h and then periodically in order to sustain oxygen concentration at the level of approximately $2\,g\,O_2/m^3$. The final part of the cycle consisted of a 2 h sedimentation phase followed by decantation during which treated wastewater was discharged and the reactor was loaded with raw sewage.

The laboratory equipment consists of 3 independent SBR reactors with a chamber—each with $10\,dm^3$ capacity. Sewage was collected in the primary sedimentation tank of a municipal wastewater treatment plant (Hajdów) in Lublin, where the daily sewage flow Q_d is approx. $60{,}000\,m^3/d$.

For measurement of smell active compounds, 2 measuring devices were used: a gas sensor array consisting of 8 MOS type sensors to analyse the smell profile above the sewage surface and a dynamic olfactometer for evaluation of odour concentration. Determined odour concentration is the result obtained for the mixture of malodorous compounds (odorants), i.e. odorous substances, irrespective of whether their odour seems agreeable or not. The results of these two methods were compared. Measurements were conducted during a typical performance of the SBR reactor. Moreover, the failure introduced intentionally contributed to an increase in the odorous compound concentration, which allowed for obtaining a wide range of odour concentrations.

2.1. E-nose

The gas sensor array consists of 8 gas sensors of MOS (metal oxide semiconductors) type. These are resistive sensors with conductance proportional to the concentration of volatile chemical compounds. The e-nose was designed for general environmental applications; therefore, the implemented sensors facilitate detection of a wide range of gases present in water/wastewater facilities or food and agricultural industry. Signals from all sensors form a unique smell profile, so-called gas fingerprint, which characterizes the analysed gas. TGS Figaro sensors used were all of the same type from the 2,600 series. Sensor details are presented in Table 2. The heater and the sensing elements of the sensors were continuously powered with separate 5 V DC low-noise voltage regulators. Sensing elements together with precise resistors formed a resistor bridge circuit. Additionally, the temperature and relative humidity in the sensor chamber were measured. The gas sampling line contained a desiccant-membrane dryer DM-110-24 Perma Pure filled with granulated silica gel. The sampling flow rate was adjusted to 200 ml/min.

Table 1
Assessment of odour nuisance of sewage treatment works and other different environmental pollution sources using e-nose

Environmental application	E-nose; sensors; sampling; measurement	Analysis method	Description	Refs.
Wastewater treatment plant	Neotronics Scientific Ltd. model D; 12CP (polypyrrole); 600 ml/min, odour profiles at 1 min	CCA	Correlation between TON and e-nose in the range 125–781,066 ou_E/m^3	[10]
Compost facility	5 × e-nose; 6MOS	Supervised modelling, DFA	Assessment of odour annoyance in the vicinity of waste treatment plant using e-nose compared with meteorological measurements, correlation of an e-nose with odour conc. in the range circa 0–4,000 ou_E/m^3	[20]
Waste treatment plant, chemical plant	Airsense PEN2; 10MOS	ANN, DFA, PCA	Correlation of an e-nose with odour conc. 0–200 ou_E/m^3 ($R^2 = 0.94$), discrimination between different samples from biofilters	[21]
Wastewater	EOS25, EOS28, EOS35; 3 min meas./12 recovery	PCA	Classification of odour sources with high accuracy $R^2 = 0.95$ (for samples 100–150 ou_E/m^3), high correlation ($R^2 > 0.9$) of e-nose response with odour conc. in the range 20–80 ou_E/m^3	[27]
Wastewater	Neotronics Scientific Ltd. model D; 12CP (polypyrrole)	Canonical discriminant and correlation	Classification of wastewater, correlation of e-nose response with BOD	[28]

Note: CP—conducting polymer, MOS—metal oxide semiconductors, QCM—quartz crystal microbalance, CCA—canonical correlation analysis, DFA—discriminant function analysis, ANN—artificial neural network, PCA—principal component analysis, TON—threshold odour number, BOD—biological oxygen demand.

Table 2
Overview of the gas sensors implemented in the e-nose [29]

Sensor type	Description	Measurement range
TGS2600-B00 Figaro	General air contaminants	1–30 ppm (H_2)
TGS2602-B00 Figaro	General air contaminants (high sensitivity to VOC and odorous gases)	1–30 ppm (EtOH)
TGS2610-C00 Figaro	Butane. LP gas	500–10,000 ppm
TGS2610-D00 Figaro	Butane. LP gas (carbon filter)	500–10,000 ppm
TGS2611-C00 Figaro	Methane. natural gas	500–10,000 ppm
TGS2611-E00 Figaro	Methane. natural gas (carbon filter)	500–10,000 ppm
TGS2612-D00 Figaro	Methane. propane. iso-butane, solvent vapours	1–25% (LEL)
TGS2620-C00 Figaro	Alcohol. solvent vapours	50–5,000 ppm
DS18B20 Maxim-Dallas	Temperature sensor	−55–125˚C
HIH 4000 Honeywell	Humidity sensor	0–100%

The e-nose employed in the measurements had already been successfully used for measurement of the concentration of single odorants such as methylamine, dimethylamine, benzaldehyde, methanol, acetic acid [30] and many others. The e-nose was also used for analysis of malodorous gases collected in the surrounding of nuisance emission sources such as piggeries, landfills and municipal rendering plants [31]. The results show that it is possible to distinguish between different types of malodorous gases, which facilitate application of the measuring device in WWTPs.

2.2. Dynamic olfactometry

The second method of measurements was a dynamic olfactometry used as a sensorial technique for assessment of the odour concentration in samples, according to the EN-13725 regulation: "Air quality-determination of odour concentration by dynamic Olfactometry". A group of selected people assessed odour concentration on the dynamic olfactometer Ecoma Mannebeck model TO-7 employing the "yes–no" method. The dynamic olfactometer is an instrument that allows for mixing polluted air samples with odour-free air at a specified ratio. A diluted sample flows to multiple sniffing ports of the sensory panel. Measurement of odour concentration involves a gradual decrease in the sample dilution until the odour is perceived by 50% of assessors (perception threshold). Odour concentration c_{od} is assumed as a dilution value when the perception threshold is reached. The unit of $1\,ou_E/m^3$ (European odour unit) corresponds to odour concentration of polluted air at the perception threshold. The final results are the geometrical mean of the individual results. For the collected samples, static pre-dilution in Tedlar bags was performed. The olfactometer facilitated changing the dilution in the range from 1:2 to 1:64,000 with a dilution ratio 2. All measurements were conducted within 8 h after sample collection.

2.3. Data analysis

The artificial neural network (ANN) is frequently used for analysing multidimensional data obtained from gas sensor arrays. The principle of the work of gas sensor arrays combined with ANNs trained by special algorithms resembles the human sense of smell, but it is still a very simplified model of neurobiological mechanisms. One layer of hidden neurons is applied [32,33], and when the input–output relations are more sophisticated, it is reasonable to apply additional layers. Nielsen [34] suggests that the number of hidden neurons should not be smaller than $2n+1$, where n is the number of inputs. In research described in publications, the number of hidden neurons does not exceed 35 [17,25,35]. A logistic sigmoid and a hyperbolic tangent were used for activation of the hidden layer and an identity function for the output layer.

For data analysis, a feedforward artificial neural network multilayer perceptron (MLP) was used. The architecture of the net consisted of 10 inputs (all sensors), one hidden layer with n-neurons and one output neuron. The architecture of the net was determined in order to maximize the generalization ability of the net at minimal complexity. Network learning is a process of iterative adjustment of weights in order to minimize the net output error. The initial values of weights were set randomly with normal standardized distribution: mean $\bar{w}_{ij} = 0$, variance $s = 1$. To learn the process, the BFGS (Broyden-Fletcher-Goldfarb-Shanno) iterative algorithm was applied [36]. From the entire data-set, the learning (70%), testing (15%) and validation (15%) subset was randomly chosen. When the error of the net for the testing error is increasing and, consequently, becomes greater than the error for the learning subset, the learning process is terminated. The validation subset is used for quality assessment of the learned net.

3. Results and discussion

3.1. Odour concentration

The standard regular performance of SBR does not contribute to a significant smell nuisance. The odour concentration above the sewage surface was $45\,ou_E/m^3$, and after the load of raw sewage approx. $640\,ou_E/m^3$. The alteration in the odour concentration recorded during the restoration of aerobic conditions after SBR breakdown (implemented as turning off the aeration system) is shown in Fig. 1. The box of symbols denotes the mean value ± 95% of confidence interval, the upper and the lower whiskers with caps denoting max. and min. values, respectively. After SBR breakdown, the aeration processes were restored, and the odorous compound, which was created as a result of anaerobic processes, was released and the odour concentration increased to $995{,}606\,ou_E/m^3$. Considering an aeration flow rate of 4–5 l/min for each vessel, the

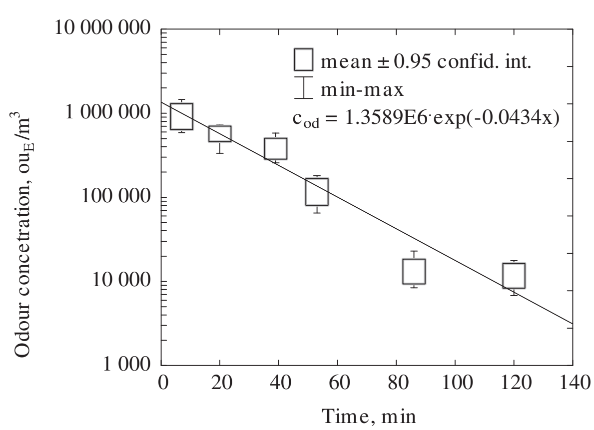

Fig. 1. Alteration in the odour concentration recorded during the first restoration phase of aerobic conditions after breakdown.

odour emission recalculated to 1 m^3 of SBR sewage was equal to 2,688 ou_E/h. The change in the odour concentration Δc_{od} can be described according to the exponential function $c_{od} = 1.3589E6 \cdot \exp(-0.043t)$, where Δt is time, min. The correlation coefficient R is −0.803. Due to the small capacity of the SBR chambers, the odour concentration very quickly recovered values of approx. 10,000 ou_E/m^3 and afterwards it slowly returned to normal conditions within the subsequent 4 h.

3.2. Selection of optimal network configuration

In order to determine the optimal architecture and parameters of the neural network, 10,000 networks with one hidden layer containing from 1 to 100 neurons were tested. For activating hidden and output neuron identity, the logistic sigmoid, hyperbolic tangent and exponential functions were used. To assess the net prediction quality, a validation subset, which was not used during the learning process, was taken. The highest value of prediction quality $\bar{Q} = 0.997$ was found for the net with the logistic sigmoid for hidden neurons and the identity function for output neurons. Other nets with good quality have functions (hid.-out. layer) *tanh-iden, tanh-tanh, exp-exp* (all $\bar{Q} = 0.996$) and the worst nets have *iden-iden, iden-sgm, iden-exp, exp-tanh* ($\bar{Q} = 0.976/0.993$).

Hierarchical clustering was additionally performed for all the activation function combinations of the network, considering standardized validation quality, validation error and the number of learning epochs. A single link algorithm of the agglomerative hierarchical clustering method was used. In the single link clustering, the proximity of clusters is defined as the minimum Euclidean distance between any two points in the two clusters. A vertical dendrogram is shown in Fig. 2. At Euclidean distance 2, the nets can be divided into 2 groups: (i) *iden-tanh* and *iden-iden* (worst parameters), (ii) the rest of the nets. The best nets (*sgm-tanh, exp-exp, tanh-iden, tanh-exp, tanh-tanh, sgm-exp, sgm-iden*) can be distinguished at Euclidean distance 0.3.

From the tests, a conclusion can be derived that the optimal function for the hidden neurons is the logistic sigmoid and hyperbolic tangent, and for the output neurons the identity and exponential functions. These functions have been frequently used in similar investigations [25,35].

Another issue is the optimal number of hidden neurons. For each net, a BFGS algorithm and SOS (*sum-of-squares*) function were applied for error estimation. Generally, in many cases, more errors for a small number of hidden neurons can be discerned. For all the combinations of the activation function, the number of

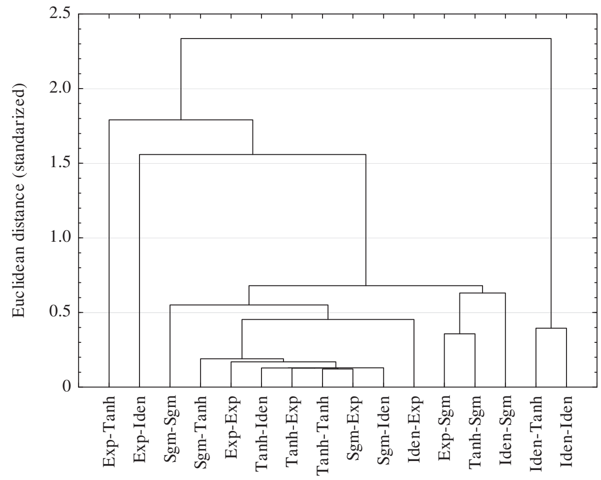

Fig. 2. Dendrogram of hierarchical clustering of the tested neural network considering standardized validation quality, validation error and learning epochs.

neurons may not exceed 20, which agrees with Nielsen's suggestion [34]. For nets with 20 to 100 hidden neurons, no statistical correlation was found between the validation quality and the number of hidden neurons (0.099), likewise in the case of the number of hidden neurons and epochs (R = 0.096).

3.3. Implementation of selected network

For predicting the odour concentration in the air collected above the wastewater surface in the SBR bioreactors, the net with the hyperbolic tangent for the hidden neurons and the identity function for the output layer was chosen (Table 3). The learning process was finished at the 61st epoch. This network does not have the highest value of validation quality, but corresponds very well with new data from the entire measurement. Networks with the logistic sigmoid, hyperbolic tangent and the exponential function for the hidden layer show the tendency to latch the net output at extreme values.

From the analysis of the input sensitivity of MLP10-20-1 (Table 4), the contribution of particular sensors for the output value can be interpreted—this value indicates an increment in the error after removal of a variable. Sensor S2 (general contamination of air, VOC) has the greatest contribution to the output. Incomparably lower contribution to the output was found for sensors S6 (methane and LPG) and S3 (methane, LPG, general contamination of air), S5 (methane), S8 (solvent vapours), S7 (methane and LP gases) and S1 (air contaminants). Sensor S4 (LP gas sensors with a filter) could be omitted. This very

Table 3
Summary of designed multilayer perceptron

Net architecture	MLP 10-20-1
Learning quality	0.97
Testing quality	0.88
Validation quality	0.98
Learning algorithm	BFGS 61
Error function	SOS
Activation function of hidden layer	Tanh
Activation function of output layer	Identity

Table 4
Analysis of input sensitivity of the MLP10-20-1 network determined for the validation subset

Sensor	Sensitivity
2602-B00	9690.1
T	64.8
2611-E00	25.9
2610-C00	14.3
2611-C00	9.6
2620-C00	6.5
2612-D00	6.2
2600-B00	5.3
2610-D00	1.9
RH	0.9

general characteristic, indicating an organic source of pollutants, is not typically chemical.

The accuracy of the odour concentration during restoration of aerobic conditions predicted by the MLP 10-20-1 network (data only from the validation subset) is shown in Fig. 3. The network satisfactorily predicts the odour concentration for measurement data that were not used for neural network learning. The dispersion of data points may indicate that the network does not interpret signal from sensors accurately. A limited amount of olfactometric results was used to the learning process; therefore, the network is not completely set to interpret all combinations of sensor signals perfectly. The network uses an ability of generalization to predict odour concentrations. On the other hand, the overlearning of the network can also contribute to error of network prediction. It should be mentioned that olfactometric results used for network learning calibration are loaded with a certain degree of uncertainty due to the subjectivity of panellists' assessment.

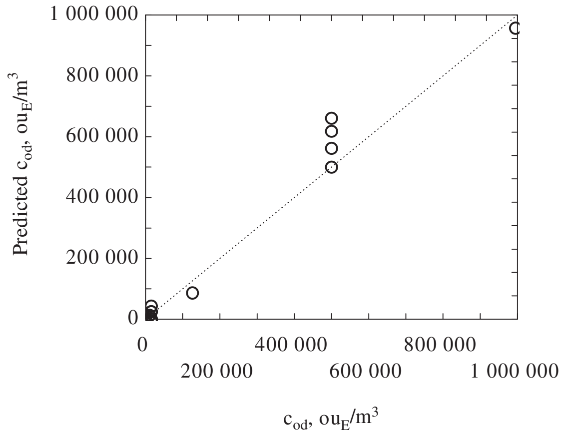

Fig. 3. Prediction accuracy of the odour concentration of the MLP 10-20-1 network for the validation subset.

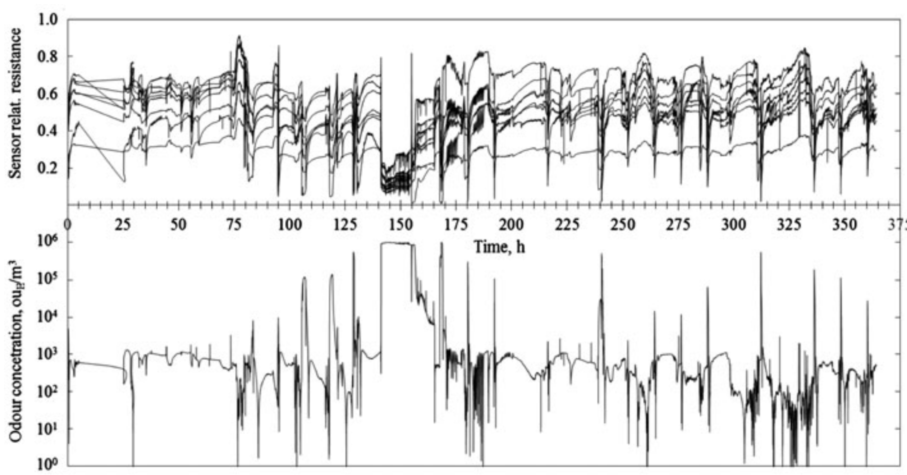

Fig. 4. Comparison of the sensor array output and the predicted odour concentration using the e-nose and multilayer MLP 10-1 × 20-1 (hidden neurons—tanh, output neuron—linear) during scheduled failure and normal performance of the SBR bioreactor.

Table 5
Comparison of the method of odour concentration prediction

Sample	Olfactometer c_{od} (ou_E/m^3)	E-nose c_{od} (ou_E/m^3)
1	540	374
2	80	182
3	40	75
4	180	66
5	320	191

The predicted odour concentration for a larger part of the measurements (disturbances and normal performance) of SBR bioreactors using the determined MLP 10-20-1 network is shown in Fig. 4. The upper plot presents sensor variations within the consecutive measurement hours. Signal values were recalculated to relative resistance as a ratio of measured sensor resistance to resistance of the sensor in clean air atmosphere. The lower plot presents the value of the odour concentration predicted using the determined network. After 75 h, the simulated breakdown of the reactor started, causing a decrease in the sensor resistance. From 140 to 155 h, restoration of aerobic conditions after the controlled breakdown was recorded. On the chart, some dependence is noticeable: when the concentration of odorous compounds increases, the signal of the sensors decreases and the network predicts a high odour concentration. After the 200th h, the treatment process returned to normal operating conditions. When raw untreated sewage is loaded to the SBR chamber, spikes of odour concentration are frequently recorded by the e-nose. These values of odour concentration should not be assumed as accurate results, but as episodes of increasing odour concentration causing a smell nuisance. The predicted odour concentration in the SBR chamber was chiefly below 1,000 ou_E/m^3.

3.4. System testing

Using dynamic olfactometry, the odour concentration was measured during normal operation of SBR bioreactors. These results were compared with predicted values using a determined method (Table 5). Pearson's correlation coefficient R is 0.85. This is a very high value, regardless of the irreproducible and subjective dynamic olfactometry results. The results confirm that the e-nose and ANN can be used to assess the odour concentration of the SBR reactor.

4. Summary

The investigations indicate that the standard regular performance of SBR does not contribute to a significant smell nuisance 45–640 ou_E/m^3 (where 640 is connected with inflow of raw sewage into the reactor), but during restoration of aerobic conditions after the breakdown, the odour nuisance rises to 995,606 ou_E/m^3. The odour emission recalculated to 1 m^3 of the chamber content was 2,688 ou_E/h.

To assess the odour concentration using 10 sensors (8 gas sensors and temperature and humidity sensors), a net with one hidden layer consisting of 20 neurons is sufficient. The best value of prediction for the validation subset has a net with a hyperbolic tangent for hidden neurons and an identity function in the output layer.

An important part of the work was to compare the methods used in the evaluation of the odour nuisance. The tests conducted after e-nose calibration show high coherence of the odour concentration evaluated using dynamic olfactometry and predicted using a described method ($R = 0.85$). The results confirm that the e-nose and ANN can be used to assess the odour concentration of the SBR reactor.

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