Statistical Prediction Models for the Odour Quantificaton in Terms of Odour Concentration: Analysis and Comparison

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Abstract

Measuring odour concentration is a significant step to achieve efficient environmental odour management in continuous, objective and repeatable manner. To deal with this, researchers developed instrumental odour monitoring systems (IOMS) by applying odour monitoring models (OMM) for prediction. At present, limited data are available in the literature regarding the exploration of different prediction models to quantify the odour emissions in terms of odour concentration.

This study presents and compares different types of parametric and nonparametric predictive models (i.e., artificial neural network (ANN), multivariate adaptive regression splines (MARSpline), partial least squares (PLS), multiple linear regression (MLR), response surface regression (RSR)) with the aim to increase the reliability of the odour concentration prediction by using IOMS for environmental odour monitoring. The experimental studies are carried out considering odour samples collected from the organic fractions in municipal solid waste. All samples undergone seedOA eNose and dynamic olfactometry analysis as reference methods. The coefficient of determination (R^2) and root mean square error (RMSE) were used to measure the goodness-of-fit of the models.

Results indicate the strengths and weaknesses of the analyzed models and highlight their accuracy in terms of odour concentration prediction.

Keywords: artificial neural network, dynamic olfactometry, environmental odour, instrumental odour monitoring system, municipal solid waste

1. Introduction

Environmental odours management emitted from the municipal solid waste (MSW) treatments, particularly linked to the decomposition of the organic matter, is a challenging task that needs to be solved (Belgiorno et al., 2012; Chang et al., 2019). Odour concentration measurement plays an important role to strategically address this problem.

At present, different methods are employed, such as sensorial, analytical and combined sensorial-analytical methods to characterize and measure the odour emissions (Zarra et al., 2012). Instrumental odour monitoring systems (IOMS) represents a recent new avenue in this field (Giuliani et al., 2012) which has a combined feature of sensorial and analytical methods. Despite of its cleverness, IOMS still possess different shortcomings, among those are related to the most suitable computational model that can be embedded in the system to accurately predict odour classification and concentrations (Zarra et al, 2018; Galang et al., 2018).

This study delves on the principal statistical methods that are applied in the IOMS to monitor environmental odours. The application of partial least square (PLS), multiple linear regression (MLR), response surface regression (RSR), artificial neural networks (ANN) and multivariate adaptive regression splines (MARSpline) used to predict the odour concentration are presented and discussed. Experimental studies are carried out by considering real odourous samples collected from the organic fraction of municipal solid waste (OFMSW). A comparative analysis based on individual accuracies was highlighted and the optimum prediction model has been pointed out.

2. Experimental Activities

2.1. Samples preparation and analysis

A sample of 5 kg total of organic fraction, composed of well-defined quantities of the different waste fraction materials, was prepared to carry out the experimental activities. The realization of the same type of sample was repeated to conduct 8 different campaigns. For each campaign, 10 different air samples were collected from the investigated experimental waste samples, by using the vacuum sampler in accordance to the EN13725:2003, at different times elapsed from their production. Also, 2 blank air samples were considered to represent the lowest detection limit of 0,00 OU_E/m^3. A total of 82 samples in the entire sampling program were carried out.

All the samples have been analyzed by dynamic olfactometer (DO) and with the seedOA IOMS to generate the data set used to elaborate and validate the odour concentration prediction model.

2.2. Model evaluation and validation

The whole obtained data set was split into two groups: the first composed of 71 profiles, used in the training phase of the IOMS, and the second represented by 11 profiles, for the validation of the elaborated model. Coefficient of determination (R2) and root mean square error (RMSE) are applied to attest the veracity of the models according to Galang et al (2018). Higher R^2 indicates a high level of confidence while lower RMSE presents closeness of the measured and predicted observation.

3. Results and Discussion

Figure 1 depicts the obtained R^2 values for all the models during training period.

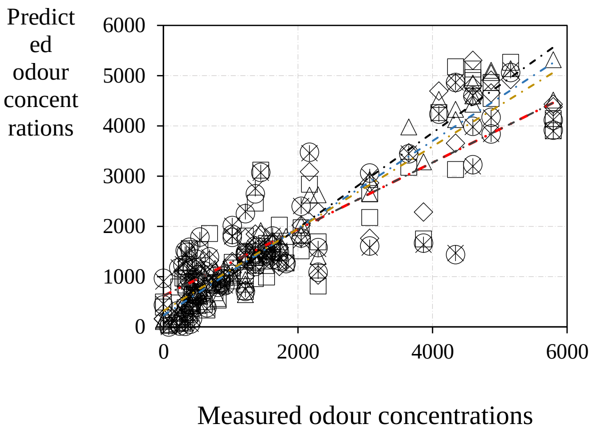

Figure 1. Correlation between the measured odour concentrations vs. the results of the different prediction models during IOMS training (Remarks: each color of a regression line represents a technique with corresponding symbol of its data (i.e., Δ = ANN, O = PLS, ✳ = MLR, ◊ = RSR, □ = MARSpline))

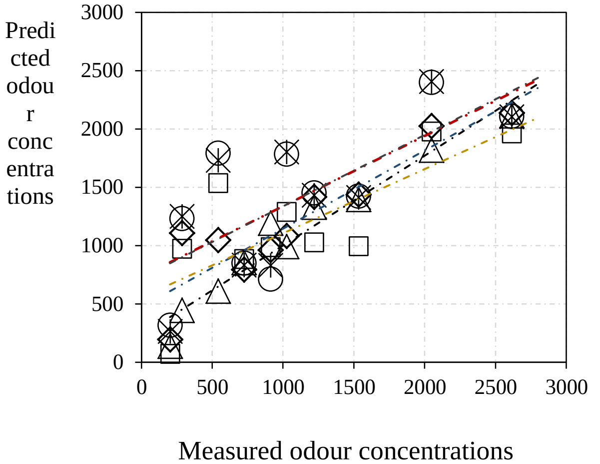

Figure 2. Correlation between the measured odour concentrations vs. the results of the different prediction models after validation (Remarks: each color of a regression line represents a technique with corresponding symbol of its data (i.e., Δ = ANN, O = PLS, ✳ = MLR, ◊ = RSR, □ = MARSpline))

The R^2 for ANN, MARSpline, PLS, RSR and MLR (Fig. 1) were 0,9660, 0,8261, 0,7172 , 0,9042 and 0,7178 respectively, while for the RMSE (OU_E/m^3) were found the following values: 289,59, 651,59, 838,08, 487,10 and 837,39. As shown the ANN highlight the best performances.
The relevance of the prediction models was evaluated by applying a separate set of data to verify their individual generalizing capability. Figure 2 presents the obtained R^2 values for all the models after validation.
The R^2 for ANN, MARSpline, PLS, RSR and MLR (Fig. 2) were 0,9464, 0,5710, 0,5158, 0,8230 and 0,5254 respectively, meanwhile, for the RMSE (OU_E/m^3) were found the following values:216,35, 482,97, 594,31, 348,34 and 583,97. The validation confirms that ANN highlight the best performances to predict the odour concentrations.

4. Conclusion

The performance of IOMS has been verified in the measurement of odour concentrations by using real environmental odour samples collected from the organic fraction of the municipal solid waste. Among the investigated techniques, ANN highlights the most robust and reliable results in terms of R^2 (training, 0,9660; validation, 0,9464) and RMSE (training, 289,59 OU_E/m^3; validation, 216,35 OU_E/m^3).

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