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ODOUR POLLUTION OF AIR

ZANIECZYSZCZENIE POWIETRZA ODOREM

A b s t r a c t

The human sense of smell is certainly the most versatile apparatus to analyze smells, but measurements take a lot of time and require employing a group of trained people [1]. Other techniques, like gas chromatography, allow to obtain accurate data of the chemical composition of examined gas, but do not inform about the real nature of smell. To identify the odour, devices comparing and determining its nuisance are used; in scientific literature they are called 'electronic noses'. In conveyed measurements a device was used with an array of eight resistive TGS Figaro gas sensors of 2600 series, each of which reacted to another class of a chemical compound [2]. Response of gas sensor array was collected for a mixture of air with odour-active compounds like dimethylamine, acetic acid, benzaldehyde of different concentrations. For the analysis of odour profiles there were used artificial neural networks with one hidden layer, containing from several to tens of neurons.

Keywords: odour pollution, gas sensors array, artificial neural networks

S t r e s z c z e n i e

Ludzki zmysł powonienia jest najlepszym aparatem do analizy odorów, ale pomiary są czasochłonne i wymagają zaangażowania do zespołu oceniającego przeszkolone osoby [1]. Inne techniki, jak chromatografia gazowa, która pozwala uzyskać dokładne informacje o składzie chemicznym badanej próbki powietrza, nie informują o rzeczywistej naturze zapachu odczuwanej przez ludzi. Do identyfikacji zanieczyszczeń odorowych oraz określania ich uciążliwości są wykorzystywane w ostatnich latach wieloczujnikowe urządzenia, nazywane w literaturze naukowej mianem „elektroniczny nos". Podczas przeprowadzonych badań użyto matrycy złożonej z ośmiu rezystancyjnych czujników gazu TGS Figaro serii 2600 uczulonych na różne klasy związków chemicznych [2]. Odpowiedzi matrycy czujników zostały zebrane dla substancji zapachowo-czynnych, takich jak dimetyloamina, kwas octowy i aldehyd benzoesowy o różnych stężeniach w powietrzu. Do analizy profilów zapachowych wykorzystano sztuczne sieci neuronowe z jedna ukrytą warstwą zawierającą od kilku do kilkudziesięciu neuronów.

Słowa kluczowe: zanieczyszczenia odorowe, matryca czujników gazu, sztuczne sieci neuronowe

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1. Introduction

Odour nuisance usually does not cause any direct side effects. However, it influences the psychical health of people. The result of this is a greater percentage of people suffering from depression, insomnia and neurosis in the areas threatened with odour emissions. These areas are not attractive from the touristic point of view. Due to a large number of complaints about odour nuisance incoming to the Inspectorates of Environmental Protection, the Environment Ministry noticed the above mentioned problem and thus in the year 2007 it elaborated the draft act against the odour nuisance. Consideration of this problem is an attempt to elaborate an objective instrumental research method of odour nuisance measurement replacing or complementing the olfactometry measurements. According to the assumptions of 22 December 2010 statute on prevention of smell nuisance, it is estimated that about 1600 analyses of smell nuisance are conducted during the year.

Nowadays two measurement techniques are applied for evaluation of air quality: olfactometry and chromatography. Chromatography enables us to obtain a precise qualitative and quantitative analyses of contaminated air. However, it does not inform about the smell nuisance of a gaseous mixture. Until now, the dynamic olfactometry which uses the estimation of group of people has been the most useful in this area. Determining the air quality with the olfactometry technique is time-consuming and expensive. That is why it seems important to develop the sensory techniques of measurement which would enable us to obtain the results correlated to olfactometry.

1.1. Artificial nose

Human sense of smell is a complicated apparatus. It is located in the area of about 4 cm^2 and contains from 10 to 30 billion of sensors divided into 10–100 types with different sensitivity and selectivity. Multisensory device called the "artificial nose" imitates the natural smell sense [3]. In this case the gas sensors detecting the particular odorous substances play the role of smell receptors. It should be understood that the number of sensors can indicate the lower efficiency in odour determination comparing to the typical olfactometry measurements. Most of devices use over a dozen sensors [4].

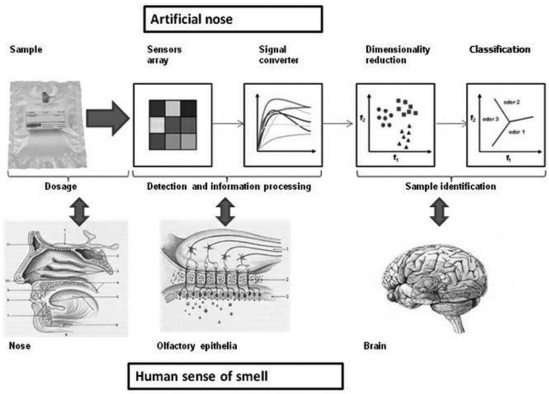

Fig. 1. Comparison of artificial nose and human sense of smell

Rys. 1. Porównanie sztucznego nosa z ludzkim zmysłem węchu

Each of the implemented sensors has a partial sensitivity on a particular chemical compound, not only odour-active. With this, each sensor placed in the atmosphere of examined gas will generate a particular signal. The set of all signals is called the smell profile and is characteristic for a particular gas or a mixture of gases with particular concentrations and proportions.

Optic, thermal, electrochemical and gravimetric sensors can be applied for measurements [2]. Popular and reasonably cheap sensors applied in measuring sensors are resistance, semiconducting gas sensors which belong to the group of electrochemical sensors. Detection of air gases using the resistance sensors is possible due to the phenomenon of electric conductivity change depending on gas concentration. Under the influence of reductive atmosphere at a temperature of 200–500°C a layer of semiconductor changes its resistance R depending on the examined gas concentration [5].

1.2. Artificial Neural Network

Electronic nose system is built up of two parts: a sensors array and a data analysis system with ability to classify, differentiate and recognize the patterns. Often artificial neural networks are applied for this purpose.

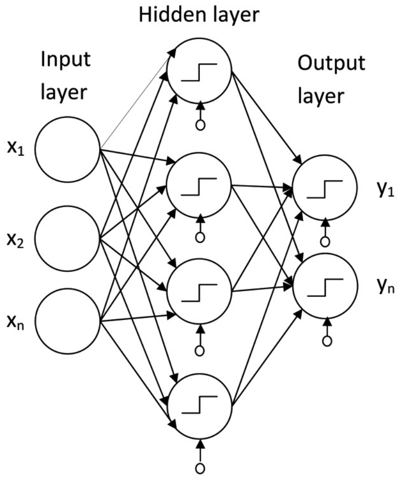

Fig. 2. Multi Layer Perceptron

Rys. 2. Perceptron wielowarstwowy

Multi Layer Perceptron (Fig. 2) is a commonly applied structure for e-nose data processing. In each neuron input signals are summed, weighed, and the result is computed using the transfer function. In each layer MLP neural network also a component of displacement is present. It is an additional neuron which at the output always gives the unity [6]. This value goes to all neurons of the next layer of weighted scales, which is sometimes called the threshold. Such a network, with an adequate number of layers and neurons in layer, can model the dependence of almost any complexity [7].

The network topology does not fully determine its characteristics. The transfer function is also an important feature responsible for the activation of signal transmission from the previous neurons; it specifies a particular mathematical relationship. The transfer function applied can be: identity a, sine sin(a), logistic sigmoid $\frac{1}{1-e^{-a}}$, hyperbolic $\frac{e^{a}-e^{-a}}{e^{a}+e^{-a}}$, exponential e^{-a}, softmax $\frac{\exp(a_i)}{\sum \exp(a_i)}$.

The number of hidden layers is also of fundamental importance. Small amounts of neurons cause a high training error and a high generalisation error to occur due to underfitting. On the contrary, the ANN with too many neurons has a high generalisation error due to overfitting [8]. Very rarely the numbers of hidden neurons in an analysis of e-nose data exceed tens, for example 30 [9]. Generally, the number of hidden neurons should be between the input layer size and the output layer size. In my paper it is mentioned as "the rule of thumb" [10, 11].

2. Materials and methods

Samples with benzealdehyde, acetic acid and dimethylamine were prepared in tedlar bags filled with synthetic air. Using the chromatographic syringe the chemical compound was dosed to the known volume of tedlar bags filled with high quality synthetic air (purity class 5.5). The concentration of the sample was controlled with a gas chromatograph. The flow rate 1 dm^3/min is caused by the membrane micropump built into the measurement device.

In the device eight TGS Figaro sensors were set up into the matrix, shown schematically in Fig. 3. The air flows axially into the device chamber, where sensors are located, through the inlet pipe in the chamber cover. Several openings allow the equal flow of the air stream over each sensor. The sensor matrix together with the membrane micropump and the microprocessor controller form a mobile device for in-situ odour measurement. Measured data are stored on the memory card for further analysis.

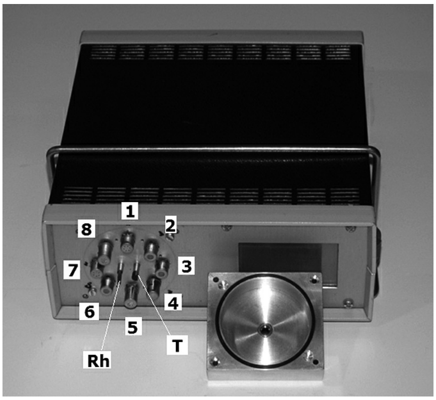

Fig. 3. Array of sensors together with removed sensor chamber cover

Rys. 3. Matryca czujników pod zdjętą przykrywą komory czujników

Table 1

Gas sensors used during measurements

No.	Type	Description
1.	TGS2600-B00	Sensor of H_2
2.	TGS2610-C00	Propane sensor, LGP50
3.	TGS2611-C00	Methane sensor [CH_4]
4.	TGS2612-D00	Propane and isobutane sensor [C_3H_8, C_4H_{10}]
5.	TGS2611-E00	Methane sensor with carbon filter [CH_4]
6.	TGS2620-C00	Ethyl alcohol sensor
7.	TGS2602-B00	Sensor of toxic gases [NH_3, H_2S, C_2H_5OH, $C_6H_5CH_3$]
8.	TGS2610-D00	Propane and butane sensor [C_3H_8, C_4H_{10}]
T	DS18B20	Temperature sensor, Maxim-Dallas
Rh	HIH-4000	Relative humidity sensor

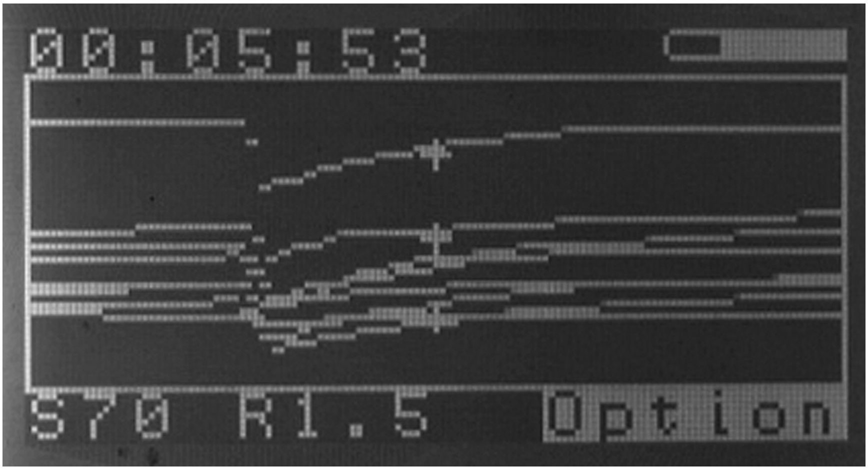

Fig. 4. Example of information displayed on device screen that allows to watch online sensors response

Rys. 4. Przykład informacji wyświetlanych na ekranie urządzenia pomiarowego pozwalających na bieżąco obserwować odpowiedzi czujników

3. Analysis and discussion

The results of measurement by multisensory device are shown in polar diagrams. Axes of the graph represent individual sensors and the values on the axes indicate how the sensor responds to the gas sample at different concentrations. Relative resistance $\frac{R_s}{R_o}$ was determined, where the R_s is a sensor resistance [kΩ] to the sample, and the R_o is the sensor resistance [kΩ] in an atmosphere of synthetic air.

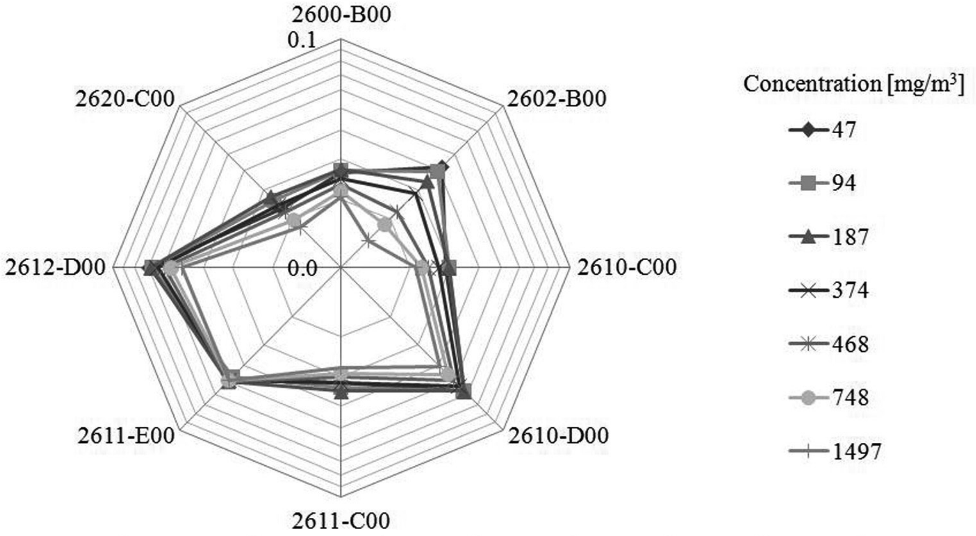

Fig. 5. Polar plot of benzaldehyde

Rys. 5. Wykres polarny dla aldehydu benzoesowego

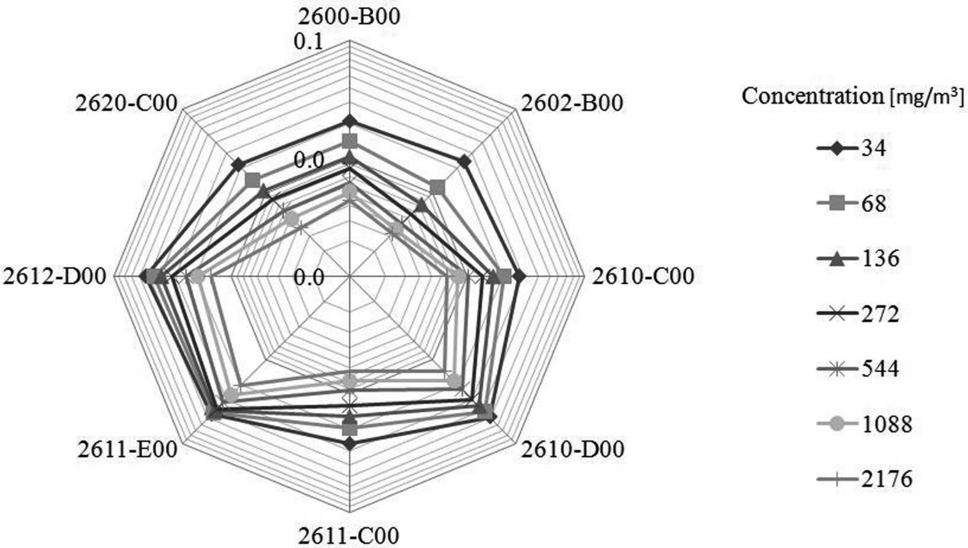

Fig. 6. Polar plot of dimethylamine

Rys. 6. Wykres polarny dla dimetyloaminy

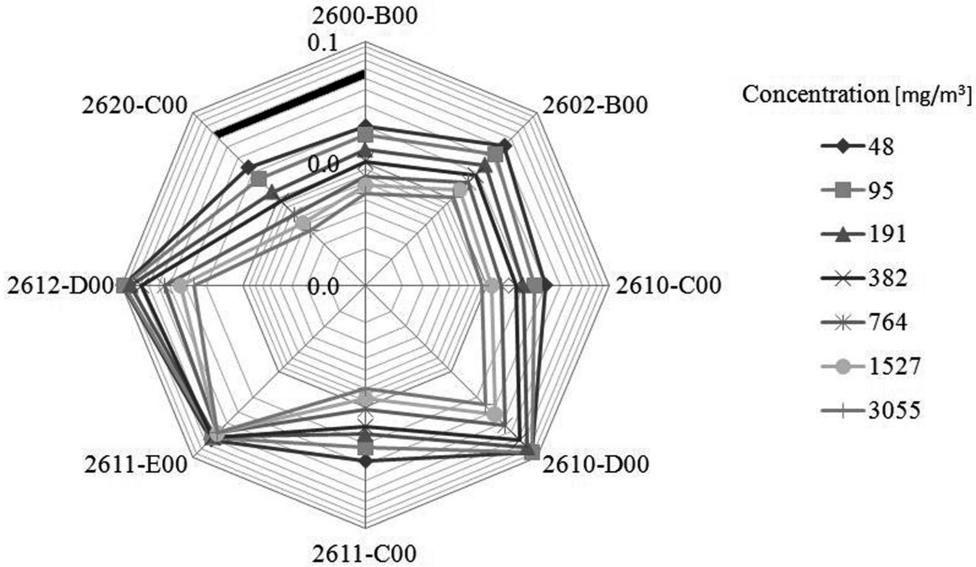

Fig. 7. Polar plot of acetic acid

Rys. 7. Wykres polarny dla kwasu octowego

The differences between the smell profiles of samples are noticeable. The characteristic feature of benzaldehyde samples is relatively large sensor TGS2602-B00 reaction in comparison to other sensors. Multidimensional data sets, to be useful, must be analyzed by means of artificial neural networks. The popular computer program Statistica 9, which was used to analyze the results obtained for benzaldehyde, acetic acid and dimethylamine, is very helpful for data processing.

The first step of the analysis was configuration and learning of an artificial neural network which is used to identify the air pollutants (classification). The network has 8 inputs for each gas sensor, and 5 outputs which represent measured gas pollutants (analysis included also the results for methanol and methylamine).

For classification of odours pollution 5 artificial neural networks were selected, consisting from 20 to 50 neurons in the hidden layer. For the network learning the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm was used. The number of epochs of the learning process did not exceed 23. SOS (sum-of-squares) or entropy function were used as a function to determine an error.

An example analysis result of a selected neural network classification for dimethylamine is shown in Fig. 8. The certainty degree for all the ANN is the largest for the measured compound, which indicates a recognition of this compound.

The second step of the analysis is determining the prediction of neural networks for pollution concentration. In these cases it is one quantitative output, giving information on concentration of the pollutant. Table 2 contains selected networks for benzaldehyde.

Table 2

Summary of ANN for measured odour pollutants classification

Net	Learning algorithm	Error function	Activation function (hidden neurons)	Activation function (output neurons)
MLP 8-20-5	BFGS 14	Entropy	hyperbolic	softmax
MLP 8-27-5	BFGS 18	Entropy	logistic sigmoid	softmax
MLP 8-50-5	BFGS 16	Entropy	hyperbolic	softmax
MLP 8-49-5	BFGS 23	SOS	hyperbolic	exponential
MLP 8-31-5	BFGS 17	SOS	hyperbolic	logistic sigmoid

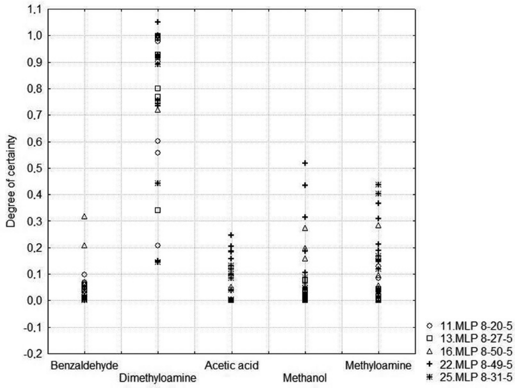

Fig. 8. Degree of certainty for dimethylamine

Rys. 8. Stopień pewności dla dimetyloaminy

Table 3

Artificial neural networks for determining benzaldehyde concentration

Net	Learning algorithm	Error function	Activation function (hidden neurons)	Activation function (output neurons)
MLP 8-15-1	BFGS 33	SOS	logistic sigmoid	Linear
MLP 8-18-1	BFGS 81	SOS	Linear	sine
MLP 8-24-1	BFGS 29	SOS	Linear	sine
MLP 8-23-1	BFGS 20	SOS	sine	Linear
MLP 8-9-1	BFGS 168	SOS	logistic sigmoid	logistic sigmoid

Increasing the number of neurons does not automatically improve the accuracy of ANN. Multi layer perceptron with 23 hidden neurons has prediction error of more than 250 mg/m^3 of bezeldehyde concentration. On the contrary, the MLP with 9 hidden neurons predict concentration with very good accuracy (r = 0.99). Table 3 contains selected networks for dimethylamine.

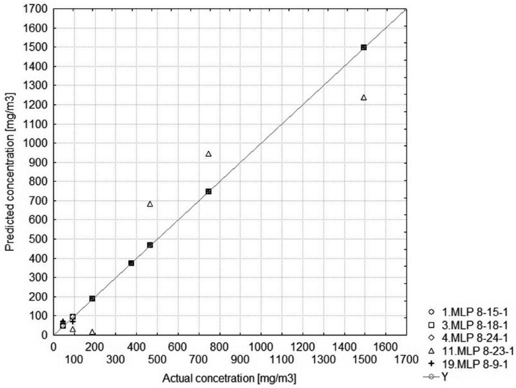

Fig. 9. Prediction of benzaldehyde concentration for selected networks

Rys. 9. Predykcja stężenia aldehydu benzoesowego za pomocą wybranych sztucznych sieci neuronowych

Table 4

Artificial neural networks for determining dimiethylamine concentration

Net	Learning algorithm	Error function	Activation function (hidden neurons)	Activation function (output neurons)
MLP 8-4-1	BFGS 51	SOS	sine	exponential
MLP 8-18-1	BFGS 10000	SOS	hyperbolic	exponential
MLP 8-10-1	BFGS 61	SOS	exponential	Linear
MLP 8-25-1	BFGS 22	SOS	sine	hyperbolic
MLP 8-17-1	BFGS 273	SOS	Linear	sine

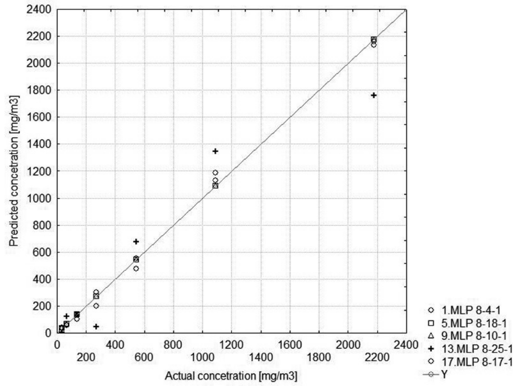

Fig. 10. Prediction of dimethylamine concentration for selected networks

Rys. 10. Predykcja stężenia dimetyloaminy za pomocą wybranych sztucznych sieci neuronowych

Similarly to benzaldehyde, the number of hidden neurons does not affect the accuracy of ANN. The network with 4 and 10 hidden neurons has correlation coefficient r = 0.98.

4. Conclusions

The conducted research has shown that a single air pollutant can be recognized and its concentration determined using e-nose systems coupled with artificial neural network analysis. As it is impossible to identify individual components of the odours, the ANN can be used for odour intensity prediction.

Designated configuration of artificial neural network with synaptic weights can be loaded into the memory of e-nose microcontroller. This allows to design a compact portable artificial nose system which contains both the measuring module and the intelligent module of results interpretation.

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