

# Water distribution networks leaks estimation in faulty sensor context: a graph approach

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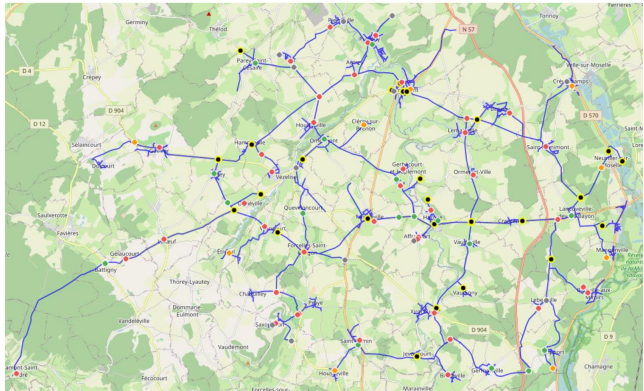


# Context

## Status of Water Distribution Network (WDN)

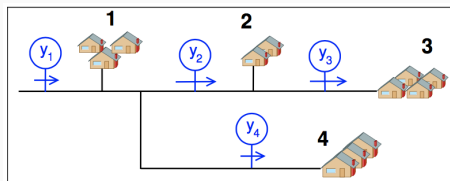
- Currently, at best 20%, of drinking water is lost
- How to best avoid leaks ? → **Detecting them and prioritise interventions**
- SPHEREAU FUI Project : Towards a more efficient water management

- Rural site in France
- 82 flowmeters
- Water direction is known
- 4 years data each 15 minutes



# A case study

Just focus on one part



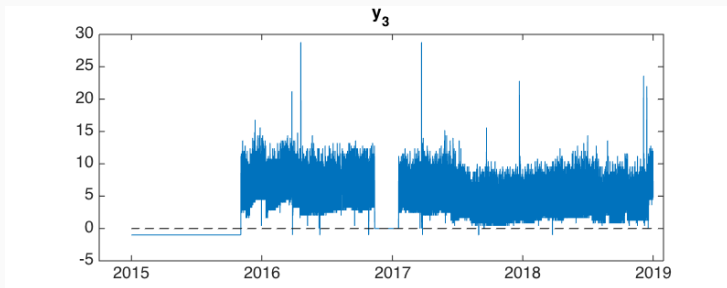
- **1,2,3,4** are District Metered Areas (DMA)
- $y_1, y_2, y_3, y_4$  are flowmeters

Is it possible to really estimate leaks?

Let us have a look at  $y_3$

# A case study

$y_3$  represents the consumption over a whole DMA



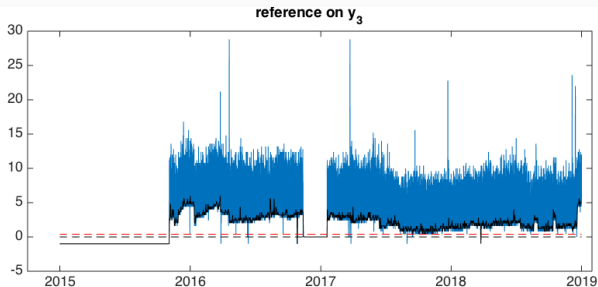
- -1 indicates a missing data
- 0 are real 0 (the sensor is dead)
- **Regular water consumption never reaches 0**

**Is it possible to really estimate leaks?**

Inseparability of night consumption and leaks → it is only possible to estimate leaks with respect to a **certain reference**

# A case study

Possible references : Minimum night flow



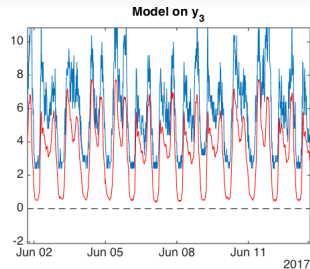
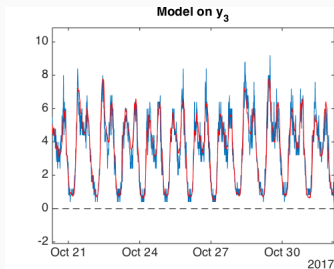
- Night flow has less variability
- The reference is the minimum night flow
- **Leaks are the difference between measurements and reference**

## drawback

What if leaks appear during the day?

# A case study

## More Robust approach : Modelling



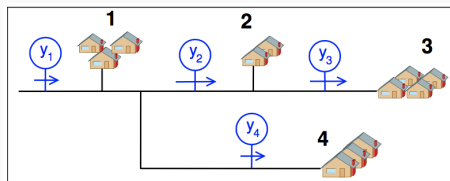
- **Contribution 1** : Kernel modelling of water demand
- Average over the day can be taken
- The reference is the difference between measurements and the model

### In any case

The data must contain an unleaky time region  
Leaks can be detected up to some reference

# Water management traditional approach : the water balance

What about DMA 1?

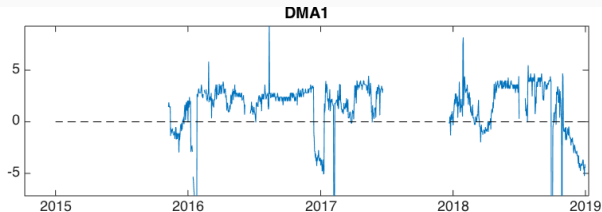


- Total Consumption :  $\mathcal{T}_{C_1}(k) = y_1(k) - y_2(k) - y_4(k)$
- Leaks :  $\mathcal{L}_1(k) = y_1(k) - y_2(k) - y_4(k) - \tilde{r}_1(k)$
- Equivalent Leaks :  $\mathcal{L}_1(k) = \varepsilon_1(k) - \varepsilon_2(k) - \varepsilon_4(k)$

$$\begin{cases} \mathcal{T}_{C_1}(k) = y_1(k) - y_2(k) - y_4(k) \\ \mathcal{T}_{C_2}(k) = y_2(k) - y_3(k) \\ \mathcal{T}_{C_3}(k) = y_3(k) \\ \mathcal{T}_{C_4}(k) = y_4(k) \end{cases} \quad \begin{cases} \mathcal{L}_1(k) = \varepsilon_1(k) - \varepsilon_2(k) - \varepsilon_4(k) \\ \mathcal{L}_2(k) = \varepsilon_2(k) - \varepsilon_3(k) \\ \mathcal{L}_3(k) = \varepsilon_3(k) \\ \mathcal{L}_4(k) = \varepsilon_4(k) \end{cases}$$

# When problems arise

## What about DMA 1?

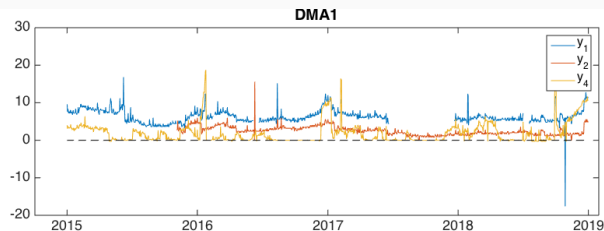


- how to handle missing data?
- Sometimes Consumption becomes strongly negative?



# When problems arise

## Details on the sensors



- Strong correlation between  $y_1$  and  $y_2$
- Low correlation between  $y_4$  and  $y_1$
- Sometimes  $y_4$  exceeds  $y_1$
- → Sensors can be faulty

## Problematic

Is it possible and how to identify leaks in a sensor faulty context?

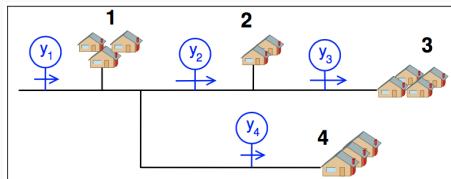
- 1 Noisy sensors modelling
- 2 Graphs parallelism
- 3 Identification of leaks
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# Outline

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# Assumptions

Sensors may contain additive default



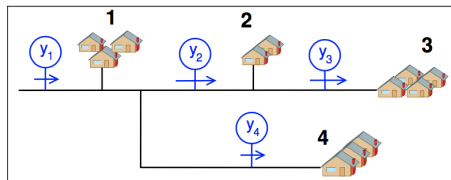
- $y_i(k) = y_i^o(k) + \mathcal{D}_i(k)$
- $\varepsilon_i(k) = y_i^o(k) + \mathcal{D}_i(k) - r_i(k)$

$$\begin{cases} \mathcal{L}_1(k) + \mathcal{D}_1(k) - \mathcal{D}_2(k) - \mathcal{D}_4(k) = \varepsilon_1(k) - \varepsilon_2(k) - \varepsilon_4(k) \\ \mathcal{L}_2(k) + \mathcal{D}_2(k) - \mathcal{D}_3(k) = \varepsilon_2(k) - \varepsilon_3(k) \\ \mathcal{L}_3(k) + \mathcal{D}_3(k) = \varepsilon_3(k) \\ \mathcal{L}_4(k) + \mathcal{D}_4(k) = \varepsilon_4(k) \end{cases}$$

## Problematic

How to identify  $\mathcal{L}_i(k)$  and  $\mathcal{D}_i(k)$  ?

# Assumptions



- Potentially, each DMA contains leaks
- Potentially, each sensor is faulty

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & -1 & 0 & -1 \\ 0 & 1 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}}_A \underbrace{\begin{bmatrix} \mathcal{L}_1(k) \\ \mathcal{L}_2(k) \\ \mathcal{L}_3(k) \\ \mathcal{L}_4(k) \\ \mathcal{D}_1(k) \\ \mathcal{D}_2(k) \\ \mathcal{D}_3(k) \\ \mathcal{D}_4(k) \end{bmatrix}}_X = \underbrace{\begin{bmatrix} 1 & -1 & 0 & -1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_B \underbrace{\begin{bmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \\ \varepsilon_3(k) \\ \varepsilon_4(k) \end{bmatrix}}_Y$$

# General Problematic

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & -1 & 0 & -1 \\ 0 & 1 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}}_A \underbrace{\begin{bmatrix} \mathcal{L}_1(k) \\ \mathcal{L}_2(k) \\ \mathcal{L}_3(k) \\ \mathcal{L}_4(k) \\ \mathcal{D}_1(k) \\ \mathcal{D}_2(k) \\ \mathcal{D}_3(k) \\ \mathcal{D}_4(k) \end{bmatrix}}_X = \underbrace{\begin{bmatrix} 1 & -1 & 0 & -1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_B \underbrace{\begin{bmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \\ \varepsilon_3(k) \\ \varepsilon_4(k) \end{bmatrix}}_Y$$

## Problematic 1

Is it possible to uniquely estimate  $\mathbf{X}$ ?  $\rightarrow$

- Number of equations is the number of DMA
- Number of unknowns  $n_{DMA} + n_y$
- Underdetermined problem

Can we propose a regularized identification scheme?

# Preliminary Problematic

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & -1 & 0 & -1 \\ 0 & 1 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}}_A \underbrace{\begin{bmatrix} 0 \\ 0 \\ \mathcal{L}_3(k) \\ \mathcal{L}_4(k) \\ 0 \\ 0 \\ \mathcal{D}_3(k) \\ 0 \end{bmatrix}}_X = \underbrace{\begin{bmatrix} 1 & -1 & 0 & -1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_B \underbrace{\begin{bmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \\ \varepsilon_3(k) \\ \varepsilon_4(k) \end{bmatrix}}_Y$$

## Preliminary Problematic

What about overdetermined cases

- We know which defaults are present
- Their value is still unknown

# Preliminary Problematic

$$\underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}}_{A_s} \underbrace{\begin{bmatrix} \mathcal{L}_3(k) \\ \mathcal{L}_4(k) \\ \mathcal{D}_3(k) \end{bmatrix}}_{\mathbf{X}_s} = \underbrace{\begin{bmatrix} 1 & -1 & 0 & -1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_B \underbrace{\begin{bmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \\ \varepsilon_3(k) \\ \varepsilon_4(k) \end{bmatrix}}_Y$$

## Preliminary Problematic

Is it possible to uniquely estimate  $\mathbf{X}_s$ ?  $\rightarrow$

- Answer is straight forward : Yes iff  $\text{rank}(A_s) = n_X$
- But...Very uninteresting in practice
- **Water managers are not mathematicians!**

Can we give a comprehensive topological answer to this identifiability problem?

$\rightarrow$  Use of graphs



# Outline

- 1 Noisy sensors modelling
- 2 Graphs parallelism**
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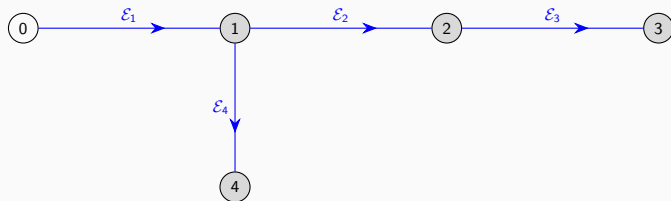
# Strategy

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & -1 & 0 & -1 \\ 0 & 1 & 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix}$$

## Train of thoughts

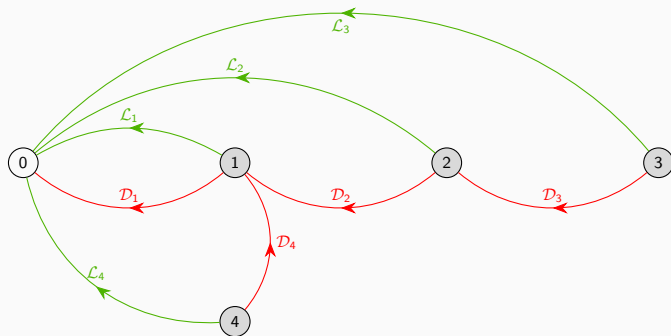
- Matrices  $A$  and  $B$  look like incidence matrices of graphs. Let  $\mathbf{I}_G$  be the incidence matrix of the directed graph  $G$ , then:
  - $\mathbf{I}_G(i, j) = 1$  if edge  $j$  has its arrow leaving node  $i$
  - $\mathbf{I}_G(i, j) = -1$  if edge  $j$  has its arrow entering node  $i$
  - $\mathbf{I}_G(i, j) = 0$  if edge  $j$  is not incident on node  $i$ ,
- Note that by construction, matrices  $A$  and  $B$  embed directly the topology of the network.
- **What are the corresponding graphs?**

## Graph/Matrices analogy

Residual Graph  $G_{\mathcal{R}}$ 

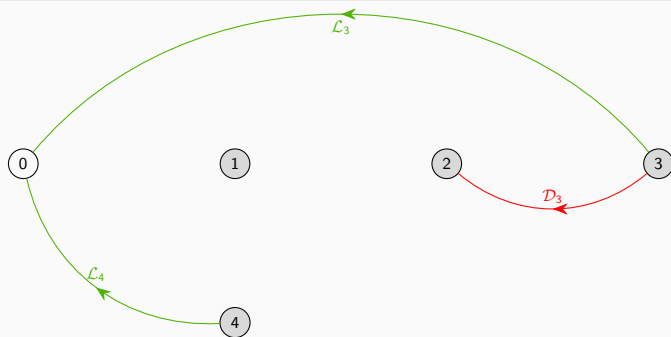
$$\mathbf{l}_{G_{\mathcal{R}}} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 1 & -1 & 0 & -1 \\ 0 & 1 & -1 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ & \mathbf{B} & & \\ & & & \end{bmatrix},$$

## Graph/Matrices analogy

Fault Graph  $G_{\mathcal{F}}$ 

$$\mathbf{I}_{G_{\mathcal{F}}} = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 \\ -1 & 0 & 0 & 0 & -1 & 1 & 0 & 1 \\ 0 & -1 & 0 & 0 & 0 & -1 & 1 & 0 \\ 0 & 0 & -1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & -1 & 0 & 0 & 0 & -1 \end{bmatrix} = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & 0 & 0 & 0 \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix} = \begin{bmatrix} & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \\ & & & & & & & \end{bmatrix} = -\mathbf{A}$$

## Graph/Matrices analogy

Fault Graph  $G_{\mathcal{F}}$ 

$$\mathbf{I}_{G_{\mathcal{F}}} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ -1 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ & & \\ & & \\ & & -\mathbf{A}_s \\ & & \end{bmatrix},$$

# Preliminary conclusions

## Remarks

- **Contribution 2 : It is possible to derive an algorithmic construction of graphs for the given problem**
  - The residual graph has exactly the same topology as the physical network
  - In the proposed representation, sensors come as edges, which is the dual version of usual water network graph representations
  - A node 0 is needed : It adds a redundant equation
- Solving  $\mathbf{A}X = \mathbf{B}Y \Leftrightarrow$  solving  $-\mathbf{I}_{\mathcal{F}}X = \mathbf{I}_{\mathcal{R}}Y$  (and  $\text{rank}(\mathbf{A}) = \text{rank}(\mathbf{I}_{\mathcal{F}})$  )
- **What are the sufficient and necessary conditions on  $G_{\mathcal{F}}$  to guarantee identifiability?**

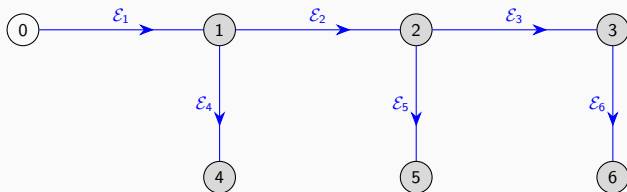
## Contribution 3

**Theorem 1 : The defaults are identifiable iff  $G_{\mathcal{F}}$  is a directed tree**

# Example

## Example

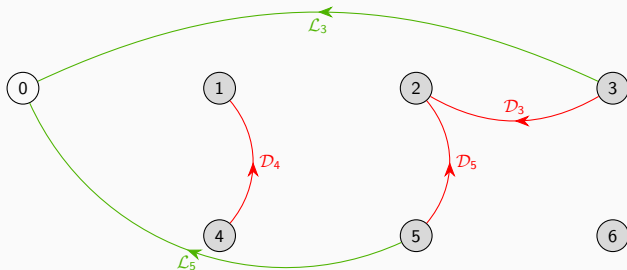
Let the following WDN



Is the default combination  $\mathcal{L}_3, \mathcal{L}_5, \mathcal{D}_3, \mathcal{D}_4, \mathcal{D}_5$  identifiable?

# Example

Answer : No



$G_{\mathcal{F}}$  is not a directed tree (it contains loops)

## Other advantages

- This result can also indicate the resilience against appearance of new defaults
- Complexity for computing the rank of  $\mathbf{A}$  by gaussian elimination:  $\mathcal{O}(n^3)$
- Checking if  $G_{\mathcal{F}}$  is a directed tree:  $\mathcal{O}(n)$



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# Original Problem

What to do if the presence of default is unknown?

- The problem is underdetermined  $\rightarrow$  Regularisation
- Physical assumption : Leaks must be positive

## Contribution 4

$$\hat{X} = \min_x \|AX - BY\|^2 + \mathcal{R}$$

$$s.t \quad \mathcal{L}_i > 0 \quad \forall i \in [1, \dots, |E_{G_{\mathcal{R}}}| - 1]$$

$\mathcal{R}$  is the regularization term

## Propositions for $\mathcal{R}$

- The solution with the least number of defaults is the most acceptable
- $\mathcal{R} = |X|_0 \rightarrow \ell_0$  norm relaxed as  $\ell_1$  norm = LASSO
- The solution closest to yesterday solution is the most acceptable (requires a ground truth on day 1)
- $\mathcal{R} = |\Delta X|_0 \rightarrow \ell_0$  norm relaxed as  $\ell_1$  norm = LASSO
- **Problem : possibly multiple solutions**

# Proposition using previous results

## Statement

- Theorem 1 → it is possible to determine all identifiable default structures
- Strategy : Replace one quadratic optimization scheme by multiple quadratic analytic solutions

## Algorithm

- Step 1 (offline): determine all identifiable structures
- Step 2 (online) : identify all identifiable structures using LS
- Step 3 (online) : retain the physical plausible solutions
- Step 4 (online) : retain the solutions fulfilling the regularisation

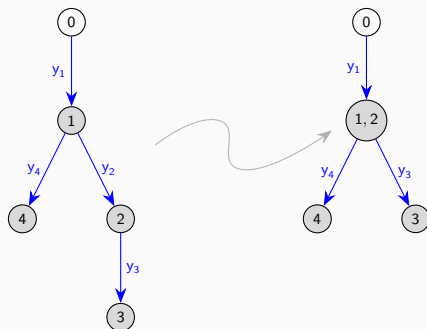
## Advantages

- It is possible to display a range of solutions
- It is possible to enforce *a priori* by acting on step 3 (If we know some defaults are present)

# Handling missing data

## Merging nodes

What if sensor 2 is down?



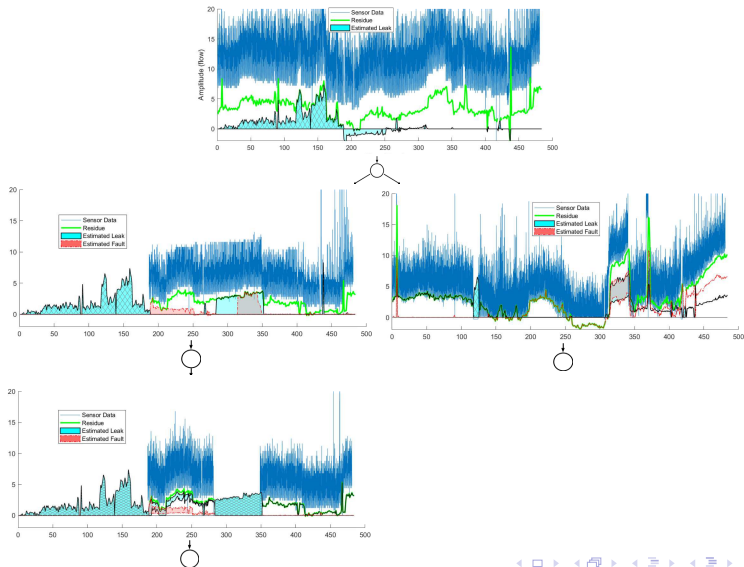
## Consequences

- Any leak  $\mathcal{L}$  estimated on the merged DMA 1, 2 corresponds to a leak positioned either on DMA 1 or on DMA 2

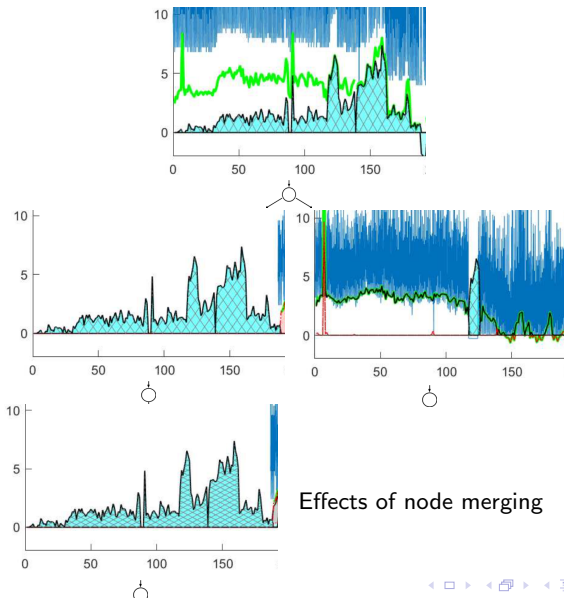
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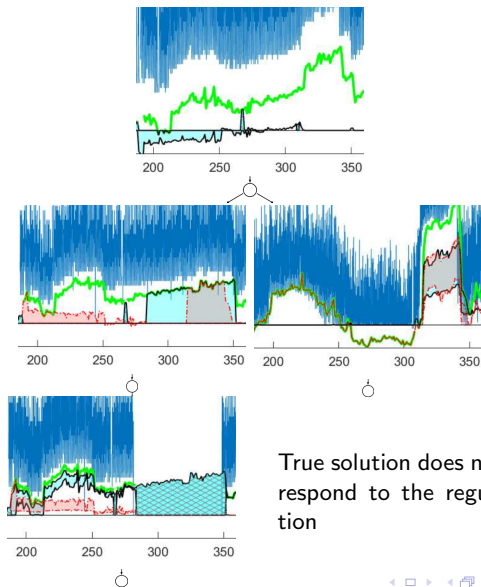
## Results on a true data set



## Results on a true data set (zoom 1)

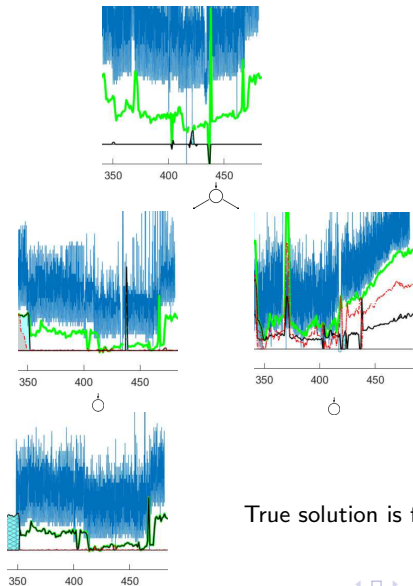


## Results on a true data set (zoom 2)





## Results on a true data set (zoom 3)



True solution is found

# Outline

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# Conclusions

## Context

- Leak identification in water dynamical networks
- Realistic assumptions : Sensors are faulty

## Contributions

- Graphs transposition for the identifiability problem
- Sufficient and necessary identifiability conditions fully expressed in graph topology
- Proposition of a regularised identification scheme algorithm
- Test on real data

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