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Data Processing Approaches for Sensors Humidity and Drift Compensation in Environmental Odour Monitoring

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The application of Instrumental Odour Monitoring Systems (IOMS) for environmental odour monitoring has become increasingly relevant in recent years, thanks to their capability to operate continuously, allowing near real-time discrimination of odour events generated by industrial plants, which can cause annoyance to nearby populations. This study refers to the application of an IOMS for monitoring odour emissions at the fenceline of a Waste Treatment Plant (WTP). The main focus is the development of appropriate data processing approaches applied to the sensor signals recorded by the IOMS during operation, in order to counteract interference related to variations in ambient humidity and drift effects. The study was conducted over a period of more than one year, during which dedicated olfactometric campaigns were carried out to train and test the IOMS odour classification and regression models. The results show that the application of specific data pre-processing strategies effectively reduce the impact of interferents on IOMS outputs, leading to improved model performance: acceptable IOMS performance is maintained even though the system is affected by drift effects. Conversely, models developed without proper compensation for humidity and drift exhibit significantly reduced performance.

1. Introduction

Odour pollution is a significant environmental issue, often associated with increased discomfort and complaints from citizens living near industrial plants(Bax, Sironi and Capelli, 2020). In recent regulations, odour has been recognized as a pollutant that requires monitoring (Bokowa *et al.*, 2021). For this reason, the use of electronic noses (e-noses), also referred to in this field as Instrumental Odour Monitoring Systems (IOMS), has gained considerable interest for monitoring odour emissions due to their capability to operate continuously, analysing ambient air and discriminating among different odours. However, their application in the environmental field is hindered by the presence of unwanted interferents, such as variations in ambient humidity (Robbiani *et al.*, 2023), which can modify sensor responses, as well as by long-term stability issues (i.e., sensor drift) (Ren *et al.*, 2024) affecting sensors installed in IOMS. The work presented here refers to the application of an IOMS for monitoring odour emissions at the fenceline of a Waste Treatment Plant (WTP) producing biomethane and compost from the organic fraction of municipal solid waste. The main objective of the paper is the development of appropriate data pre-processing methodologies to account and compensate for interference related to ambient humidity variations and sensor drift. To validate the proposed approaches, the IOMS was used to characterize samples collected from different odour sources of the plant over a period of 16 months, from March 2024 to July 2025. Four campaigns, conducted between March 2024 and September 2024, were carried out to train the instrument to recognize the different odour classes associated with WTP emissions. Two independent campaigns, conducted in March 2025 and July 2025, were used for field validation and to test the performance of the trained IOMS in terms of odour classification and quantification.
The use of field data acquired on a real plant over such a long period of time and the development and testing of the approaches in a complex real-world scenario surely represents one of the main strengths of this work, making it different from other studies developing more advanced data processing strategies, but mostly applied to oversimplified contexts.

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2. Material and methods

2.1 Plant description

The plant investigated in this study is a Waste Treatment Plant (WTP) dedicated to the conversion of the Organic Fraction of Municipal Solid Waste (OFMSW) into biomethane and compost.
Upon receipt, the waste is pre-treated to remove inorganic residuals before undergoing anaerobic digestion. The products of anaerobic digestion are digestate and biogas, both of which are intermediate products that are further processed. Specifically, biogas is upgraded to biomethane by removing impurities through a filtration process, while the digestate is mixed with lignocellulosic material and undergoes an aerobic process to produce compost.
The different process buildings of the WTP are controlled by a series of ventilation systems that extract exhaust air and convey it to a biofilter unit to reduce the concentration of volatile organic compounds (VOCs) before release into the atmosphere.
Different odour emission sources associated with various sections of the plant were identified:

- Fugitive emissions associated with the OFMSW reception building;
- Fugitive emissions associated with the OFMSW pre-treatment facilities;
- Conveyed emissions from the biofilters;
- Fugitive emissions of biogas from the biodigester and from valves or ducts used for its transport to the upgrading section.

2.2 Monitoring system

The monitoring system described in this study consists of one IOMS WT1, commercialized by Ellona (Toulouse, France), and a Vantage Pro2 weather station, commercialized by Davis Instruments Corporation (Hayward, USA).
Regarding the IOMS, the sensor chamber includes four metal oxide sensors (MOS), two electrochemical sensors specific for ammonia and hydrogen sulfide, one photoionization detector (PID) for VOC detection (calibrated in isobutylene), and sensors for measuring relative humidity and temperature inside the chamber.
The installation point of the IOMS was selected based on the final objective of the monitoring system, which is to detect odour emissions that may cause nuisance to nearby residents. For this purpose, a parametric dispersion model was applied to identify the directions of odour plumes that most frequently impact receptors, thereby allowing the optimal installation point of the IOMS to be defined at the fenceline of the plant.

2.3 Dataset acquisition

Six olfactometric campaigns were conducted from March 2024 to July 2025 with the aim of collecting gas samples from WTP emission sources to train and validate the IOMS. Odour samples were collected in different months in order to account for variability associated with environmental conditions, seasonality, and intrinsic variations in process operating conditions.
The samples obtained from the odour sources were analysed using dynamic olfactometry (EN 13725:2022) (CEN., 2022) to determine their odour concentration. Once the concentration of the pure sample had been established, dilution with ambient air was realized directly in the field, producing several diluted samples for analysis with the IOMS. For application at the fenceline, it is essential to reduce sample concentrations to levels similar to those expected during normal IOMS operation.
For the definition of the training dataset, samples acquired during the campaigns of March 2024, April 2024, July 2024, and September 2024 were used, while samples collected and analysed in March 2025 and July 2025 were used as an external test set. These two “test” campaigns were conducted as field validation in accordance with UNI 11761:2023 (UNI., 2023), with the purpose of assessing the reliability of the IOMS in properly discriminating and quantifying odour events generated by the plant.
Table 1 summarizes the total number of samples analysed by the IOMS, specifying the number of independent samples collected for each odour class, the number of diluted samples analysed by the IOMS, and their odour concentration ranges. Four main odour classes were considered: ‘Air’, representing ambient air at the plant fenceline in the absence of odour; ‘Biogas’, including samples collected from the digester and upgrading area; ‘Biofilter’, including samples collected at the outlet of the biofilters; and ‘Sheds’, including samples collected from the buildings dedicated to waste reception and pre-treatment.
During field analysis, it was observed that, due to improper operation of the biofilter unit, odours belonging to the ‘Biofilter’ class were very similar to those of the ‘Sheds’ class. This issue made the classification of the two classes particularly challenging for the IOMS; therefore, it was decided to merge these samples into a single macro-class called ‘Organic’.

Table 1: Samples analysed by the IOMS for the definition of train and test set with respective odour concentration range.

Odour Class	N° independent samples	N° diluted samples		Odour concentration range [ou_E/m^3]
		Train	Test	
Air	42	31	11	20-60
Biofilter	20	36	29	30-500
Biogas	14	40	23	20-870
Sheds	17	46	20	20-370

2.4 Data processing

For the study, a specific data pre-processing approach was developed. The signal pre-processing is focused on the normalization of sensor resistance according to Eq. (1):

$$y_{norm} = (y - y_{ref})/y_{ref} \quad (1)$$

where y is the raw MOS resistance, y_{ref} is the baseline reference MOS resistance and y_{norm} is the normalized MOS resistance. The reference resistance used for normalization is a "dynamic" value that correlates the resistance of a specific MOS sensor in non-odorous ambient air with the absolute humidity recorded during the analysis. In this way, the reference value is continuously adjusted to account for variations caused by different humidity levels. However, variations in sensor resistance are not only related to humidity interference but also to long-term drift, which can permanently alter sensor behaviour. To address both issues, the reference baseline is evaluated using two different strategies. In the first approach, the reference resistance is analysed over multiple months to identify unwanted variations associated with drift phenomena. Subsequently, Orthogonal Signal Correction (OSC) (Fearn, 2000) is applied to remove these undesired variations by eliminating signal components that are not correlated with the variable of interest.
In the second approach, the long-term variation problem is addressed by evaluating the reference baseline using a sliding window that considers only the most recent data acquired prior to the time of analysis.
In both cases, the reference baseline is estimated using regression functions based on exponential and power-law equations (Eq. (2) and Eq. (3)):

$$y_{ref} = A * \exp^{-\mathrm{kAH}} + c \quad (2)$$

$$y_{ref} = A * AH^{-k} + c \quad (3)$$

where *A* is a scaling factor, *k* is the decay coefficient, *c* is the offset parameter, and *AH* is the absolute humidity level recorded during the analysis.
After pre-processing, informative features are extracted from all MOS and electrochemical sensors. These features are used as input for a Principal Component Analysis (PCA), conducted as an exploratory analysis to reduce dataset dimensionality, identify possible clusters, and detect outliers.
Following this preliminary step, a feature selection procedure is carried out using the Boruta algorithm (Kursa, Jankowski and Rudnicki, 2010), in order to include only the most informative features in the model development.
For the implementation of the machine learning models, a two-step procedure was followed, consisting of the development of a classification model followed by a regression model. The classification model is based on a Support Vector Machine (SVM) classifier, which allows discrimination among the different odour classes. Then, based on the identified class, specific regression models were developed using Support Vector Regression (SVR) to estimate the odour concentration of the analysed samples.
Based on the different pre-processing approaches adopted, five different models were trained and evaluated using an external independent test set, as reported in Table 2.

Table 2: Models acronym with relative description.

Model acronym	Model description
No pret	Implementation of decision models without applying specific pre-processing
OSC exp	Implementation of decision models using OSC correction and exponential functions as pre-treatment
OSC pow	Implementation of decision models using OSC correction and power-law functions as pre-treatment
Slid exp	Implementation of decision models using sliding window and exponential functions as pre-treatment
Slid pow	Implementation of decision models using sliding window and power-law functions as pre-treatment

2.5 Model evaluation metrics

The IOMS output was evaluated using the metrics defined in the UNI 11761:2023 for the field validation.
To evaluate the odour classification accuracy, the overall accuracy index (Eq. (4)) and the recall index for each class (Eq. (5)) are considered.

$$Accuracy = \frac{correct\ classified}{total\ samples} = \frac{TP_i + TN_i}{total\ samples} \tag{4}$$

$$Recall = \frac{TP_i}{TP_i + FN_i} \tag{5}$$

where TP_i, TN_i, and FN_i indicates the true positives, true negatives and false negatives for each class *i* respectively.
On the other hand, regarding the regression models used for odour quantification (i.e., estimation of the odour concentration), the performance of the IOMS was assessed using Bland-Altman analysis (Giavarina, 2015). The choice of Bland–Altman analysis is related to the uncertainty associated with the reference method for odour concentration measurement, namely dynamic olfactometry (EN 13725:2022). Since concentrations estimated by dynamic olfactometry are subject to a significant level of uncertainty (approximately 50%), the use of traditional regression evaluation metrics is not appropriate. Instead, a method such as Bland–Altman analysis is more suitable, as it allows comparison between outputs of different methods with similar uncertainty.
Bland–Altman analysis evaluates the agreement between the outputs of dynamic olfactometry and the IOMS regression model by analysing the differences in the logarithm of odour concentration, thereby providing the bias, which is the mean of the differences, and "Limits of Agreement" (upper LoA and lower LoA), which define the range within which 95% of the differences between the two measurements are expected to lie. To apply Bland–Altman analysis, it is first necessary to verify whether the differences between the values estimated by the two methods are normally distributed. This can be done using the Shapiro–Wilk test, confirming that the resulting p-value is greater than 0.05.

3. Results

3.1 IOMS classification models

This section reports the results of the IOMS classification performance assessed using the external test set. To increase the robustness of the developed models, each SVM model was tuned using four different internal validation sets and subsequently evaluated on the test set. In this way, for each implemented model, four sets of classification metrics were obtained, and their average values are reported in Table 3, with the 95% confidence interval reported in square backets.
The model developed without any pre-treatment achieved the worst performance, with a global accuracy of 44% and a very low recall for the 'Organic' odour class (4%). In comparison, the models applying the pre-treatment approaches achieved significantly better results, with accuracies ranging from 88% to 93%.
The difference in performance is mainly related to an anomalous variation in the sensor resistance baseline values that occurred after the training period. Due to this drift effect, the sensor responses during field validation differ substantially from those observed during the training phase, and without proper compensation, the IOMS is no longer able to correctly classify the different odour classes.

Table 3: Classification accuracies and recalls for the models implemented.

Model	Accuracy	Recall		
		Air	Biogas	Organic
No pret	44% [39%-48%]	100% [100%-100%]	89% [82%-96%]	4% [0%-16%]
OSC exp	93% [90%-95%]	100% [100%-100%]	91% [80%-100%]	91% [84%-98%]
OSC pow	89% [85%-92%]	100% [100%-100%]	82% [71%-92%]	89% [81%-97%]
Slid exp	91% [91%-91%]	100% [100%-100%]	91% [91%-91%]	89% [89%-89%]
Slid pow	88% [87%-89%]	100% [100%-100%]	97% [93%-100%]	80% [80%-80%]

3.2 IOMS regression models

The IOMS was also tested to evaluate its ability to correctly estimate the odour concentration of the analysed samples, compared with the reference method, dynamic olfactometry (EN 13725:2022). The comparison was carried out for each model using Bland–Altman analysis.
For all models with pre-treatment, the Shapiro–Wilk test was performed, resulting in p-values higher than 0.05, indicating that the hypothesis of normality of the differences cannot be rejected and that Bland–Altman analysis can be applied. For the no pre-treatment approach, this criterion was not met; therefore, it was not possible to perform Bland–Altman analysis. As shown in Figure 1, the regression model without pre-treatment is not capable of correctly estimating odour concentration, instead producing a nearly constant predicted value (as indicated by the vertical line). As observed for the classification task, the regression models developed for the IOMS are also affected by sensor drift, leading to poor estimation of odour concentration.

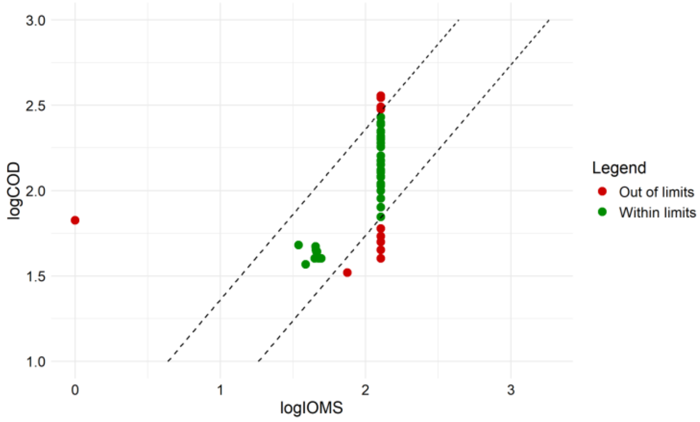

Figure 1: Comparison between odour concentrations estimated by the IOMS regression model (x-axis) developed using raw sensor signals, without applying OSC- or sliding window-based drift compensation, and odour concentrations measured by dynamic olfactometry (y-axis). Green points represent values within dynamic olfactometry confidence interval (i.e., dashed lines) while the red points represent the values outside.

The application of Bland–Altman analysis provides information on the bias, defined as the mean of the differences between the logarithms of the odour concentrations estimated by dynamic olfactometry and by the IOMS, as well as the upper and lower LoA, as explained in section 2.5. These parameters already provide a useful indication of the models' ability to estimate odour concentration; however, it is more informative to evaluate quantification performance using the same criteria for accuracy and intermediate precision defined in EN 13725:2022 for dynamic olfactometry. According to the standard, the accuracy criterion is satisfied if the logarithm of the bias is less than 0.217 (Eq. (6)), while for the intermediate precision criterion, the standard deviation of the observations (i.e., the differences between odour concentrations estimated by dynamic olfactometry and by the IOMS), in non-logarithmic form, multiplied by 1.96, should be lower than 3 (eq. (7)).

$$Accuracy\ criterion: |\log_{10} bias| < 0.217 \tag{6}$$

$$Intermediate\ precision\ criterion: 1.96 * std.dev < 3 \tag{7}$$

All the parameters just described as calculated for the different models tested are reported in Table 4. The accuracy criterion is satisfied by all models; however, all models exhibit values higher than 3 for the intermediate precision criterion. Nevertheless, the values obtained are close to the required limit, indicating that the IOMS performance related to odour quantification are comparable to those of the reference method.

Table 4: Bland-Altman parameters and intermediate precision criterion value for the different models.

Model	|bias|	Upper LoA	Lower LoA	Standard deviation	Intermediate precision criterion
OSC exp	0.08	0.40	-0.57	1.77	3.47
OSC pow	0.03	0.51	-0.56	1.88	3.68
Slid exp	0.02	0.49	-0.46	1.75	3.43
Slid pow	0.10	0.50	-0.70	2.02	3.95

4. Conclusions

The present study investigated the application of an IOMS at the fenceline of a WTP for the classification and quantification of odour sources. The main focus of the work was the development of specific data processing approaches based on pre-processing strategies designed to compensate for interferences related to humidity variations and sensor drift. Four different models were developed and compared with a classical approach based on raw data processing without any dedicated pre-processing. For this case study, an independent external test set was used to evaluate the performance of both classification and regression models. This test set consisted of odour samples analysed in a separate time period following the training phase. It is important to highlight that, after model training, an anomalous condition caused one of the sensors in the array to undergo a drastic change in baseline resistance, leading to a different response behaviour during field validation.
The results demonstrate that, in the absence of pre-treatment, IOMS performance is significantly affected by this drift. More in detail, the model achieved a low classification accuracy on the external test set (44%), and the regression model was not able to correctly estimate odour concentration values. Conversely, the models developed using dedicated pre-processing strategies were still able to correctly classify odour samples, with accuracies ranging from 88% to 93%. Moreover, their quantification performance was found to be comparable with the quality criteria defined in EN 13725:2022. Future studies will focus on trying to generalize the approaches here developed to other case studies and to other sensor arrays.

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