Data quality improvement in automated water quality measurement stations

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Stats & Control Meeting 2014

École Polytechnique Montréal

May 22-23 2014

Problem definition

Hydrological systems

Effective management of water bodies

Reliable water quality information

Trustable further application

Modeling, Decision making, Control

Problem definition

- Better description of water systems with fast dynamics

Application of In-situ Automated Continuous Monitoring Stations!

Problem definition

- In situ automated continuous monitoring stations:
  - Information-rich data sets √
  - Capturing pollutions dynamics √
  - Reduce costs √
  - Huge/complex data sets X
  - Errors and uncertainties X
  - Insufficient sensor reliability X

➡ **Data evaluation/validation is crucial**

In situ monitoring stations

- Municipal treatment plant
  (Copenhagen, Denmark)
- Water quality variables:
  - pH, TSS, NH_4, Turbidity,...
- Sample time: 5-60 sec
- Practical issues:
  - Maintenance, fouling, clogging...

Representative data?!

Data quality assessment methods

- Manual procedures
  - Tedious and time consuming
- Automatic data quality evaluation procedures

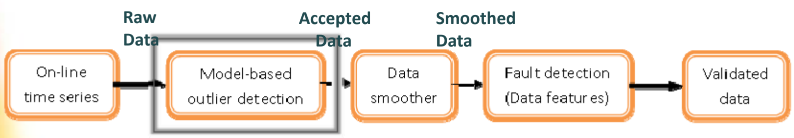
Using time series information!

  - Corrupted, doubtful, unreliable data
  - Noise
  - Sensor faults
  - Outliers

Automated data quality assessment tools

- Univariate method developed at model*EAU,*

Département de génie civil et de génie des eaux, Université Laval



Current Model-based outlier detection method

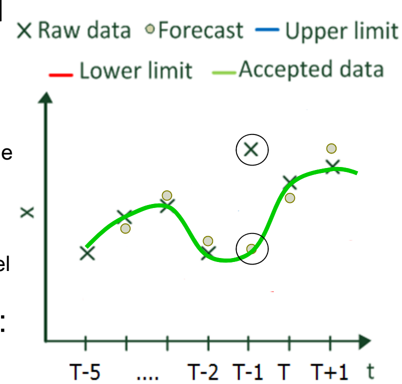
Exponential smoothing model

- At T forecasting T+1:
  - Variable $\hat{x}$
    - 3[rd] order exponential smoothing mode

$$x_t = a + bt + \frac{1}{2}ct^2$$

  - STD of forecast error $\hat{\sigma}_e$
    - 1[st] order exponential smoothing model
- Dynamic Prediction interval:

$$x_{\lim} = \hat{x} \pm K \cdot \hat{\sigma}_e$$



Model-based outlier detection

- Alternative method: Desired properties
  - Real-time, on-line applicable
  - Systematic
  - Appropriate for the system under study
  - Automatically applicable
  - Not complicated

Autoregressive moving average with integrator (ARIMA) applied to a moving window data

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ARIMA model

- Proposed ARIMA model : $$y(k) = \frac{C(z^{-1})}{A(z^{-1})(1-z^{-1})} e(k)$$

  with: $$A(z^{-1}) = 1 + a_1 z^{-1} + \ldots + a_{na} z^{-na}$$ $$C(z^{-1}) = 1 + c_1 z^{-1} + \ldots + c_{nc} z^{-nc}$$

- Calculation of j-step ahead forecast value according to data available at time k:

$$\hat{y}(k+j\,|\,k) = \frac{F_j}{C(z^{-1})} y(k)$$

With F_j calculated according to Diophantine equation:

$$\frac{C(z^{-1})}{A(z^{-1})} = E_j + z^{-j} \frac{F_j}{A(z^{-1})}$$

From degree j-1

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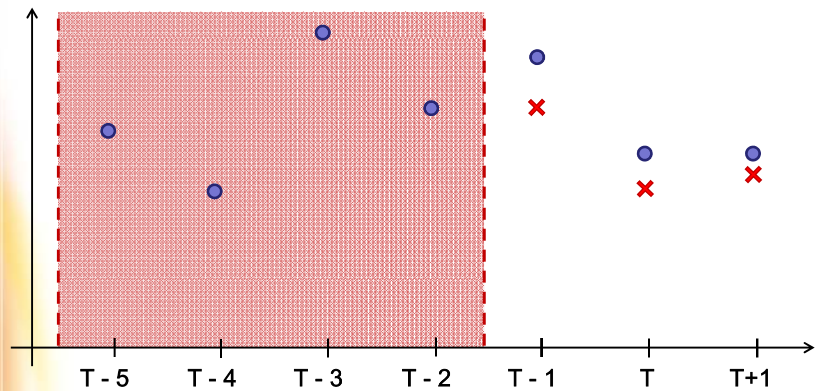
Moving Window approach



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ARIMA model with Moving Window

- Algorithm for window size N:
  1. Consider N data values in window
  2. Identify ARIMA model parameters
  3. Forecast of j-step ahead values
  4. Move data window one step further
  5. Repeat steps 2 to 4

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Challenge!

- Specification of Window Size (WS) ?
  - If WS too small ⇨ More sensitive to noise
  - If WS too large ⇨ Averaging the dynamic variations
- Solution ?

Selection of WS that considers the dynamics of the variable

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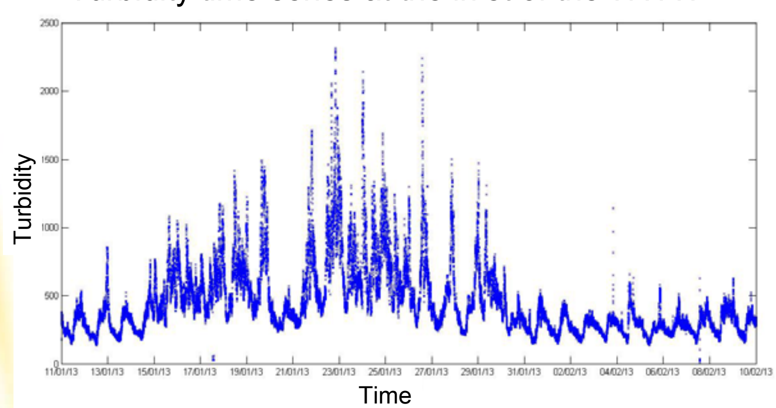
Raw data

Turbidity time series at the inlet of the WWTP



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Raw data

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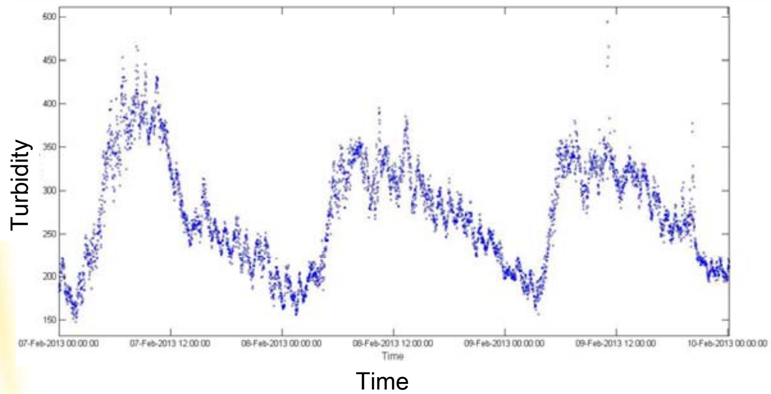

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Application to the system

- Window size of 30 data points for 1 min sampling time
- Estimation of ARIMA model parameters with one pole and one zero

$$y(k) = \frac{(1 + c_1 z^{-1})}{(1 + a_1 z^{-1})(1 - z^{-1})} e(k)$$

- Calculation of one step ahead forecast value (j=1)
- Calculation of dynamic forecast error and prediction interval $x_{\lim} = \hat{x} \pm K \cdot \hat{\sigma}_e$
- Detection and replacement of outlier

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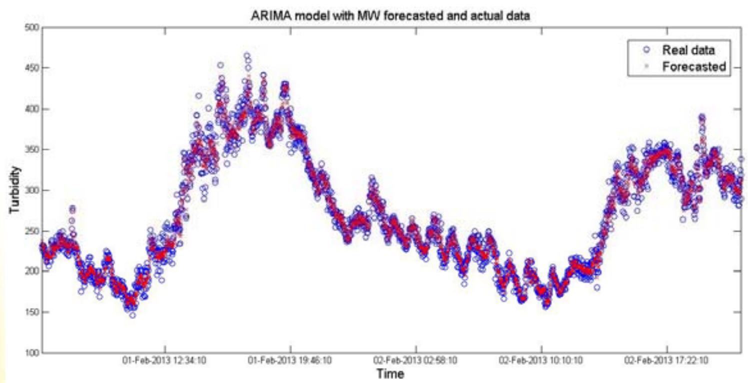
Results

1 step-ahead forecast for a dry period



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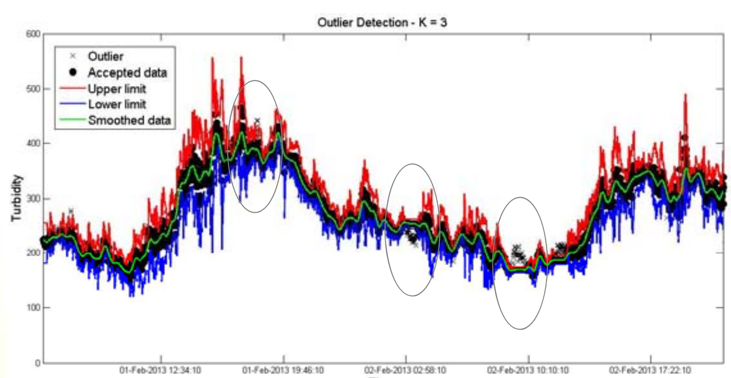
Results

Outlier detection



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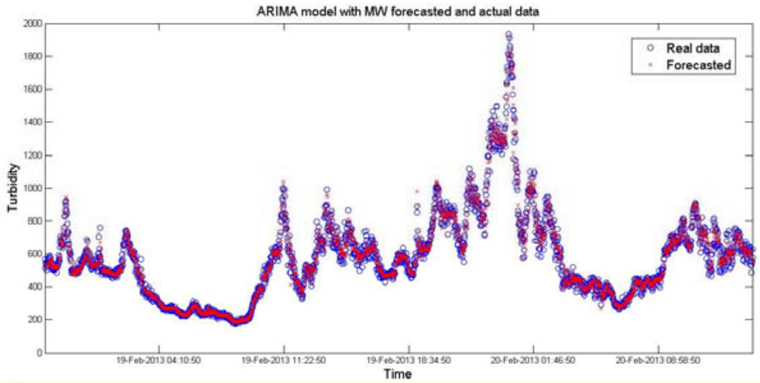
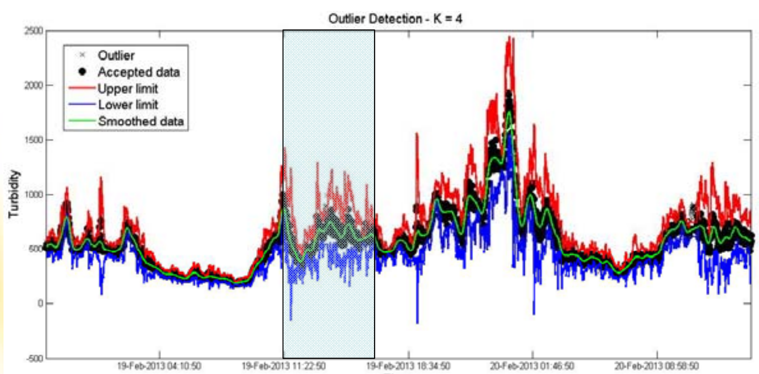
Results

1 step-ahead forecast for a wet period



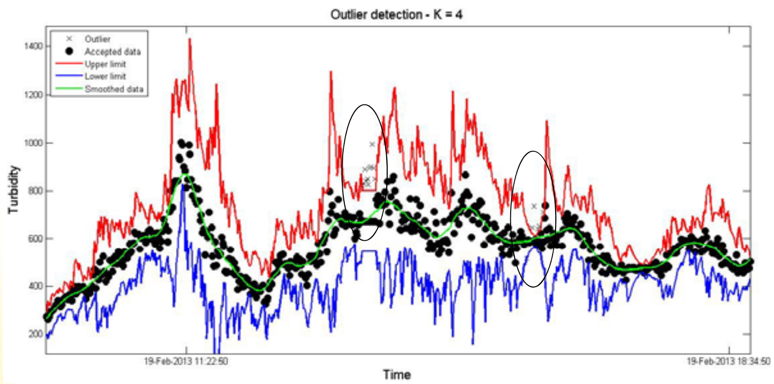
Results

Outlier detection



Results

Outlier detection



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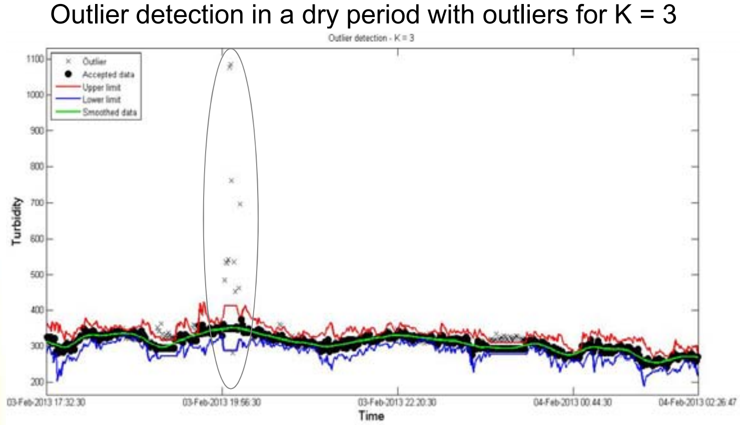
Results

Outlier detection in a dry period with outliers for K = 3



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Conclusion

- ARIMA model with moving window is fitted to water quality time series to produce one step-ahead forecast
- The outliers are detected by considering prediction intervals calculated according 1^{st} order exponential smoothing model

Future works

- Application of the Multi Model Filtering Algorithm (MMFA) to the system under study
  - Identification of set of models according to different modes of system's behavior
  - Designing Kalman filters for each of the different modes of behavior
  - Calculating conditional probability of each of the models to represent the observed system behavior