

Multi-Season Field Evaluation of a Temperature-Modulated SMOX Sensor Array for NO₂ and O₃ Monitoring

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Summary:

Semiconducting metal oxide gas sensor arrays, when combined with temperature modulation, have demonstrated promising performance in laboratory tests for outdoor air-quality applications. However, their suitability for long-term field deployment across multiple seasons remains insufficiently validated. In this study, the system was deployed alongside an air-quality reference station over 17 months. The model for predicting NO₂ and O₃ achieved a normalized root-mean-square error of less than 8%, demonstrating robust multi-season outdoor performance.

Keywords: Outdoor Air Quality, SMOX, Temperature Modulation, Gas Sensor, Convolutional Neural Networks

Introduction

Driven by the need for spatially resolved air pollution monitoring in urban areas, low-cost gas-sensing solutions have attracted increasing attention [1], [2]. Temperature-modulated semiconducting metal oxide (SMOX) gas sensor arrays are promising due to their low-cost, small size and high sensitivity. Laboratory studies have demonstrated the ability to quantify mixtures of four major air pollutants (CO, NO₂, O₃, SO₂) within concentration ranges relevant to outdoor air-quality applications [3]. So far, demonstrations in real outdoor air have been limited to ozone prediction during a three-month summer period [3]. Due to cross-sensitivity to environmental factors, long-term and multi-season validation is essential. This study, therefore, presents a 17-month field evaluation of the sensor array for predicting NO₂ and O₃.

Materials and Methods

The custom-built E-Nose module mainly consists of a micropump (mp6, Bartels Mikrotechnik, Germany), responsible for creating a continuous flow of air through the sensor chamber, and a commercially available gas sensor array SGP40 (Sensirion, Switzerland). The gas sensor consists of four subsensors, each made of a different material, that can be temperature-controlled. A temperature-modulation profile ranging from 25 °C to 375 °C was applied in a descending-then-ascending staircase pattern, with a sudden decrease in temperature at the center. Each modulation cycle lasted 190 seconds and was applied simultaneously to all pixels, except for

subsensor four, which was limited to a maximum temperature of 300 °C due to material constraints. The E-Nose was deployed in close proximity to the reference station Parco Santa Chiara in Trento, Northern Italy. The station is situated in an urban background environment and provides hourly mean concentrations of ozone (O₃), nitrogen dioxide (NO₂), and sulfur dioxide (SO₂), measured in accordance with European standards. The reference data were obtained via the European Environment Agency's (EEA) publicly accessible download service.

To align the reference data with the sensor modulation frequency, the air-quality measurements were interpolated using cubic splines. A logarithmic transformation was applied to the sensor resistance, while a $\log(x + 1)$ transformation was applied to the pollutant concentrations to approximate a linear relation between the inputs and targets. The complete dataset was split into blocks of three days and randomly assigned to the train (70%), validation (10%), or test (20%) set. The convolutional neural network (CNN) architecture consists of three convolutional layers followed by two fully connected layers, as previously proposed by Kobald et al.[3]. As input, the model receives the two-dimensional sensor response (190×4) corresponding to a single modulation cycle. The output layer predicts the concentrations of both target pollutants.

Results and Discussion

The outdoor air-quality dataset spans from October 2024 to February 2026 and comprises approximately 12,000 hourly mean values. Since

the maximum concentration of SO_2 is below 5 ppb and therefore well under the threshold of 38 ppb for “Very good” air-quality, this pollutant was excluded from further analysis. The concentration distributions of O_3 and NO_2 are depicted in Figure 1 and exhibit pronounced seasonal variability. Nitrogen dioxide concentrations are higher during the colder months (October–March) and mostly remain within the “very good” levels in summer. A maximum of 53 ppb is reached, with a single outlier of 112 ppb likely attributable to a local emission event. Even more dependent on seasonal changes is the ozone concentration: The median concentration rise by approximately one order of magnitude from winter (3.6 ppb) to summer (33.6 ppb). During the warmer months (April–September), approximately 19% of hourly values fall into the “medium” air-quality category or worse, with peak ozone concentration reaching up to 101 ppb.

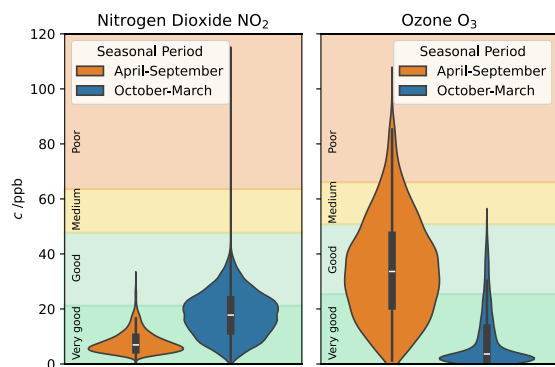


Figure 1: Distribution of NO_2 and O_3 concentration for the summer and winter seasons. In the background is the air quality index as defined by the EEA.

The sensor dataset acquired over the same time frame comprises approximately 200,000 modulation cycles, corresponding to 88% of the expected data. The predicted and reference concentrations for the test dataset are shown in Figure 2. At higher concentration levels, the majority of predictions fall within the 25% relative error margin indicated by the dashed black lines. In contrast, predictions at low concentrations (NO_2 : < 20 ppb, O_3 : < 40 ppb) exhibit substantial deviation. This is further reflected in the increased mean relative prediction errors of 17.5% for NO_2 and 28.8% for O_3 , as reported in Table 1. However, as this concentration regime corresponds predominantly to the “good” or “very good” air-quality index, the deviations may still be acceptable for applications focusing on elevated pollution levels. Further, prediction outliers often appear as drifting patterns and occur in temporally adjacent clusters. The root mean squared error (RMSE) was normalized by the concentration range, enabling comparison of predictive performance between the two pollutants. Overall, the

model performs similarly well, but slightly better for ozone prediction, with a normalized RMSE of 6% compared to 7.5% for NO_2 . The obtained prediction errors are comparable to those reported by Kobald et al. [3] for experiments conducted using a gas mixing system, with normalized RMSEs of 7.3% for O_3 and 6.3 % for NO_2 .

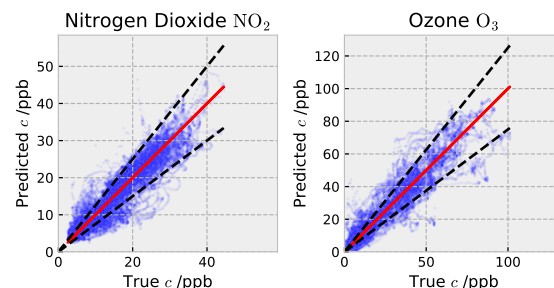


Figure 2: Prediction results based on the test dataset consisting of over 39,000 predictions from 93 days. The red line indicates the perfect prediction and the dashed black lines the 25% relative error margin.

Tab. 1: Prediction error for the test dataset.

Error Metric	NO_2	O_3
Mean Relative Error / %	17.5	28.8
RMSE / ppb	3.2	6.0
Normalized RMSE / %	7.5	6.0
Mean Absolute Error / ppb	2.3	3.3

Future work in this ongoing field evaluation should include external validation using a test set derived from the final portion of the dataset. Additional improvements in predictive performance should be evaluated by incorporating environmental variables (e.g., humidity and temperature) as inputs to the model. Overall, this study demonstrated the feasibility of temperature-modulated SMOX sensor arrays for real-world outdoor air-quality monitoring of NO_2 and O_3 .

References

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