CHEMICAL ENGINEERING TRANSACTIONS

VOL. 68, 2018

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Selena Sironi, Laura Capelli

ISBN 978-88-95608-65-5; **ISSN** 2283-9216

DOI: 10.3303/CET1868042

Artificial Neural Network in the Measurement of Environmental Odours by E-Nose

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Odour measurement plays a crucial role in environmental odour management. Continuous odour measurement systems are promoted to keep the situation always under control, such as being able to adopt the most suitable mitigation measures in real time to avoid odour complaints and impacts. Electronic Nose (eNose) represents currently the instrument of having the highest future developing potential to guarantee continuous odour measurements. To use an eNose, a training phase is however mandatory, which has the scope to create the Odour Monitoring Model (OMM) that is able to identify the presence of odour, the different odour classes and the quantification of the odorous stimuly. Statistical or biological inspired measurement techniques are applied to create the optimum OMM.
The study presents and discusses the elaboration of an Artificial Neural Network (ANN) technique to recognize environmental odour with eNose. The proposed system was architected on a feed-forward neural network with Bayesian Regularization algorithm using Matlab R2017a software.
The elaborated ANN was tested and validated using the seedOA eNose, realized by the Sanitary Environmental Engineering Division (SEED) of the Department of Civil Engineering of the University of Salerno (Italy). Tests were carried out analyzing odour samples collected at a large Wastewater Treatment Plant (WWTP). The comparison between the Odour Monitoring Model (OMM) elaborated through the proposed ANN system and the traditional statistical techniques, such as the Partial Least Square (PLS) and the Linear Discriminant Analysis (LDA), is also discussed.
Results shown the efficiency of the elaborated ANN to identify the different odour classes and predict the odour concentration in terms of OUm^{-3}. The artificial neural network shows smaller Root Mean Squared Errors (RMSE) and greater coefficient of determination (R^2) as compared to the traditional statistical methods. The main advantages of neural networks are their adaptability in terms of learning, self-organization, training and noise-tolerance.

1. Introduction

Due to the rapid growth of industrialization, some environmental conditions are altered, especially the air in the atmosphere with the addition of pollutants such as odour emissions that required intensive management (Belgiorno et al., 2012). Continuous odour emission from industrial plants can be an annoyance to the exposed community and one of the major cause of complaints to plant operators because it leads to low quality of life and generate a perception of risk (Zarra et al., 2008). Prolonged exposure to gaseous compounds responsible of the odours, despite of not being the direct cause of illness, may brought serious damage to health such as nausea, headaches and respiratory problems (Gostelow et al., 2000; Zarra et al., 2008). Waste treatment plants produced most of the unwanted odours and *in situ* controlling is mandatory to address this problem. Measurement and quantification of the odour emissions are some of the standard operations procedures in which three techniques are applied: (1) analytical, (2) sensorial and (3) combined sensorial-analytical (Gostelow et al., 2000; Giuliani et al., 2012; Capelli et al., 2014). In analytical techniques, chemical compounds in malodorous emissions are quantified and identified (Munoz et al., 2010; Zarra et al., 2014). Although identification and quantification does not signify odor nuisance, the information obtained is helpful to track the sources of odour. In sensorial analysis, the measurement relied on the human nose as the detector in odour evaluation however, it doesn't guarantee a high accuracy due to the subjective nature of assessment (Gostelow et al., 2000; Munoz et al., 2010; Giuliani et al., 2012; Zarra et al., 2014). For sensorial-analytical technique, the technology with the highest potential for future development is Electronic Nose (eNose). ENose tries to interpret the sense of human smell in an analytical way and although it possessed a good potential, the lack of legal frameworks on odour emissions is still an obstacle in order to come up with profound guidelines and standards in odor monitoring. To try to fill this gap, since 2015 in the CEN/TC246 'Air quality' was established the Working Group (WG) 41.

The intense research in eNose technology has provided significant breakthroughs in fields of continuous odour monitoring (Persaud and Dodd, 1982) by embedding artificial intelligence (AI) which represent a milestone in designing efficient odour monitoring model (OMM) such as designing an "odour expert" system use for decision making about odour control strategies and to verify odour phenomenon made up of multiple odourous mixtures (Hudon et al., 2000; Szulczynski et al., 2018). Artificial neural networks (ANN) is the computational tool under AI which consist of interconnected neurons with different weights and layers and the sum of these weighted neurons activated by a transfer function is the output (Theodoridis S., 2015). This technique doesn't rely on assumptions and capable to adopt complex and non-linear behavior (Panbude et al., 2015). In this context, ANN can improve the eNose performance due to the dynamic behavious of odour emission (Gostelow et al., 2000).

The study discusses and describes the application of the artificial neural network (ANN) technique to recognize environmental odour applying the eNose technology. The elaboration of a specific ANN in the pattern recognition architecture of an eNose system is presented. The comparison between the proposed biological technique (ANN) and statistical methods in elaborating the Odour Monitoring Model (OMM) is analyzed and provided.

2. Materials and methods

2.1 Experimental program

Research studies were carried out by collecting real samples from different treatment stages at a wastewater treatment plant in Salerno, Italy. Seven principal odour emission sources have been identified and considered for research, according to previous studies performed on the plant: (P1) grit chamber, (P2) primary sedimentation, (P3) oxidation/aeration, (P4) secondary sedimentation, (P5) sludge thickener, (P6) sludge centrifuge and (P7) effluent from sludge digester (Giuliani et al., 2013). 4 samples for every source have been collected with a weekly frequency, using nalophan bags of 7 liter volume. 28 total samples were carried out.

2.2 Odour characterization methods

All collected air samples undergone dynamic olfactometry (DO) analysis in accordance to EN 13725:2003 to quantify the odour concentration in terms of odour units per cubic meter (OU/m^3). A TO8 olfactometer (ECOMA GMBH - D) was employed and performed within 14 hour sampling, according to Zarra et. al. (2012) studies to reduce the possibility of loss of concentration. The same samples were also analysed using SEEDOA eNose (Sanitary Environmental Engineering Division, University of Salerno – Italy) in an odour – odourless air cycle (Zarra et al., 2012; Viccione et al., 2012; Giuliani et al., 2015). An odourless air readings (0,00 OU/m^3) are also measured and included in the data set to indicate values at lowest detection limit (LDL). An acquisition and recovery time of total 15 minutes was fixed for each sample. SeedOA eNose measurement chamber includes 13 gas sensors (i.e. Figaro sensors) distributed on two different levels. (Guilani et al., 2013).

2.3 eNose Odour Monitoring Model elaboration by applying the ANN technique

Two separate 3-layer feed-forward neural networks were designed (Figure 1). Both models utilized the 13 different electrical resistance profiles from seedOA eNose as input data. The accuracy, speed of convergence, the ideal number of neurons in hidden layers and choice of training algorithms are significant factors considered (Theodiris S., 2015; Kayri M., 2016).

For odour prediction, the target output was odour concentration (OU/m^3). For odour classification, binary classifiers such as "0" & "1" were applied as decision-making output and categorically clustered the output into 7 groups that represent the investigated odour sources in the WWTP: (P1 – P7). When "1" appears to a group, it indicates a probability that the odour emission was generated on that source, while "0" indicates blank (*see Table 1*).

Both models (Figure 1) employed tan-sigmoid activation function and Bayesian regularization algorithm. Table 1 presents the target matrix classifying the samples into their corresponding clusters.

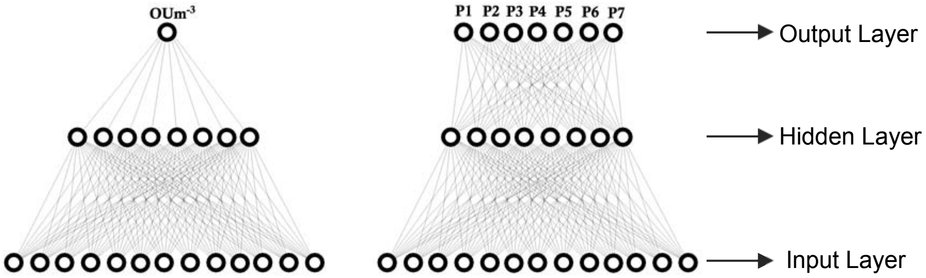

Figure 1: Architecture of the ANN for odour prediction (13-8-1) *and classification* (13-8-7)

Table 1: Output of training data for odour classification

LABEL	P1	P2	P3	P4	P5	P6	P7
P1	1	0	0	0	0	0	0
P2	0	1	0	0	0	0	0
P3	0	0	1	0	0	0	0
P4	0	0	0	1	0	0	0
P5	0	0	0	0	1	0	0
P6	0	0	0	0	0	1	0
P7	0	0	0	0	0	0	1

MatLab R2017a was used as the computational software.

2.4 eNose Odour Monitoring Model elaboration by applying statistical techniques

Supervised statistical methods such as Partial Least Square (PLS) and Linear Discriminant Analysis (LDA) were used. PLS combines both principal component analysis (PCA) and multiple linear regression. LDA analyze within-class and between-class scatter that leads to an effective solution to many pattern classification problems and are commonly used in eNose technologies for environmental odour assessment (Zarra et al., 2012, Giuliani et al., 2012). STATISTICA Statsoft 10 was used as the computational software.

2.5 Comparison studies

Comparative analysis were performed by calculating the Total Root Mean Square Errors (RMSE), coefficient of determination (R^2) and percentage of correctness (%C). RMSE is an estimator of the errors between the values measured and predicted. R^2 describes how well the model fits the observed data (close to 1 means good relationship). The percentage of correctness (%C) indicates the number of data correctly classified by the model.

3. Results and discussions

3.1 Odour Monitoring Model elaboration by applying the Artificial Neural Network

3.1.1 Odour classification

Table 2 shows the number and the percentage correctly classified by ANN per group.

Table 2: Classification percentage rate by applying ANN

LABEL	CLASSIFICATION RESULTS	%C
P1	27/28	96.43%
P2	26/28	92.86%
P3	28/28	100.00%
P4	27/28	96.43%
P5	28/28	100.00%
P6	28/28	100.00%
P7	28/28	100.00%

Results highlights that P3, P5, P6 and P7 were perfectly classified while the model had a little uncertain state in classifying P1, P2 and P4 because the ranges of electrical signal response do not vary considerably with each other. Despite of this, the results still fall under their intended classification. The overall accuracy was computed by getting the mean values of all the results which was found at 97,96%.

3.1.2 Odour stimuly quantification in terms of Odour Concentration

Figure 2 shows the odour concentrations measured through DO versus the predicted by ANN, with a zoom of the data reported in the figure at left, respectively detected for P1-P4 (area 0-1.000 OU/m^3), for P5-P6 (area 0-9.000 OU/m^3) and P7 (area 0-50.000 OU/m^3).

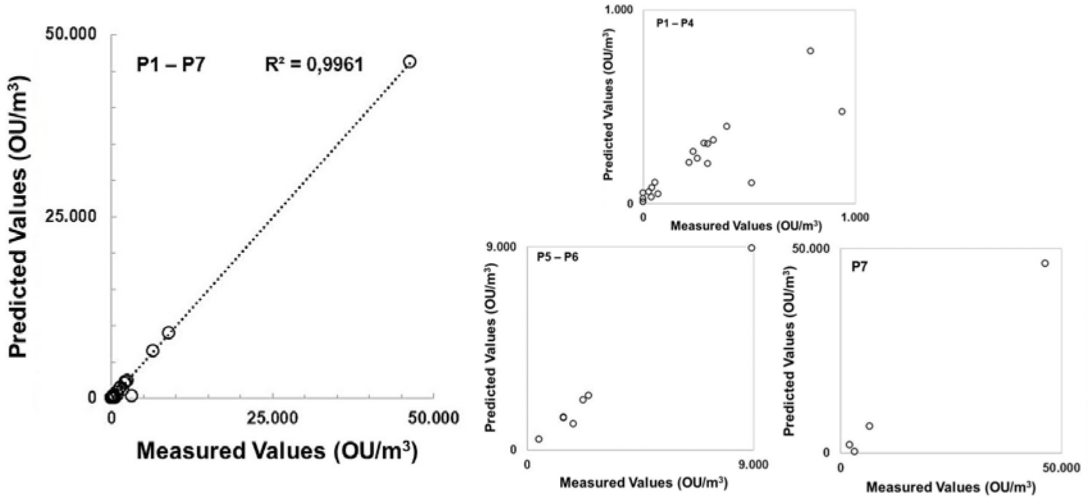

Figure 2: Correlation between the odour concentrations measured by DO and predicted by ANN referred to all data (figure on the left) and to defined sources (figures on the right).

The lowest odour concentrations were detected in P4 (27 - 54 OU/m^3), while the highest were identified in P7 (2.000 - 46.000 OU/m^3). Results show an R^2 of 0,9961 and RMSE of 523,40 (OU/m^3) which indicates very high level of confidence. The outcomes confirmed the strong performance of the elaborated ANN technique for odour concentration prediction.

3.2 Odour Monitoring Model elaboration by applying the statistical techniques

3.2.1 Linear Discriminant Analysis (LDA) Evaluation

Figure 3 shows the distribution of the investigated values in the plane of the first two roots (representing a 74.18% of the total variance out of the total 28 observations). The LDA explicit the Mahalanobis distance between the observation and the centroid per group, for the classification. The closer the case is to a group centroid, the more confidence you can have that it belongs to that group.

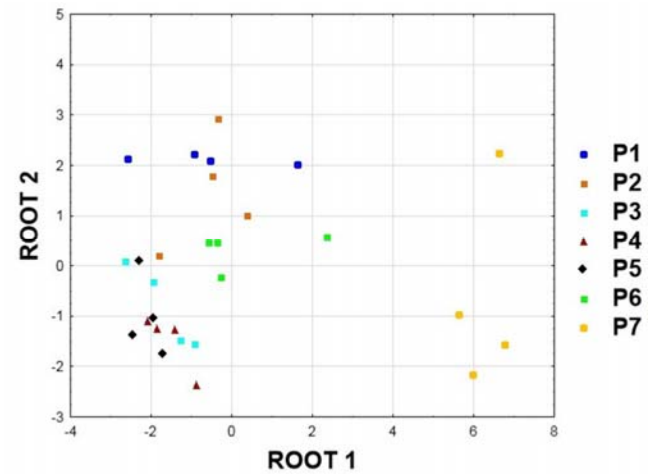

Figure 3: Score plot in the plane of the first two roots of LDA

The plot shows a high distance for the values in P3, while a minimum distance and an unambiguously defined plane can be observed for the values in P7. Table 3 reassume the classification results for the 7 classes.

Table 3: Classification percentage rate by applying LDA.

LABEL	%C
P1	75.00%
P2	50.00%
P3	25.00%
P4	100.00%
P5	75.00%
P6	75.00%
P7	100.00%

Results highlights a perfect classification for P4 and P7, while the least was for P3. The performance of LDA to P1, P2, P5 and P6 were average. LDA overall accuracy was 71,43%.

3.2.2 Partial Least Square (PLS) Evaluation

Figure 4 presents the data plot of the odour concentrations measured and predicted by DO and PLS respectively, with a zoom of the data reported in the figure at left and detected for the sources P1-P4 (area 0-1.500 OU/m^3), for the sources P5-P6 (area 0-9.000 OU/m^3) and for the source P7 (area 0-50.000 OU/m^3).

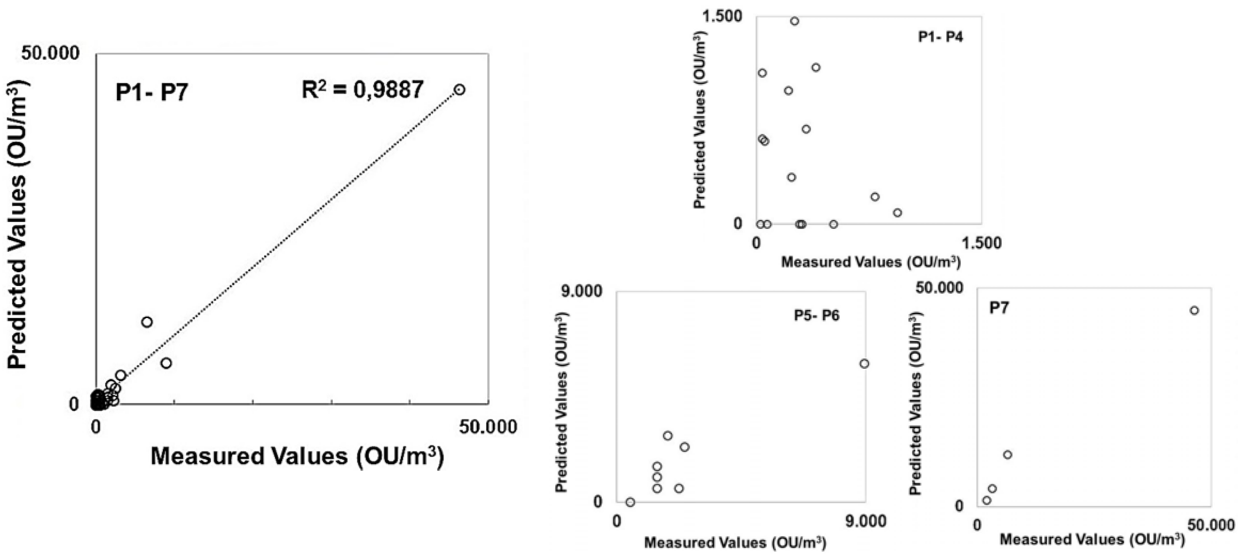

Figure 4: Correlation between the odour concentrations measured by DO and predicted by PLS referred to all data (figure on the left) and to defined sources (figures on the right)

Results shown an R^2 of 0,9887 and the RMSE is 1388,04 (OU/m^3). PLS seems to be a technique that finds greater difficulty in correlating variables in case of low values, as in the investigated case in which the most odour concentrations detected for the odourless air, P1 and P2.

3.3 Comparison studies

Table 4 summarized all the results obtained from all the evaluated techniques (ANN, PLS and LDA).

Table 4: Summary of the results from statistical and neural network technique

PREDICTION	R^2	RMSE (OU/m^3)	CLASSIFICATION	%C
PLS	0,9887	1388,04	LDA	71,43%
ANN	0,9961	523,40	ANN	97,96%

Results highlights that ANN gave a higher success rate than statistical methods in the definition of the OMM. In odour prediction, the ANN can extract patterns with greater reliability and has better tolerance with the noise however, designing the model is difficult and time consuming. In odour classification, ANN also outperformed

LDA. It was because ANN makes no explicit assumptions regarding the underlying distributions of the variables involved. Despite of the attention that ANN gained due to its robustness, there are still many possibilities that can employ to enhance its performance.

4. Conclusions

ANN and statistical methods (PLS and LDA) were developed and compared for the elaboration of an Odour Monitoring Model (OMM) to be used by eNose technology for continuous environmental odour management. The ANN models performed better than statistical methods in both fields of prediction and classification. In odour concentration prediction, R^2 for ANN and PLS was found equal to 0,9961 and 0,9710 respectively, while in odour classification, overall correct classification using ANN and LDA was calculated equal to 97,96% and 71,43% respectively. The model was trained at a range of 0,00 – 50.000 OU/m^3 with the largest number of points having a concentration less than 10.000 OU/m^3. Odourless air sample has been introduced to identify the lowest detection limit (LDL). ANN proves to be a technique that give better results in terms of odour classification and stimuly quantifications especially in presence of types of odours characterized by similar quality and by a greater detection of lower odour concentrations. Despite of the superior results in the artificial neural networks, further explorations are still possible to improve the model accuracy in terms of the structure. The presented study is a significant step on how to improve the intelligence system of electronic nose for *in situ* and continuous monitoring of environmental odours.

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