Use of electrochemical sensors for measurement of air pollution: correcting interference response and validating measurements

Eben Cross¹, David Lewis^{1,2}, Leah R. Williams¹, Gregory Magoon¹, Michael Kaminsky³, Douglas Worsnop¹ and John Jayne¹

5 ¹Center for Aerosol and Cloud Chemistry, Aerodyne Research, Inc., Billerica, MA 01821 USA ² Department of Chemistry, Connecticut College, New London, CT 06320 USA ³ Massachusetts Institute of Technology, Cambridge, MA 02139 USA

Correspondence to: Eben Cross (escross@aerodyne.com)

Supplemental.





Figure S1. Continuous 5-min average non-pollutant data acquired with the ARISense system - tracking ambient variability in temperature, pressure, humidity, solar intensity, ambient noise, and wind speed & direction at the Roxbury DEP monitoring site.

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Meteorological conditions cover a transition from warmer (summer) to cooler (late-fall) seasons in the NE US. Temperature and humidity measurements shown reflect the conditions within the gas-sampling flow cell of the integrated system, the metrics most relevant to modelling EC interference effects derived from environmental conditions. The break in ARISense data from July 30 -August 6 was intentional, corresponding with temporary removal of the system from the site to execute a short-term experiment at an alternate location. Short term interruptions in sampling occurred during the sampling interval, primarily caused by power 20 interruptions at the site. The ARISense system is programmed to automatically initiate sampling on power-up, and was able to regain stable operation each time power was restored at the site. One data-feature of note is the high degree of correlation between

the ambient noise level and wind speed. For ARISense v1 systems, the microphone integration lacked a wind-screen, resulting in wind-derived noise dominating the signal for conditions in which wind speeds ≥ 4 MPH. Subsequent versions of the system will

include a wind-screen to minimize wind-derived signal in the microphone and improve audible resolution of other noise sources in close proximity to the node.





Figure S2. Comparison of two different input matrices for modelling electrochemical sensor response to ambient NO₂ concentration. The input matrix for Model A includes the working electrode voltages from the NO2-B43F and Ox-B421 sensors along with temperature and humidity. Model B is trained with additional sensor inputs including both the working and auxiliary electrode signal from each electrochemical sensor identified as statistically interdependent via the HDMR analysis. The results underscore the fact that inclusion and/or exclusion of raw sensor measurements from the HDMR input matrix dramatically improves the data reduction. The results shown include the full co-location data set with data points representing 5-minute averages. Of the data shown, the same 35% were used to train each model. The improvements observed for the input matrix in model B underscores the utility of the HDMR approach when sufficient variability in raw sensor signal and environmental sampling conditions are captured by the input matrix.

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