DOI 10.5162/EUROSENSORSXXXVI/OT5.73

Continuous Monitoring of Odour Concentration at the Inlet of a Scrubber with an E-Nose: Focus on the Management of Interferences

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Summary:

This work describes the implementation of an e-nose for the continuous measurement of odour concentration at a scrubber at a wastewater treatment plant, with the purpose of identifying odour peaks and investigate their causes. To this purpose, application-specific sampling and data processing were developed, able to deal with the interferences occurring in a complex industrial environment. Results show that instrumental predictions are within the confidence intervals of the reference method, and the system provided useful information for the plant operators to reduce the odour nuisance.

Keywords: electronic nose, environmental odour monitoring, odour concentration, odour abatement system, continuous measurement

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Background, Motivation and Objective

Odours represent one of the major causes of citizens’ complaints to local authorities, and have recently been included among the atmospheric pollutants to be monitored and controlled [1]. The reference method for monitoring environmental odour emissions is dynamic olfactometry (DO) (EN13725:2022), which has the drawback of being expensive and discontinuous [2]. For this reason, Instrumental Odour Monitoring Systems (IOMS) for the continuous monitoring odours are gaining more and more popularity to support plant managers to promptly identify anomalous situations and put effective interventions in action to reduce the odour impact.

This work describes the implementation of an IOMS based on chemical sensors for the continuous estimation of odour concentration at the inlet of a scrubber treating the air sucked from a primary settler at a wastewater treatment plant (WWTP), with the purpose of analysing the source variability and investigating possible causes for the odour peaks observed by previous olfactometric measurements.

Description of the New Method or System

Continuous odour measurement directly at the emission source is challenging because the sensors are exposed to a harsh environment characterized by several potential (and mostly unknown) interferences, thus requiring the optimization of both IOMS hardware and software for the specific application.

As hardware, we used a commercial EN (WT1, Ellona) with 8 sensors: 4 MOX, 3 electrochemical sensors specific for H_2S, NH_3 and mercaptans, and one PhotoIonization Detector (PID). The sampling line was designed with the purpose to deal with the specificities of the application (i.e. very high moisture and H_2S concentrations) by including a 1:1 dilution system using external air and a condensate trap.

The EN was further connected to an automatic gas sampler appositely developed for this activity, consisting of a hermetic suitcase of ca. 30 L, which enables the filling of one Nalophan® bag suitable for olfactometric measurements. The sampler can be activated manually or automatically by the EN, whenever a given threshold is exceeded.

Concerning the data processing, the quantification model should include application-specific compensation for the presence of interferents that may affect sensor responses and lead to false odour detections, and also account for the high uncertainty of the reference method (DO), which is commonly considered to be about a factor of 2 [2]. For this reason, we developed a dedicated data processing pipeline including a specific normalization step, which enabled to eliminate daily oscillations of the sensors' responses, whose causes were not identified and which were totally uncorrelated with the odour concentration.

The quantification model was based on Support Vector Regression (SVR) [3], which, compared to linear regression models, is more suitable to deal with non-linear data and is also able to account for the uncertainty of the reference method. The model was trained using dynamic calibration for about 1 month: transient signals collected by the EN in the field were correlated with the odour concentration of 32 samples collected at the scrubber inlet and analysed by DO. Samples were taken on different days and under different operating conditions, with the purpose of including as much as possible the source variability in the training. Tuning of the SVR model involved two steps. First, the value of ε was fixed at the value of the average uncertainty of the olfactometer used for DO (i.e. 0.31 in logarithmic scale). Concerning C and gamma parameters, cross validation applied to a grid search method was used, returning their optimal value equal to 2 and 0.3, respectively.

Results

To eliminate the daily oscillation trend, which wasn't correlated to any other investigated parameter (humidity, temperature, wastewater flowrate, etc.), nor to the odour concentration, we decided to use an observational approach: since the oscillatory trend was repeatable over time from one day to the other, we calculated an average reference resistance value for each sensor by averaging all the resistance values registered by the sensor at the same hour for one month (Fig. 1a). By dividing the instantaneous resistance by this averaged reference value, we obtained the curves shown in Fig. 1b, where it is clearly visible that the unwanted oscillations are removed, and only deviations from the averaged reference values are visible as peaks. Fig. 2 shows the results of the SVR model testing on an independent dataset of 13 samples collected after training the model, expressed in terms of Limits of Agreement (LoA) with the reference method (DO) by application of the Bland-Altman method [4], proving a very good correlation between instrumental predictions and measured values.

Even though the algorithms used are not particularly innovative by themselves, their customization for the specific application, enabling the obtainment of useful results in a complex industrial context, which turned out to be effective in supporting the plant operators in identifying the causes of the odour nuisance, can be considered as an example of successful implementation of EN in a real-life industrial application.

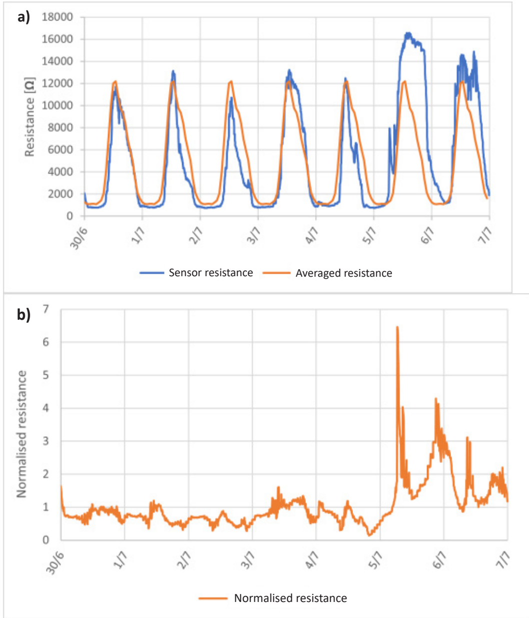

Fig. 1. a) Example of sensor resistance and averaged reference values, b) normalized responses

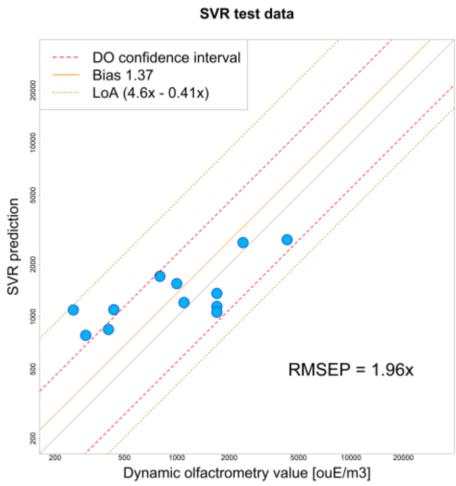

Fig. 2. Results of SVR model testing (blue dots). Red lines represent the DO uncertainty limits. The upper and lower LoA are reported in green, while the bias is represented by the continuous orange line

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