Use of forecasting models for improved PID control in wastewater treatment

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Contents

Introduction

Ammonia is removed from municipal wastewater using aeration, which is costly. Four different cascade control aeration configurations are compared to identify the *most stable* (i.e., least variable) operating condition–this will assist wastewater treatment plant operators in maintaining a low concentration of ammonia in the treated water. However, to *improve accuracy* and *reduce mechanical wear* of aeration systems the time lag associated with feedback control needs to be reduced. By forecasting the response variable, ammonia in the aeration basin, to account for the lag, it is hypothesized that the aeration control will improve. The advantages of forecasting using statistical and machine learning models is (a) no additional sampling, microbiological analysis, or proprietary software is requried to build the model and (b) the forecast can easily replace the current measured value of ammonia in the supervisory control and data aquisition (SCADA) system of the wastewater treatment facility–which lacks advanced control schema. The manuscript is organized as follows: (1) an introduction to control systems in wastewater treatment facilities, (2) summary of methods for quantifying variation in multivariate systems, (3) summary of staistical and machine learning methods used to build the ammonia forecasting models, and (4) an assessment of how forecasting models can improve conventional control in wastewater treatment.

// Literature review

Control in wastewater treatment

- PID and cascade control
- Feedback and feedfoward
- Advanced modeling and statistical process control

Nutrient removal

- Activated sludge and the role of aeration
- DO control: pros and cons
- ABAC: pros and cons

Methods and Materials

Boulder Water Resource Recovery Facility

- DO and ABAC configurations The data compiled for the following analysis can be found in the Appendix.

Stability assessment

- Total sample variance
- Generalized sample variance

Ammonia forecast

- Training and testing datasets

Statistical modeling

- Diurnal model Fit a linear model where the response is ammonia (*Z7 NH4*) and the predictors are various degrees of sine and cosine functions.

- Linear model

  - Adaptive lasso

Machine learning

- Neural network model

Results

Stability assessment

Ammonia forecast

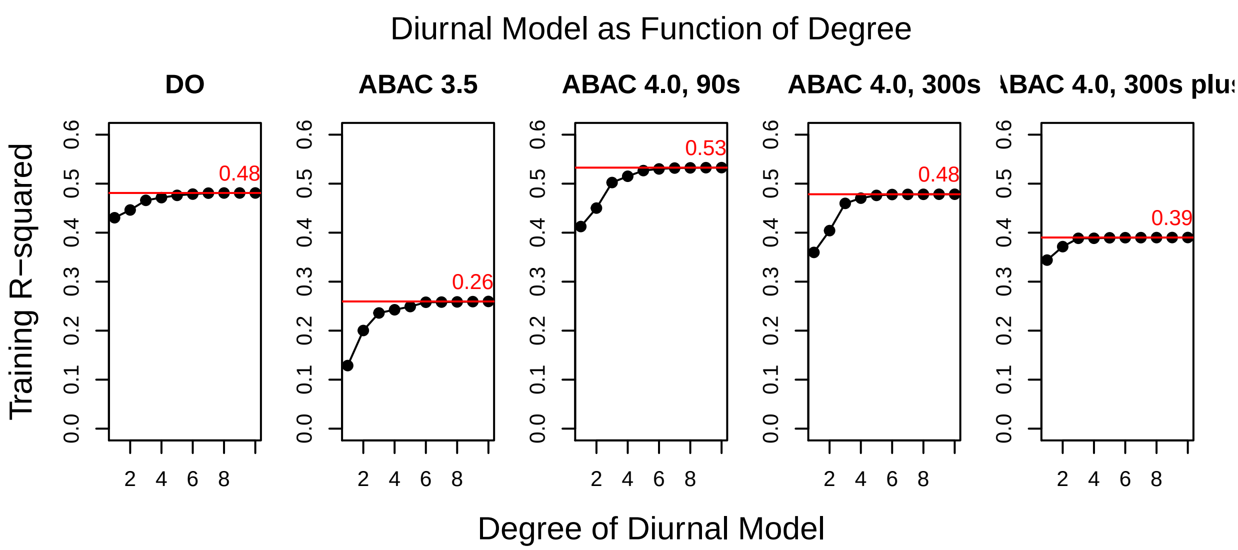
Diurnal model

The initial diurnal model fit used a single sine/cosine pair where $t = 0 - 2\pi$:

$$\hat{y}_t = a_1 sin(t) + a_2 cos(t) + b$$

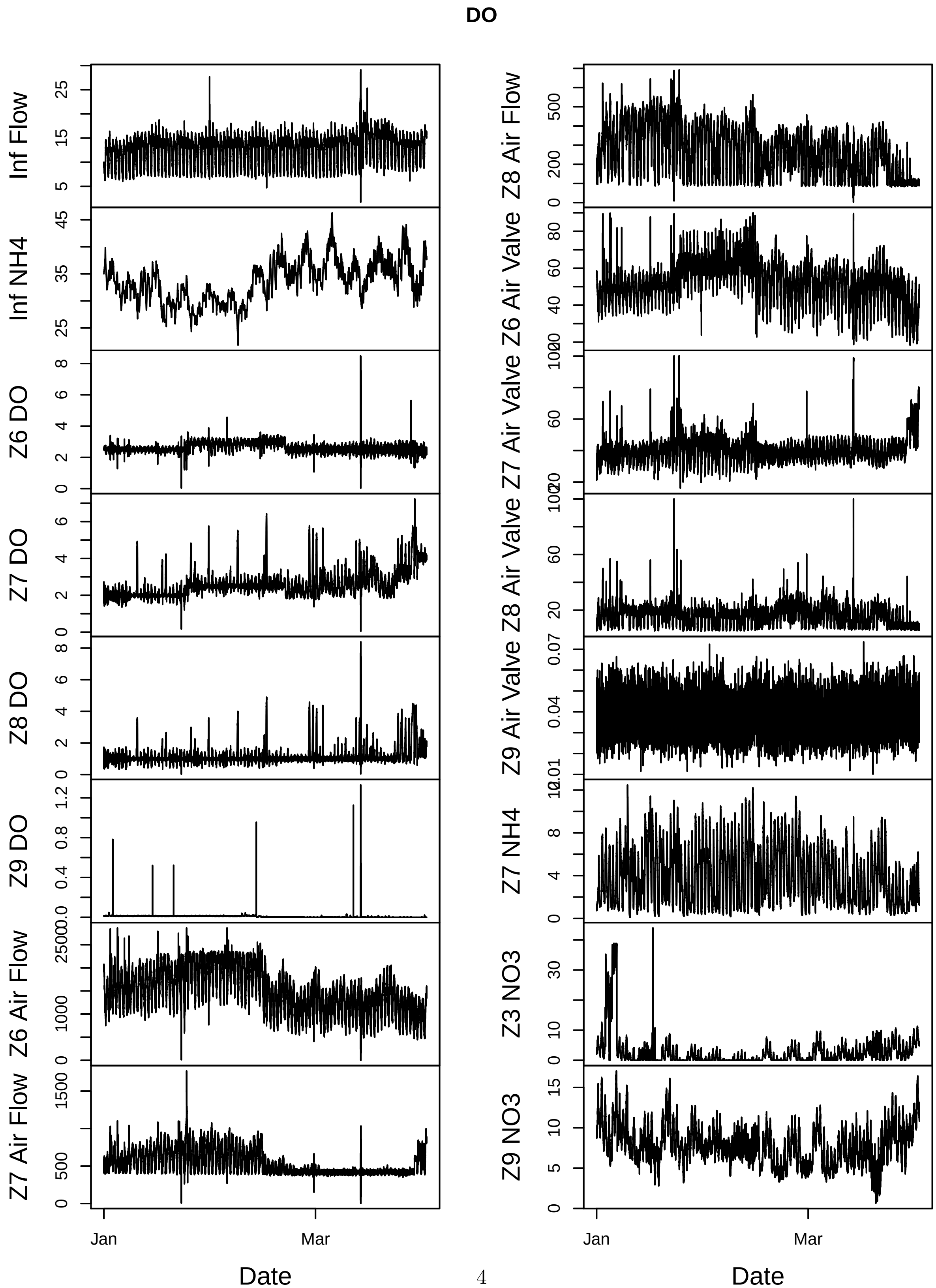
However, this approach did not capture all visible cyclic patterns. Further testing evaluated the model fit of multiple sine/cosine pairs:

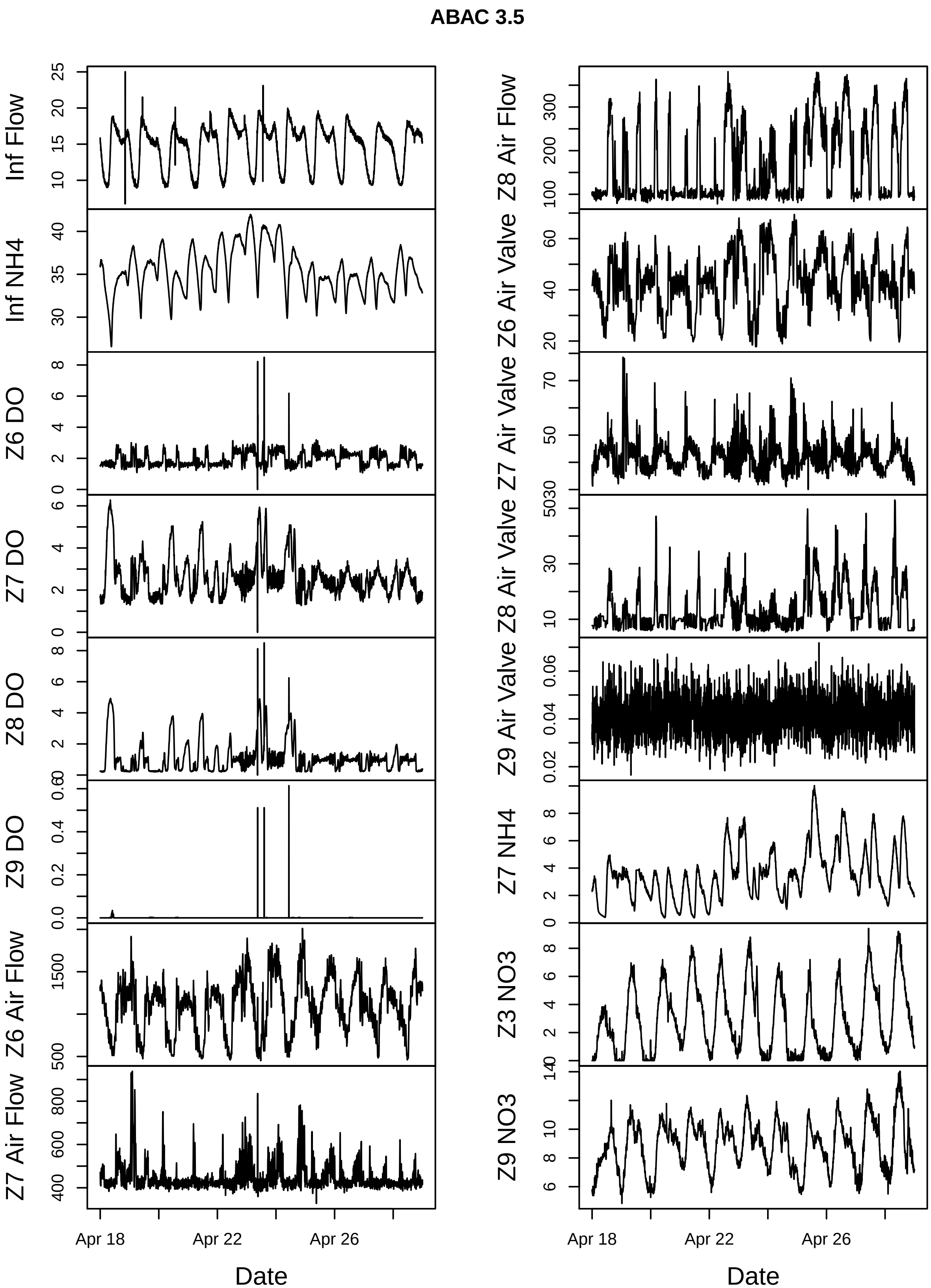
$$\hat{y}_t = a_1 sin(t) + a_2 cos(t) + a_3 sin(2 \cdot t) + a_4 cos(2 \cdot t) + ... + a_{2n-1} sin(n \cdot t) + a_{2n} cos(n \cdot t)$$



Appendix

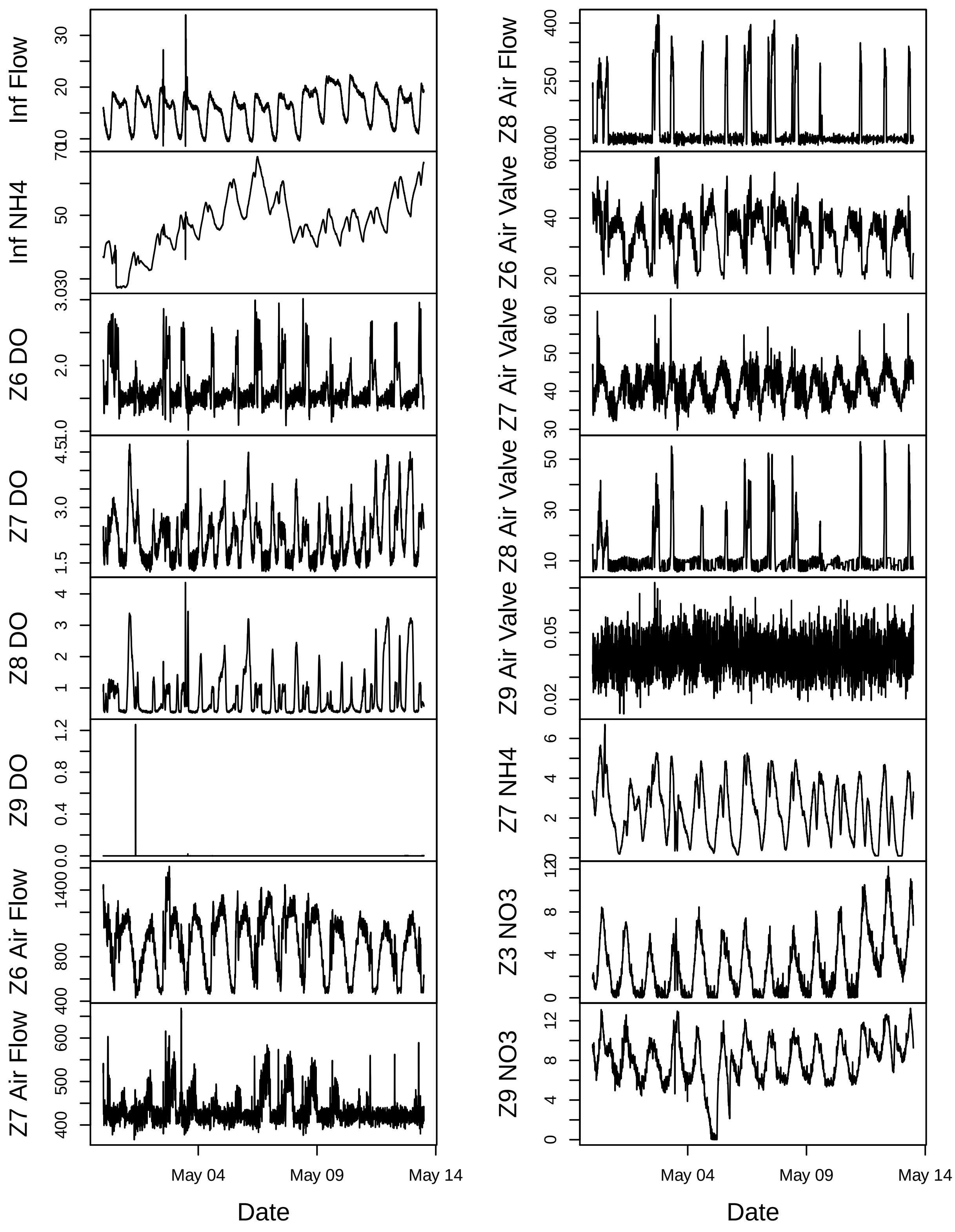
Timeseries





ABAC 3.5
Inf Flow
Inf NH4
Z6 DO
Z7 DO
Z8 DO
Z9 DO
Z6 Air Flow
Z7 Air Flow
Z8 Air Flow
Z6 Air Valve
Z7 Air Valve
Z8 Air Valve
Z9 Air Valve
Z7 NH4
Z3 NO3
Z9 NO3
Apr 18
Apr 22
Apr 26
Date

ABAC 4.0, 90s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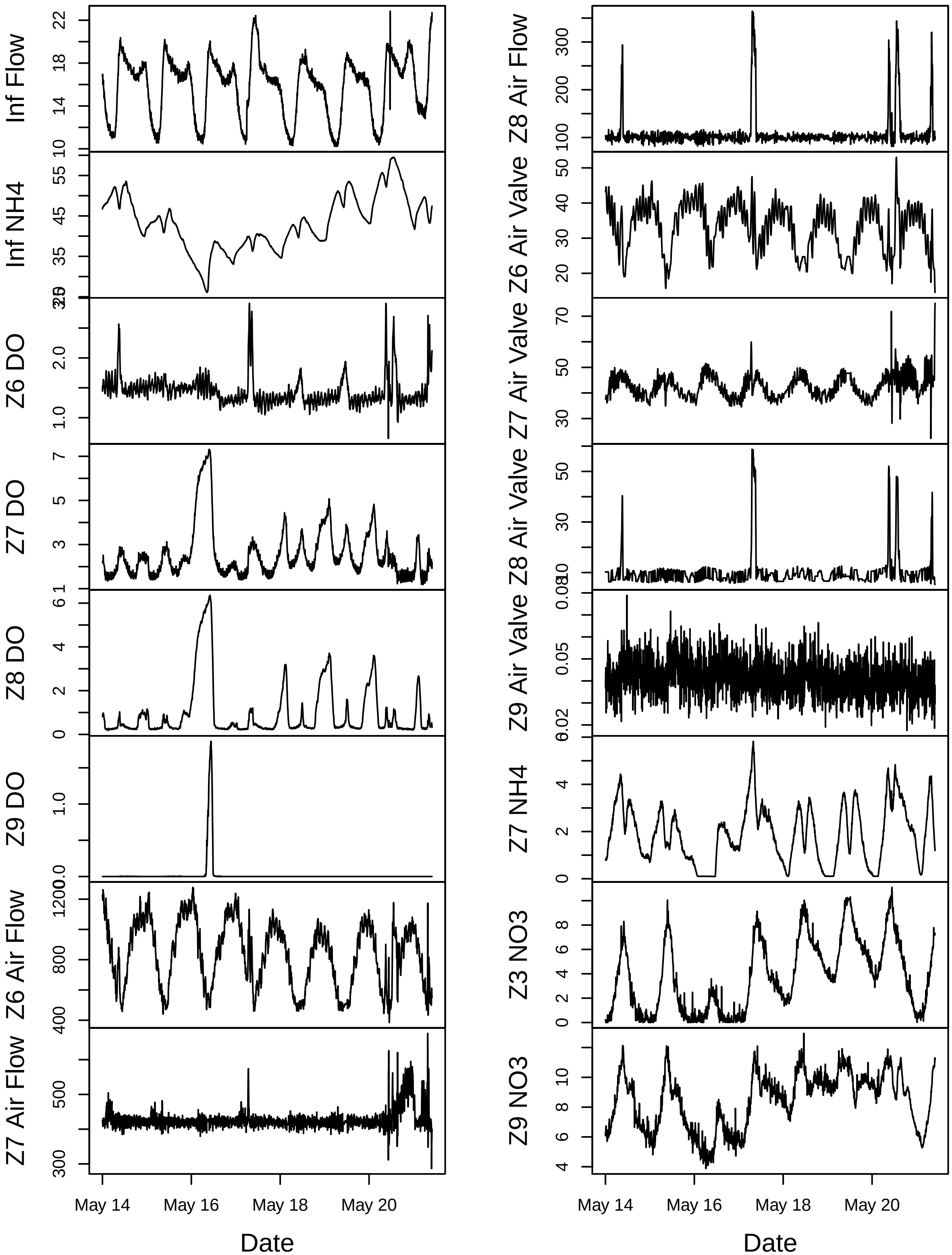
Inf NH4
Z6 DO
Z7 DO
Z8 DO
Z9 DO
Z6 Air Flow
Z7 Air Flow
Z8 Air Flow
Z6 Air Valve
Z7 Air Valve
Z8 Air Valve
Z9 Air Valve
Z7 NH4
Z3 NO3
Z9 NO3
May 04
May 09
May 14
Date

ABAC 4.0, 300s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Z6 DO
Z7 DO
Z8 DO
Z9 DO
Z6 Air Flow
Z7 Air Flow
Z8 Air Flow
Z6 Air Valve
Z7 Air Valve
Z8 Air Valve
Z9 Air Valve
Z7 NH4
Z3 NO3
Z9 NO3
May 14
May 16
May 18
May 20
Date
Date

ABAC 4.0, 300s plus