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# Odour Classification and Concentration Estimation with a Chemical Sensor Array on a Drone

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**Summary:**

We present an approach to improve the accuracy of odor concentration prediction in wastewater treatment plants using drones equipped with electronic noses. Source specific regression models are more accurate than models calibrated on all the data. Therefore, we could leverage these source-specific models to perform better predictions by integrating a source classification engine before odor prediction,. In the scenario explored, the improvement is limited by the source classification accuracy.

**Keywords:** Environmental monitoring, electronic nose, drone, odour quantification, source classification

### Background, Motivation an Objective

In a previous proposal, we suggested using a drone equipped with an Instrumental Odour Monitoring System (IOMS) to measure odour levels in real-time in a wastewater treatment plant (WWTP). The system includes a complete signal and data processing workflow that estimates the odour concentration based on EN13725.

Wastewater treatment plants have various sources of odour such as bioreactors, settlers, desanders, etc. However, it is difficult to determine the exact source that is producing the odour. These sources have diverse chemical profiles that could potentially provide information about the odour origin. Therefore, the classification of odour sources is an important aspect of odour monitoring.

In our previous work, we presented a single prediction model that incorporated data from all the odor sources. However, in this work, we propose an alternative method that involves using source-specific calibration models. To implement this approach, we have included an odor source classification model in our new workflow.

### Description of the New Method or System

The dataset used in this exploration was acquired in the Molina de Segura WWTP. The measurement campaign and machine learning development strategy has been previously described. The dataset contains 40 measurements carried out along in month in summer 2020. The dataset contains measurements carried out in the vicinity of four different odour sources, namely: Settler (m1), Biological (m2), Chimney(m3) and Desander (m4).

The new data processing workflow comprises two key modelling steps: source classification and odour concentration quantification.

To quantify the odour, Partial Least Squares (PLS) regression and feature selection via interval-PLS is performed as described in earlier research [2]. The difference here is that in addition to the global model (mg) including all the sources we have learned source-specific odour prediction models (m1 to m4)

To classify the sources, a random forest classifier is used. A significant feature of the classifier is the possibility to defer source label assignment, when the classification confidence is low. If the classification confidence is high, source

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specific calibration models are used, otherwise the global calibration model is used.

## Results

Table 1 describes the results for the general model, table 2 assuming perfect knowledge of the emitting source, and table 3 and figure 1, describe the results for the final workflow.

The best results are found when the odour source is previously known, but unfortunately this goal cannot be achieved in practice in our scenario.

The best predictive performance was obtained when 60% of the samples were predicted with the general model and 40% of the samples were predicted with class specific models. Of this 40%, 80% were correctly classified.

The final proposal only marginally improves the results of the general model.

## Illustrations, Graphs, and Photographs

*Tab.1: Summary of the predictions for the general model, s1 to s4 correspond to the sources Settler, Biological, Chimney and Desander, respectively. T is the total prediction. Bias, Std and RMSE are expressed as factors. Corr. Is correlation.*

| | s1 | s2 | s3 | s4 | T |
|---|---|---|---|---|---|
| Bias | 1.29 | 0.89 | 0.99 | 0.90 | 1.00 |
| Std. | 1.71 | 2.00 | 2.71 | 1.36 | 2.00 |
| RMSE | 1.76 | 1.96 | 2.56 | 1.36 | 1.94 |
| Corr. | 0.91 | 0.84 | 0.83 | 0.96 | 0.86 |

*Tab.2: Summary of the predictions for the source-specific models with perfect sources classification.*

| | s1 | s2 | s3 | s4 | T |
|---|---|---|---|---|---|
| Bias | 0.94 | 0.96 | 0.94 | 0.98 | 0.96 |
| Std. | 1.33 | 1.78 | 2.22 | 1.16 | 1.68 |
| RMSE | 1.27 | 1.64 | 2.11 | 1.13 | 1.67 |
| Corr. | 0.97 | 0.89 | 0.90 | 0.99 | 0. |

*Tab.3: Summary of the predictions for the models determined by the classifier output.*

| | s1 | s2 | s3 | s4 | T |
|---|---|---|---|---|---|
| Bias | 1.19 | 0.80 | 1.03 | 0.87 | 0.96 |
| Std. | 1.69 | 1.99 | 2.42 | 1.30 | 1.90 |
| RMSE | 1.69 | 2.00 | 2.32 | 1.33 | 1.89 |
| Corr. | 0.91 | 0.83 | 0.87 | 0.97 | 0.88 |

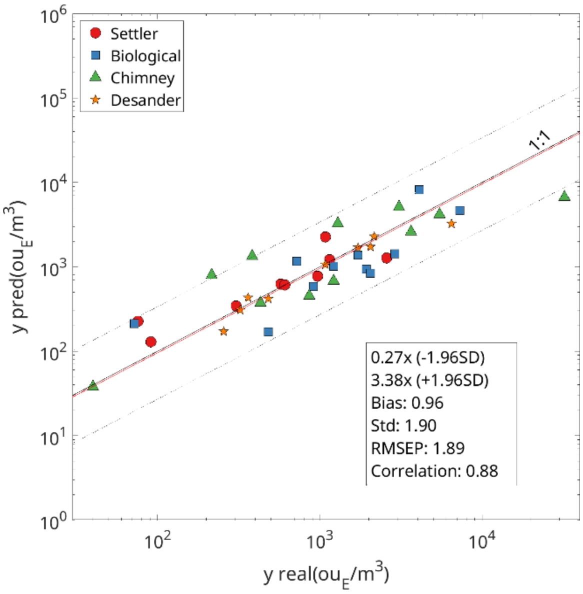


*Fig. 1. Predicted odour plotted against real odour concentrations for the models determined by the classifier.*

## References

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