CLPP

A User-Friendly Platform For Nonlinear Robust Observer Design

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French ANR-Grant CLPP

Outline

- What is CLPP for ?
- Theoretical Background
- Typical working session
- General comments

Problem Statement (1)

- Reconstructing the State of Biological/Chemical Process is mandatory for supervision and/or control task
- Analytical observers scarcely apply to real systems
- Optimization based observers need technicalities that are hard to master by process practitioners

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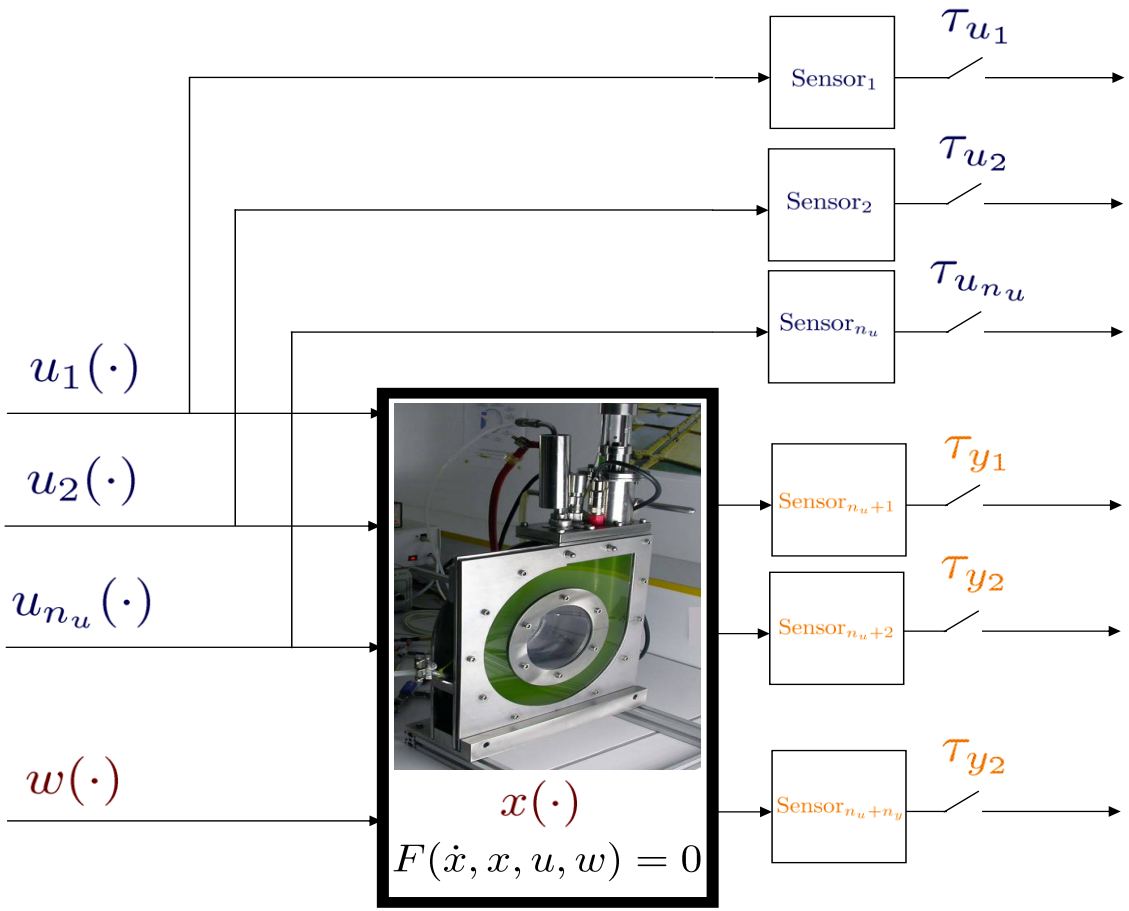
CLPP Spec.

Help process researchers to concentrate on their main problems by minimizing the Applied-Mathematics like skills that are needed to design a dynamic state/parameters reconstruction algorithms.

Problem Statement (2)



Consider a process with state x and dynamics that may be described by $F(\dot{x}, x, u, w) = 0$ where ...

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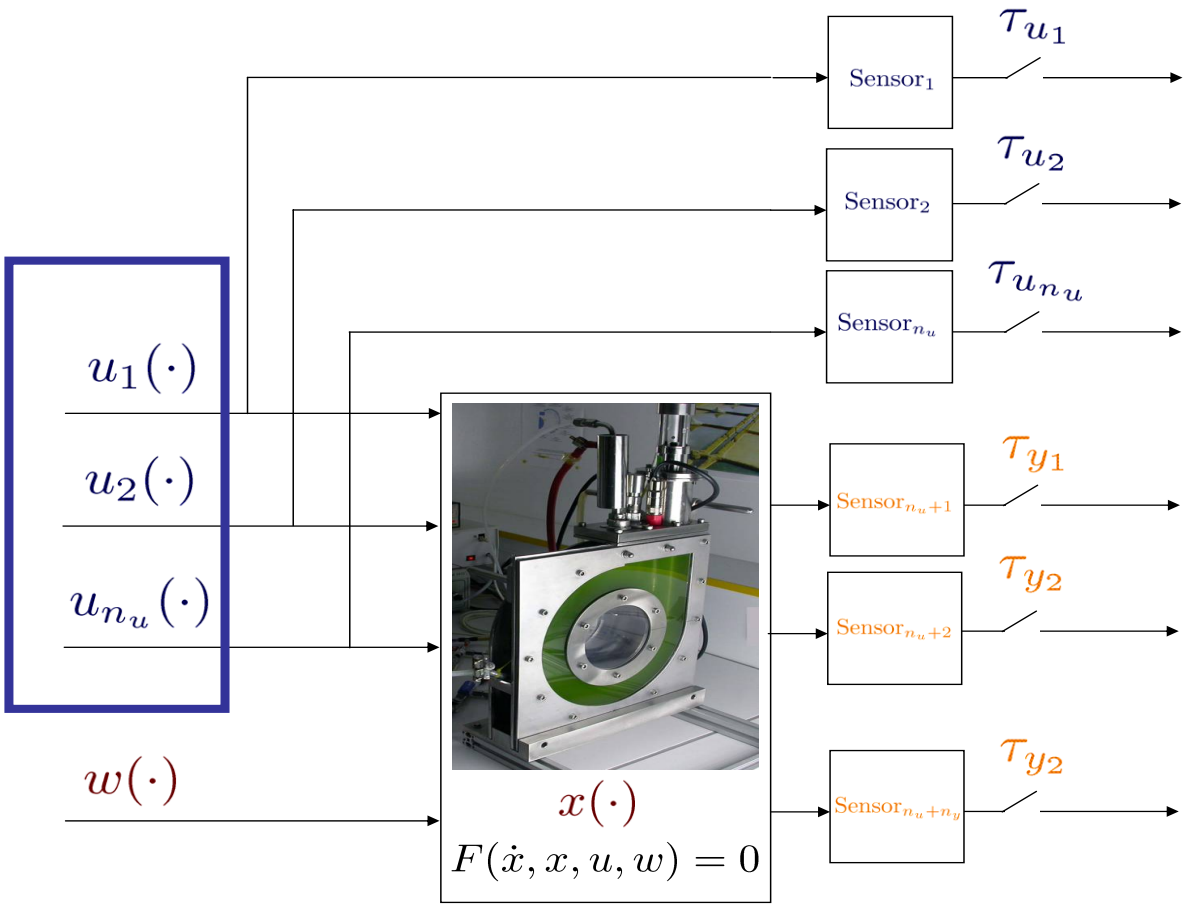

u is the vector of measured inputs :
ex. control, measured disturbances, ...

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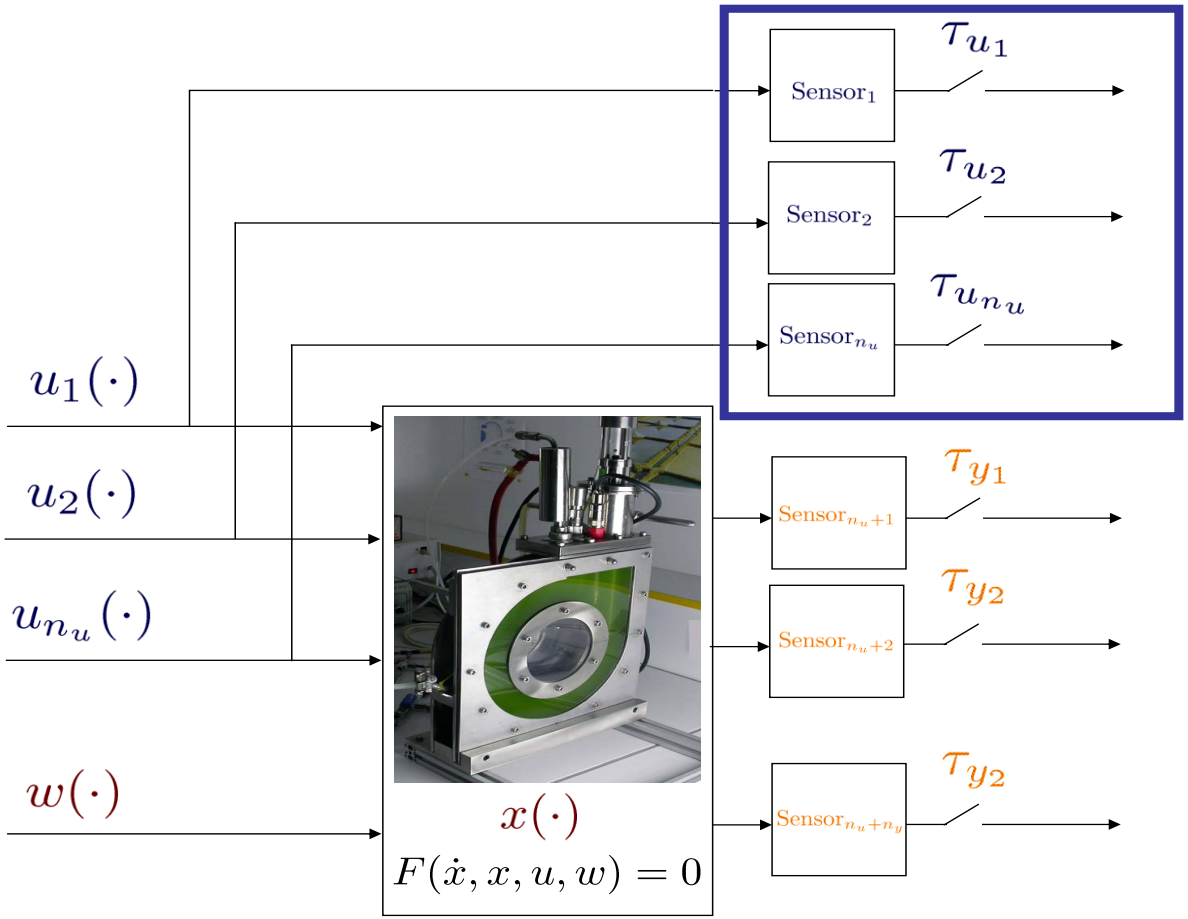

that are assumed to be acquired using dedicated sensors with different sampling rates that may not be uniform or a priori given.

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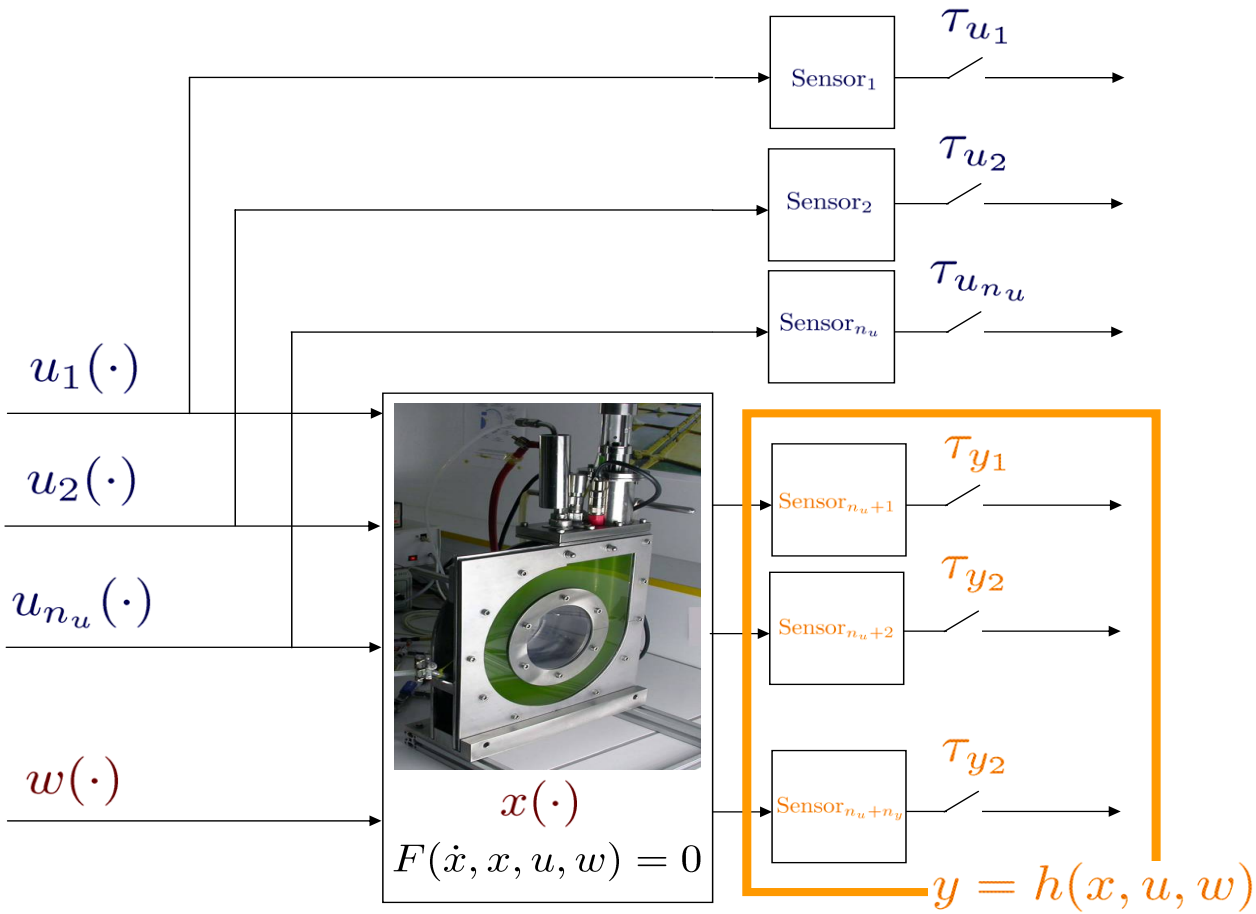

Additional measurements are assumed to be available which form the output vector $y = h(x, u, w)$.

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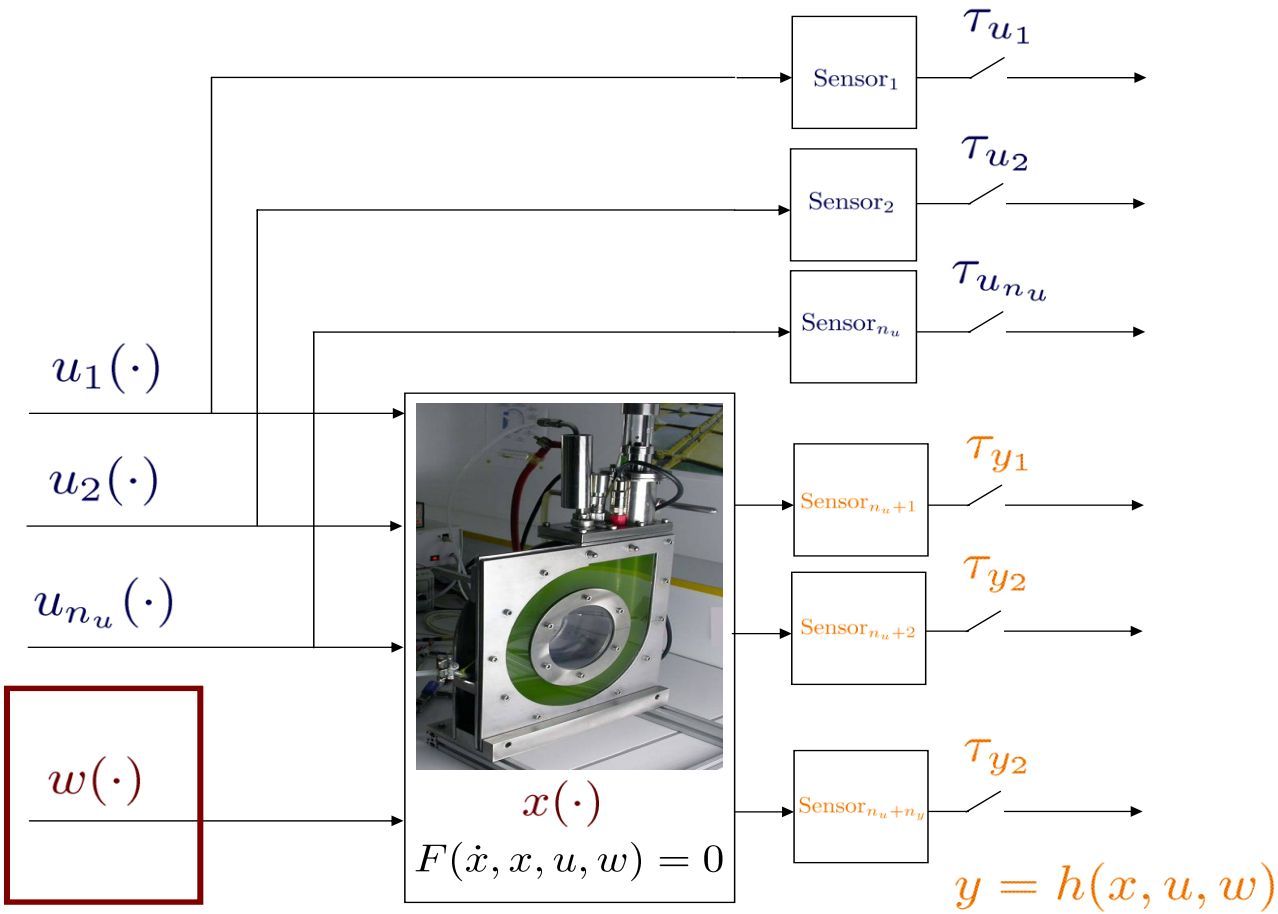

w is the vector of noise/unmeasured modeling error or uncertainty that may affect the system dynamics and the measurement.

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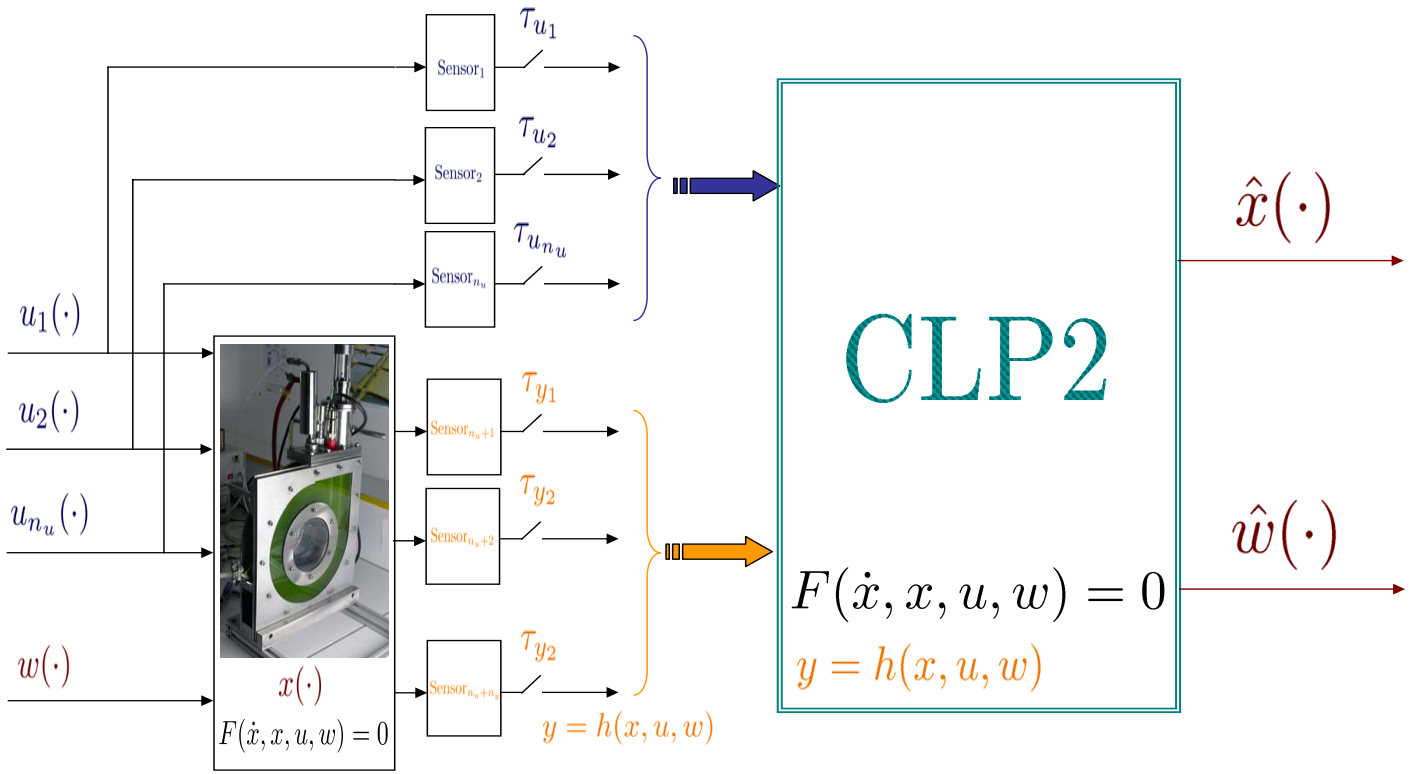
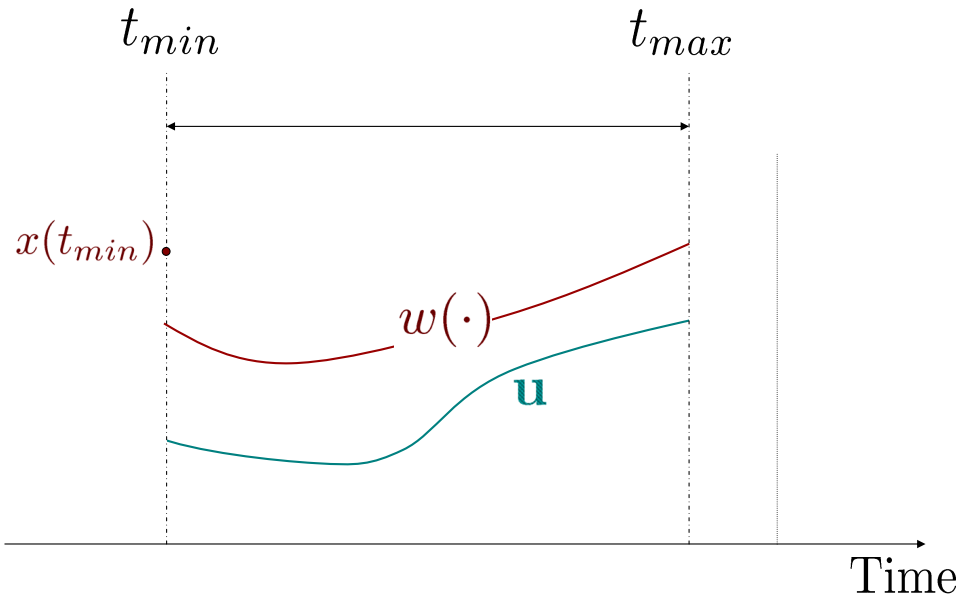


The Software CLP2 is a generic, user-friendly and automated tool that uses the available information (model+measurement) in order to produce on-line dynamic estimation of the unknowns x and $w(\cdot)$

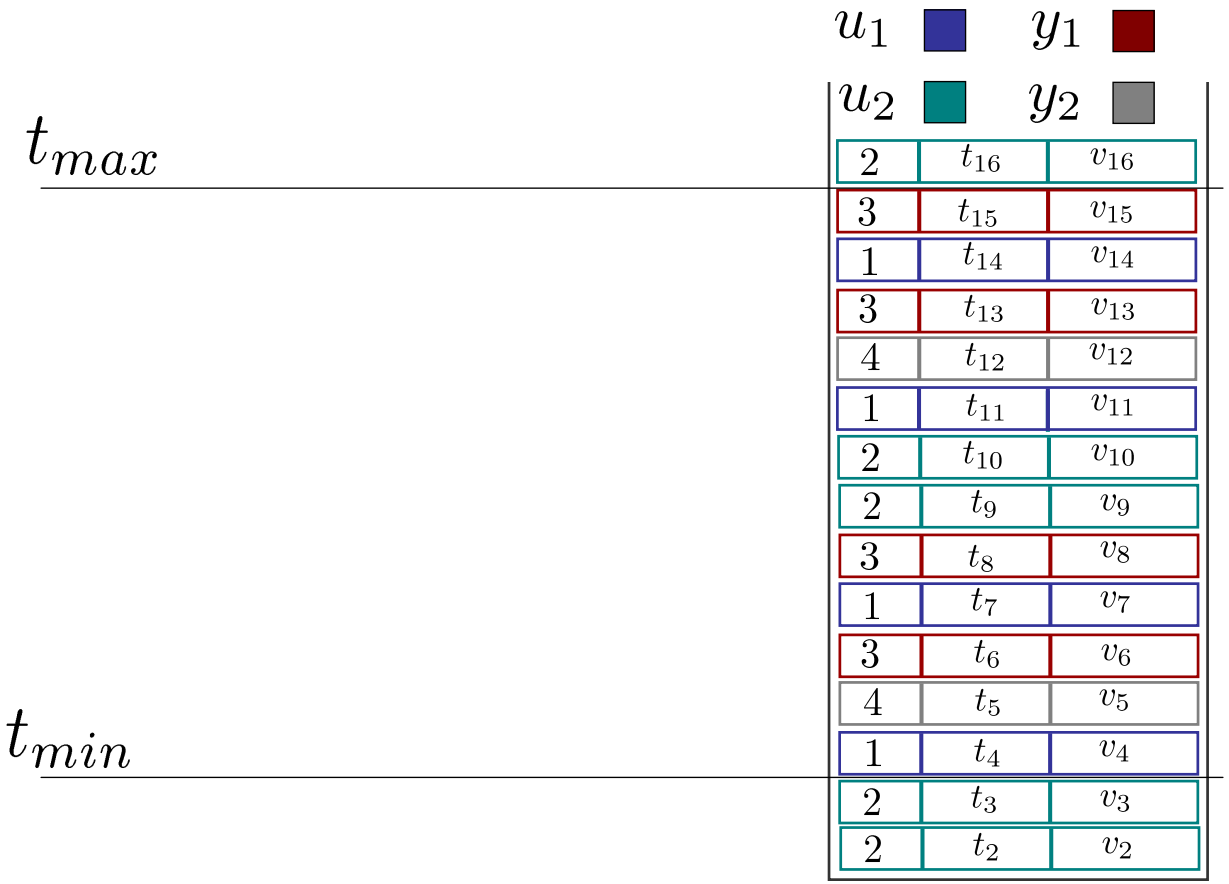
Theoretical Background (1) : reduced parametrization of unknowns



- Objective : Determine $x(t_{min})$ and $w(\cdot)$ over $[t_{min}, t_{max}]$
- $\Big(x(t_{min}), w(\cdot)\Big)$ is infinite dimensional $\longrightarrow$ use a reduced dimensional parametrization :

$$[x(t_{min}), w(\cdot)] \leftarrow \Pi(p) \quad ; \quad p \in \mathbb{P}$$

Theoretical Background (2) : Definition of the Cost Function



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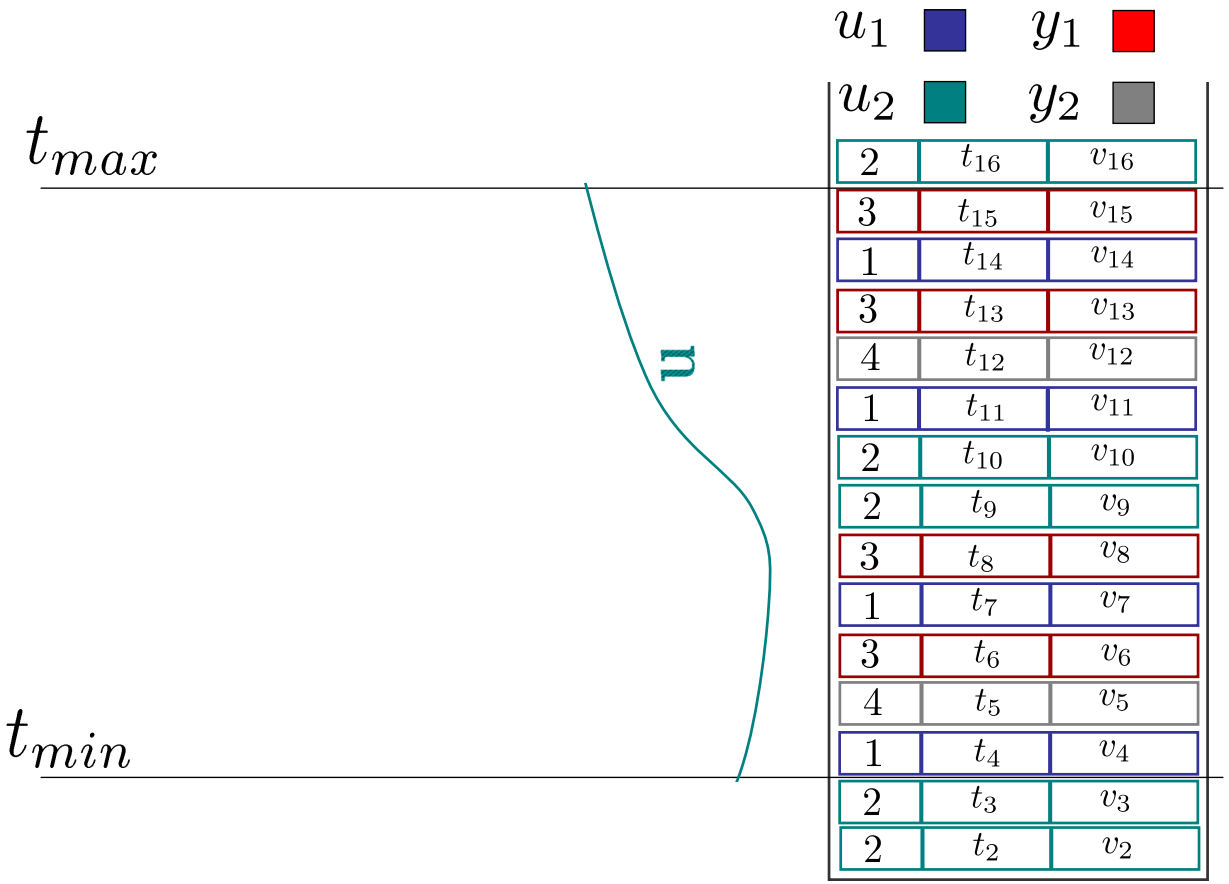

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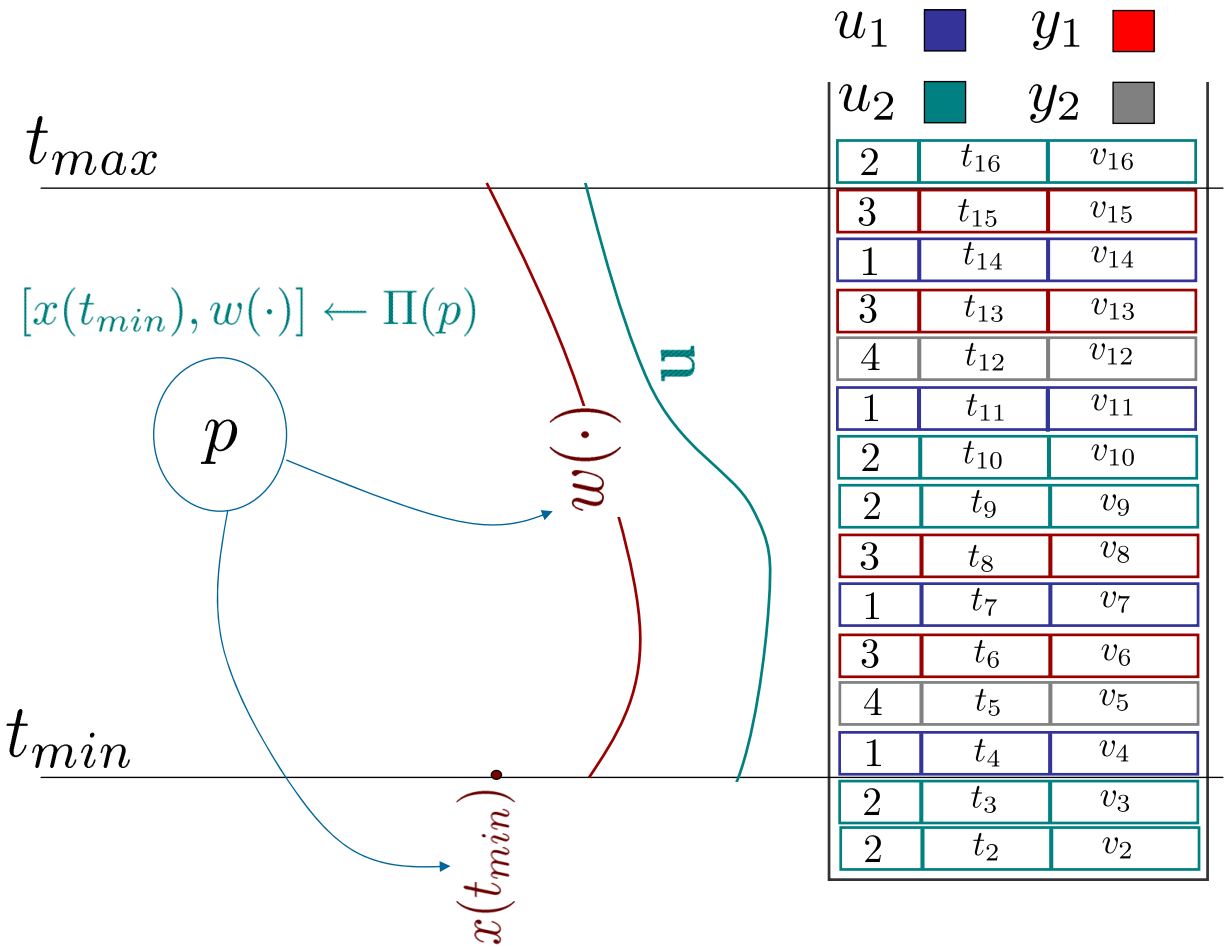

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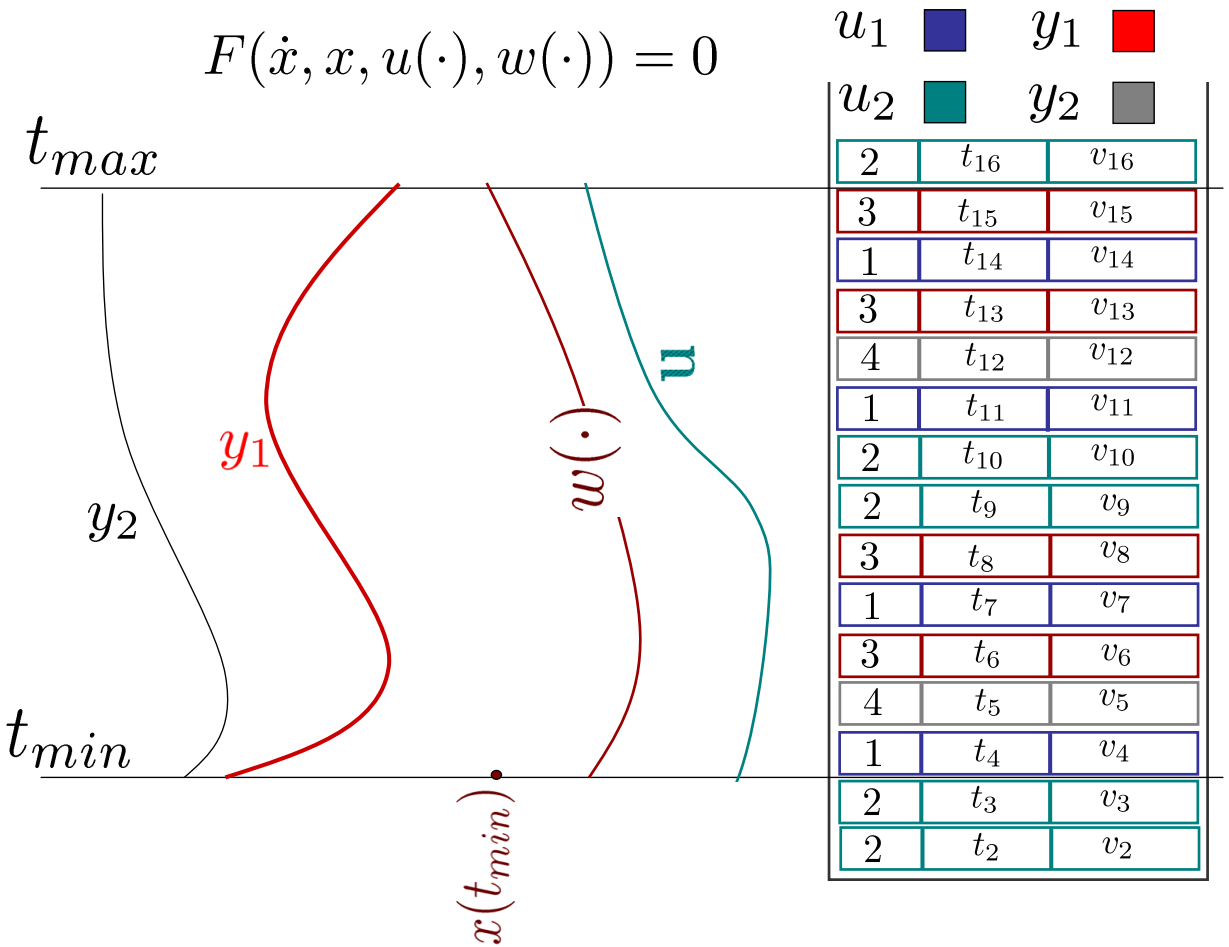

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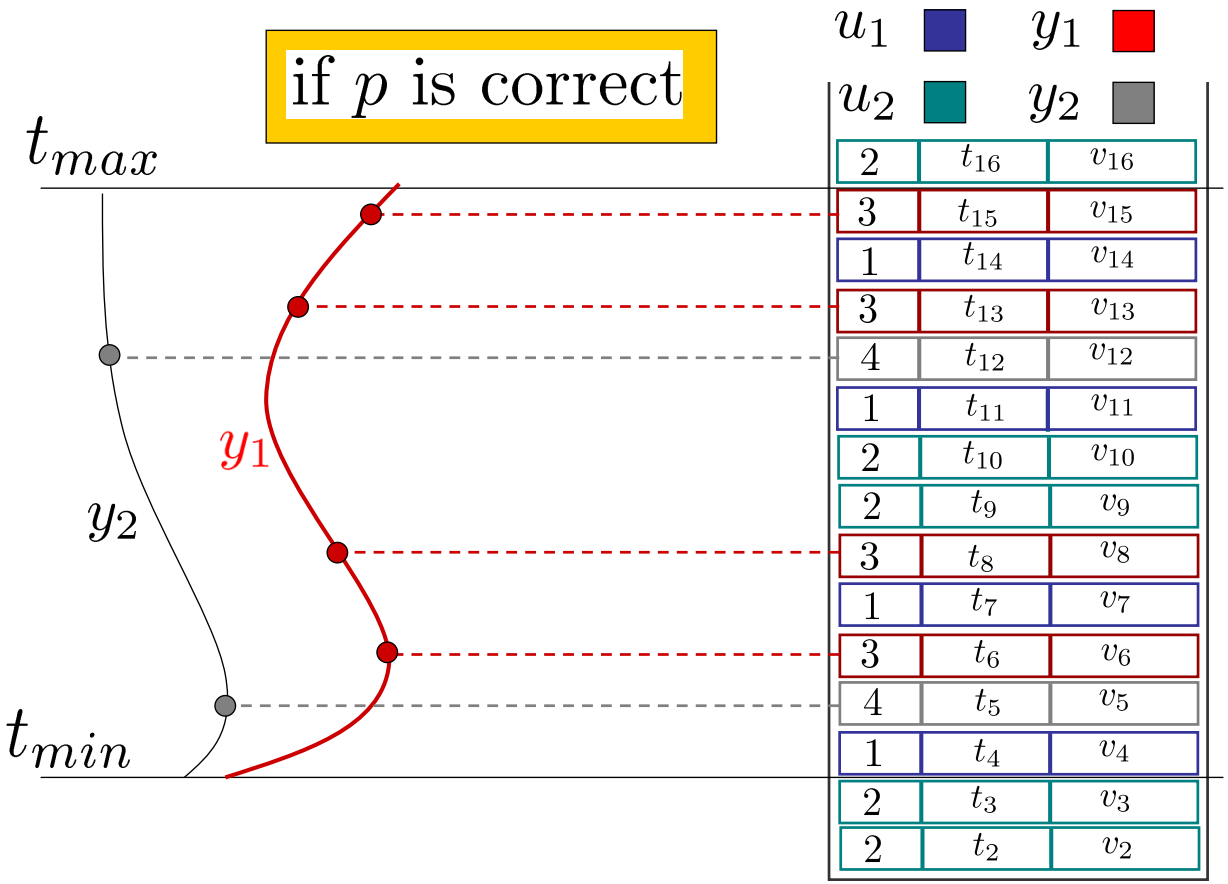

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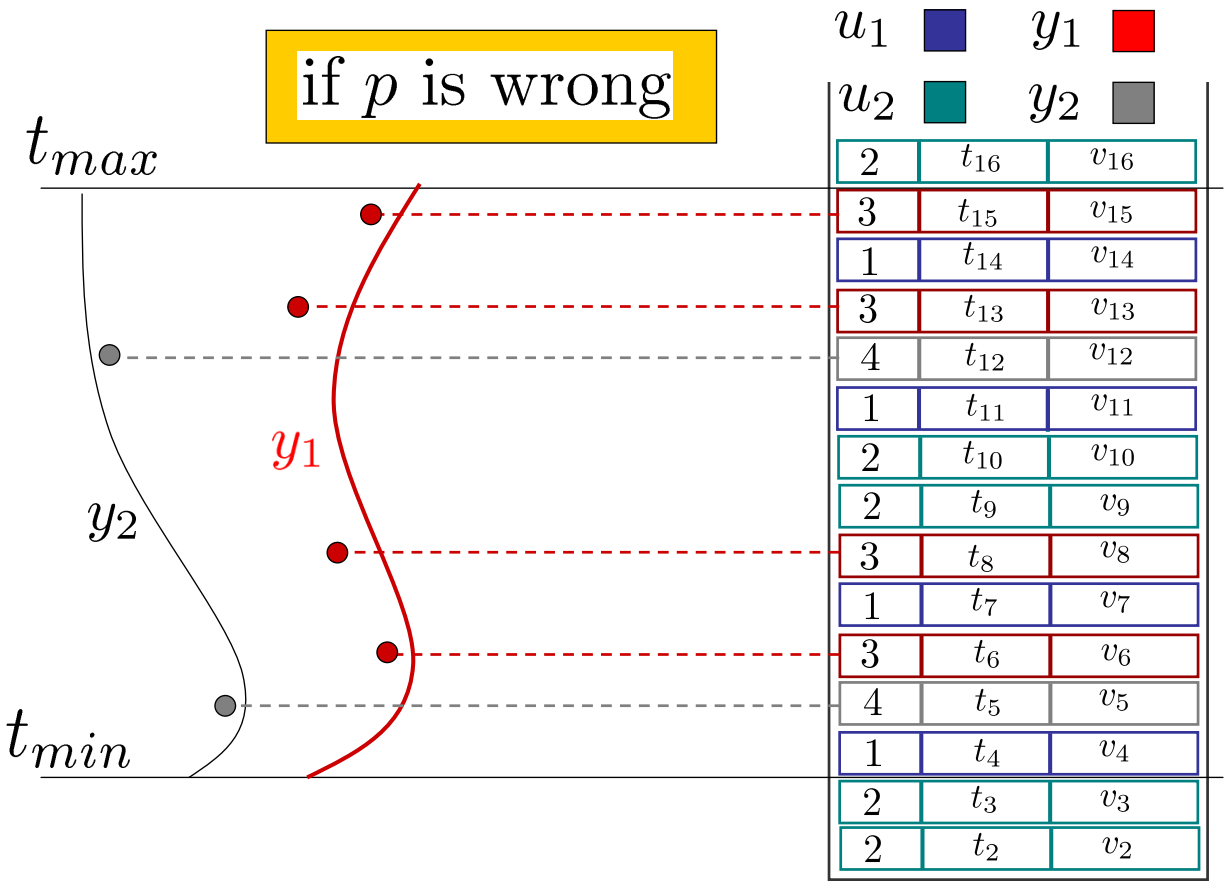

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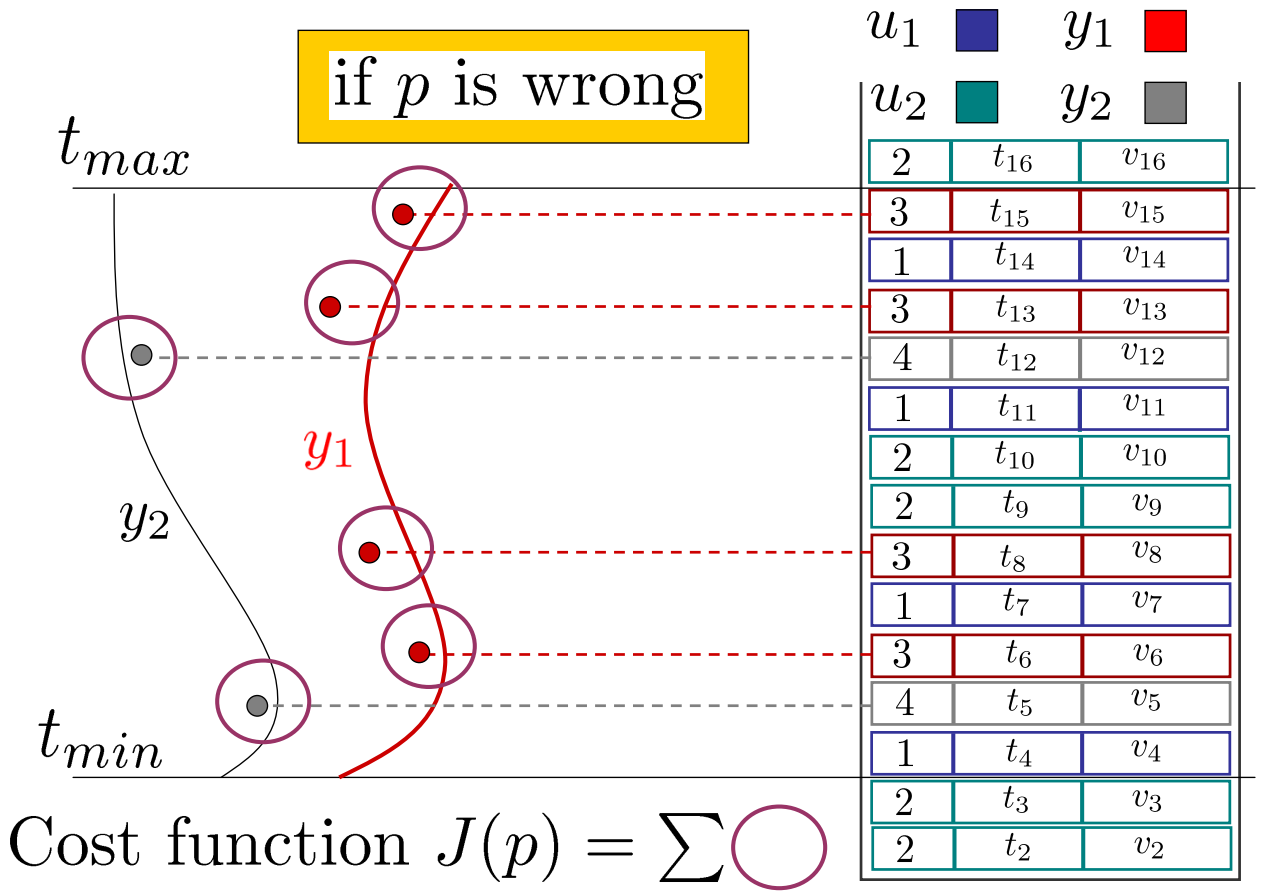

Theoretical Background (3) : Definition of the Cost Function

$$J^{(t)}(p) := \sum_{i=1}^{n_y} \Big[\sum_{k \in \mathcal{K}_i(t)} |y_i(t_k) - y_i^p(t_k|p)|^2 \Big]$$

- n_y is the number of sensors
- $\mathcal{K}_i(t)$ is index of instants in $[t_{min}, t_{max}]$ at which y_i is measured.
- $y_i^p(t_k|p)$ is the predicted output given the guess p

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More precisely, the family of cost functions :

$$J_\sigma^{(t)}(p) := \sum_{i=1}^{n_y} \Big[\sum_{k \in \mathcal{K}_i(t)} \phi_\sigma(t_k) \cdot \left| y_i(t_k) - y_i^p(t_k|p) \right|^2 \Big]$$

is used in the software to cross potential singularities.

[M. Alamir, J. Welsh and G. C. Goodwin *Redundancy vs multiple starting points in nonlinear systems related inverse problems.* Automatica, 45 :1052-1057, 2009]

Theoretical Background (3) : Updating of the unknown vector p

Given the cost function :

$$J^{(t)}(p) := \sum_{i=1}^{n_y} \Big[\sum_{k \in \mathcal{K}_i(t)} \left| y_i(t_k) - y_i^p(t_k|p) \right|^2 \Big]$$

The updating rule for p is given by :

$$p(\tau_j) := \mathcal{S}^q\left(p^+(\tau_{j-1})\right)$$

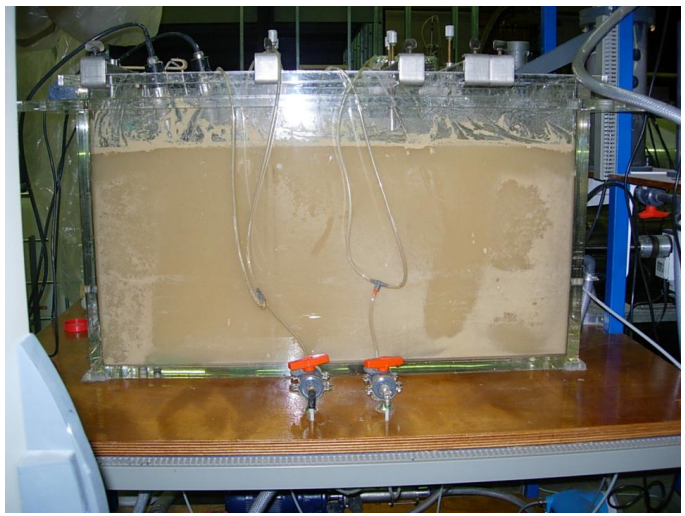
- $\mathcal{S}$ is the map representing one iteration of the optimizer
- q is the maximum number of iterations performed at each updating period
- τ_j is the updating instant
- $p^+(\tau_{j-1})$ is the new initial guess inherited from the past estimation $p(\tau_{j-1})$

Case Study : Reduced Model of Activated Sludge Waste-water Process

Reduced Model from [Gomez-Quintero et al. 2000] :

$$\begin{aligned} \dot{x} &= f(x,u,w) \quad (x,u,w) \in \mathbb{R}^4 \times \mathbb{R}^6 \times \mathbb{R}^4 \\ y &= h(x,u,w) = (x_2, x_4) \end{aligned}$$

- $x = (S_S, S_{NO_3}, S_{NH_4}, S_{O_2})$
- S_S : Biodegradable substrate concentration
- S_{NO_3} : Nitrate concentration
- S_{NH_4} : Ammonia concentration
- S_{O_2} : Dissolved oxygen
- $w \in \mathbb{R}^4$: Unknown parameters vector
- $y := (S_{NO_3}, S_{O_2})$: measurement vector

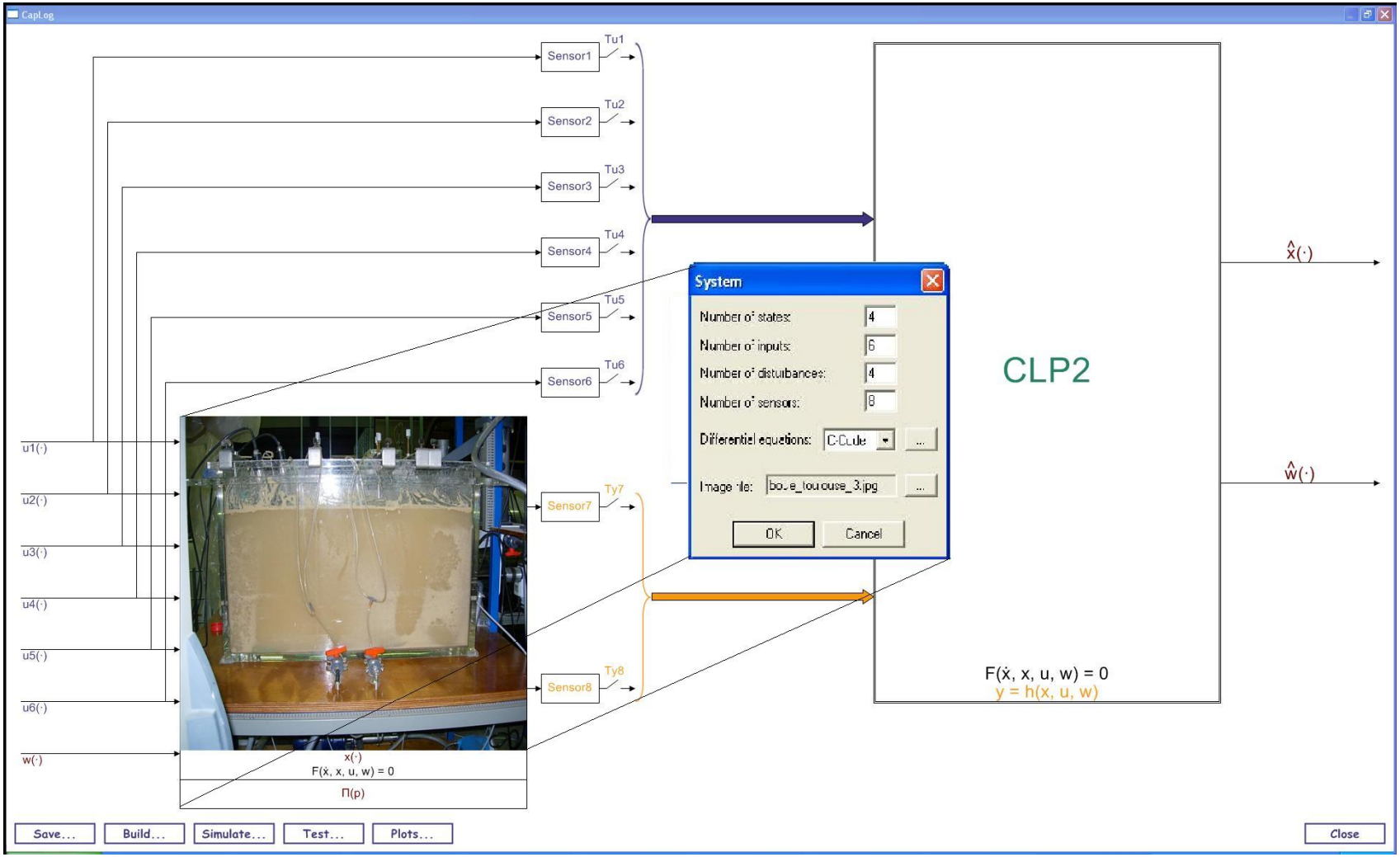


$\Rightarrow p \in [p_{min}, p_{max}] \in \mathbb{R}^8$

A Typical Working Session

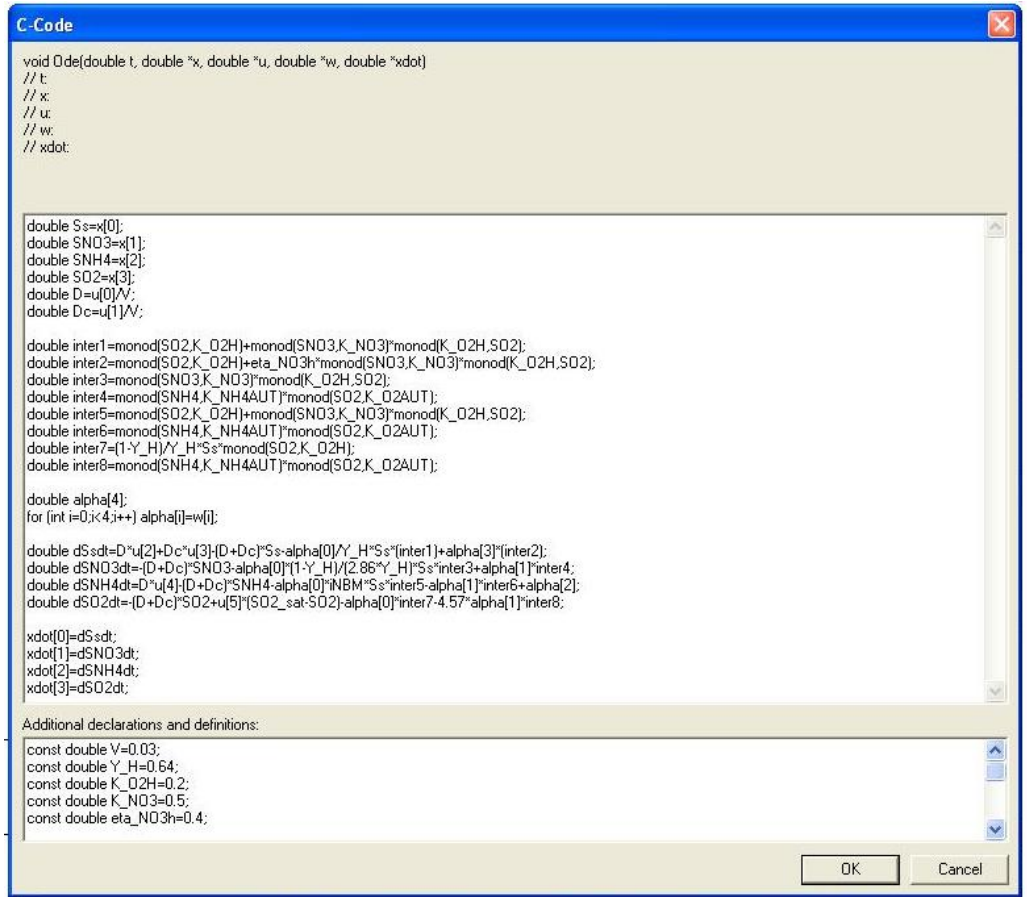
Starts a new project

A Typical Working Session



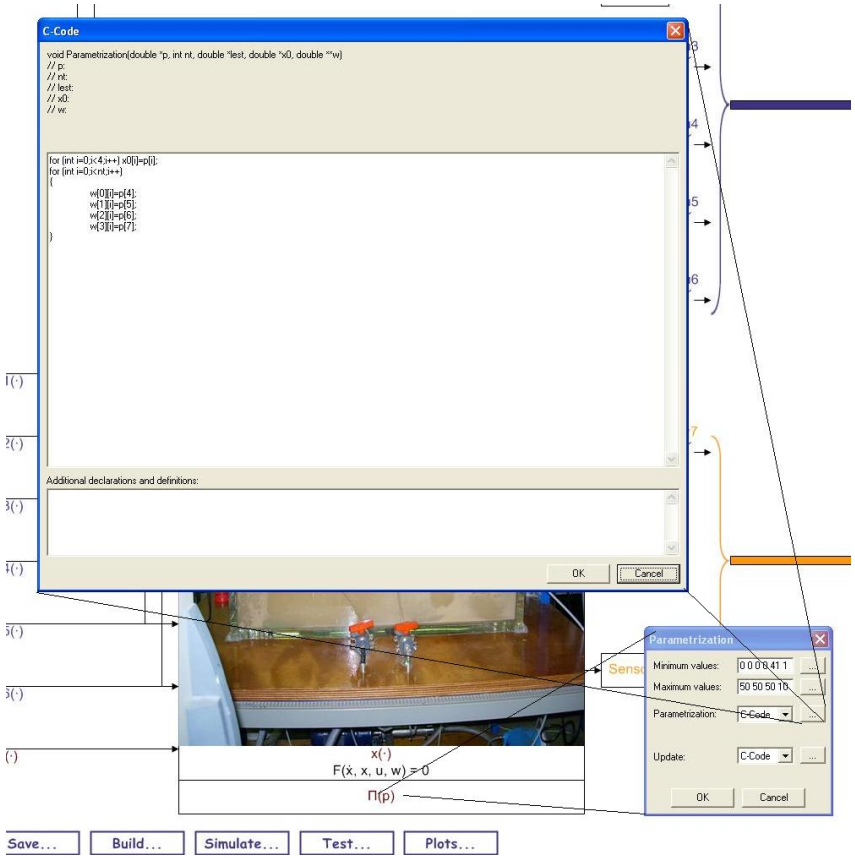
Define the dimensions of the problem

A Typical Working Session



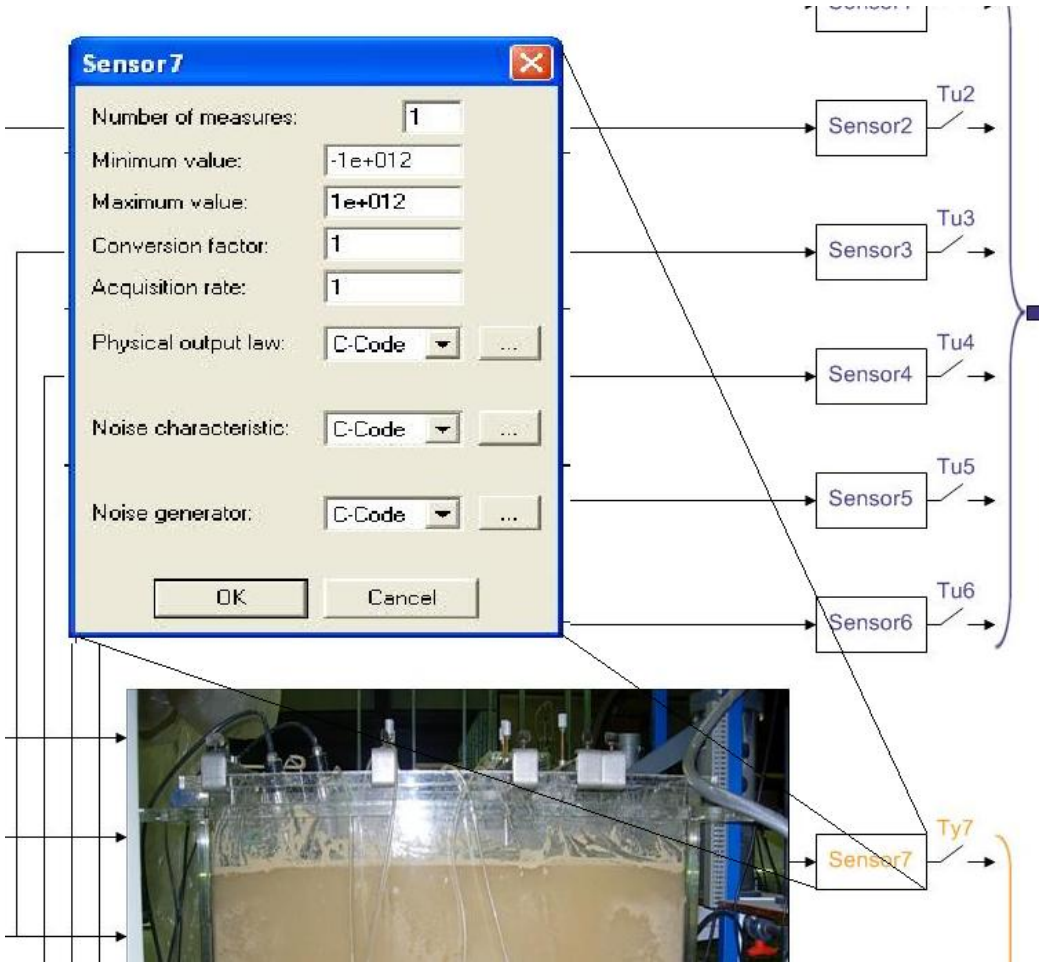
Define the system equations

A Typical Working Session



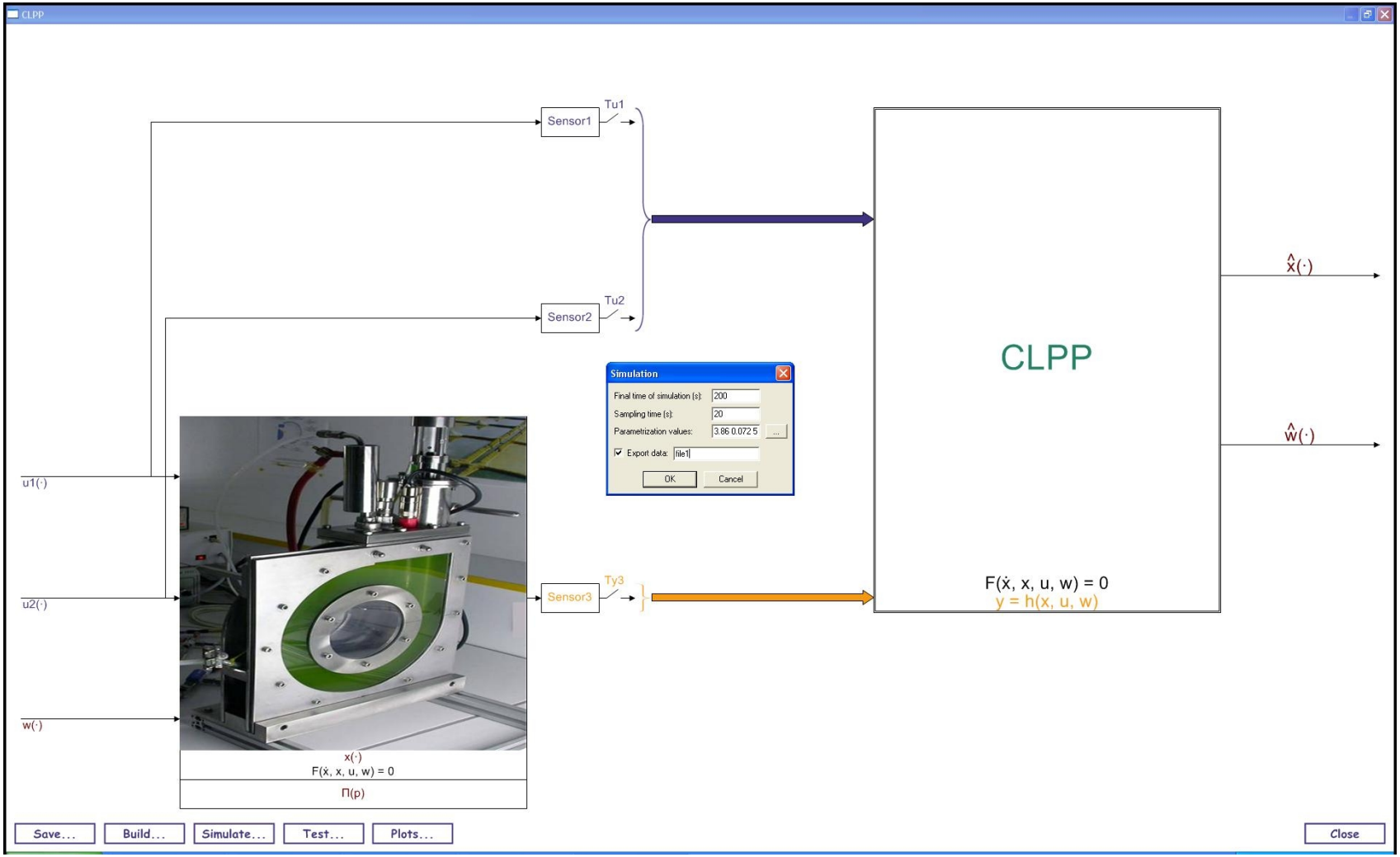
Define the parametrization map $[x(t_{min}), w(\cdot)] \leftarrow \Pi(p)$

A Typical Working Session



Define the sensors characteristic

A Typical Working Session



Simulate the system to check the set-up (1)

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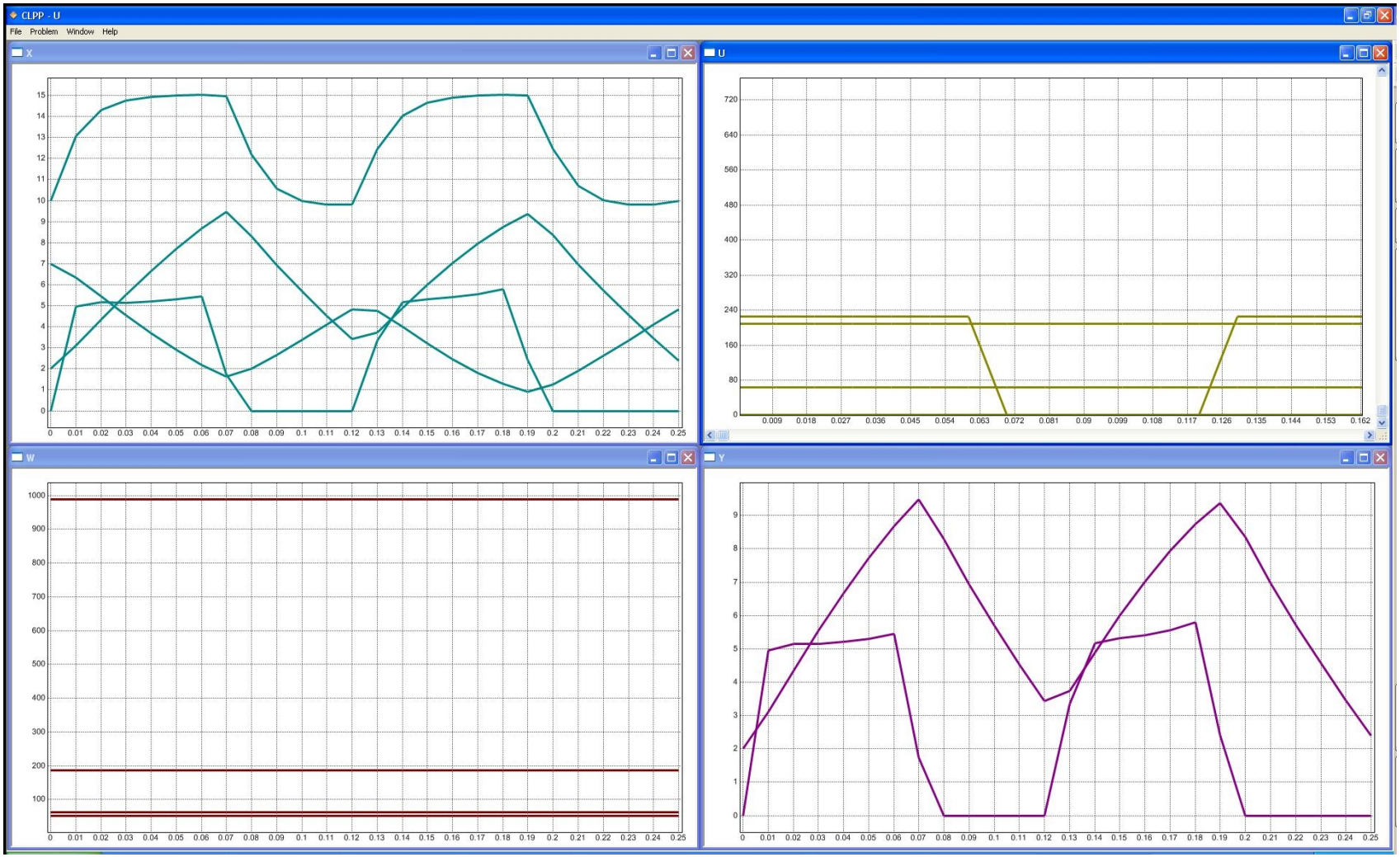

Simulate the system to check the set-up (2)

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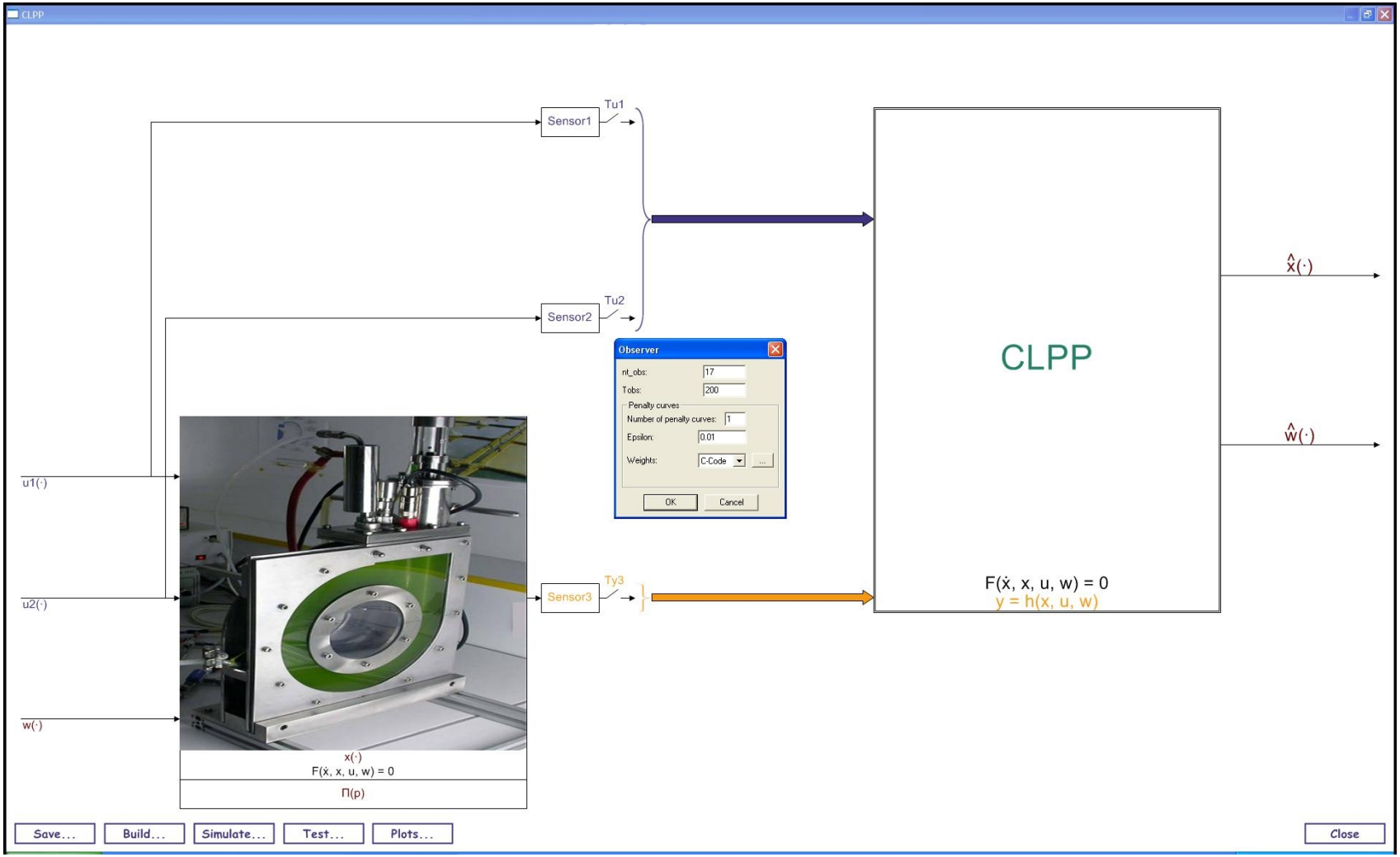
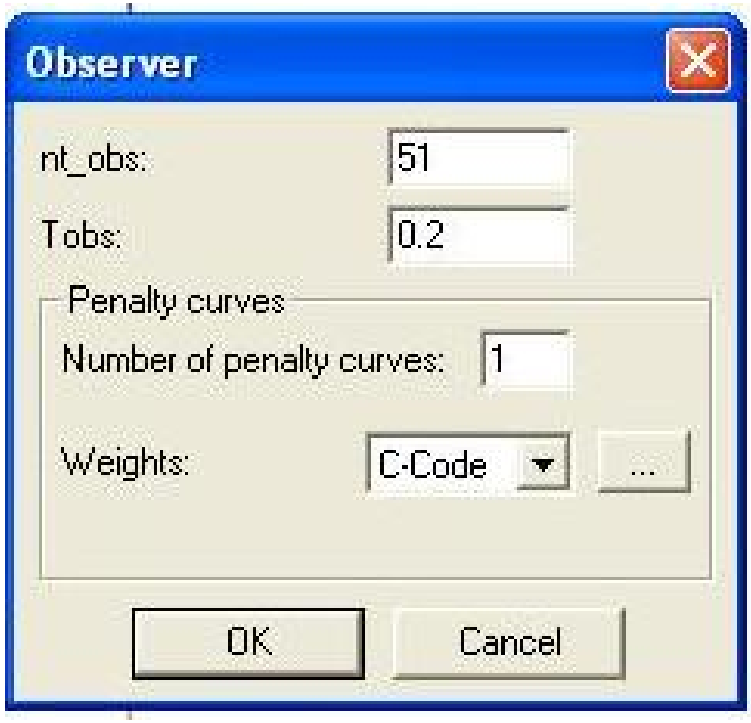


Define the observer parameters

A Typical Working Session



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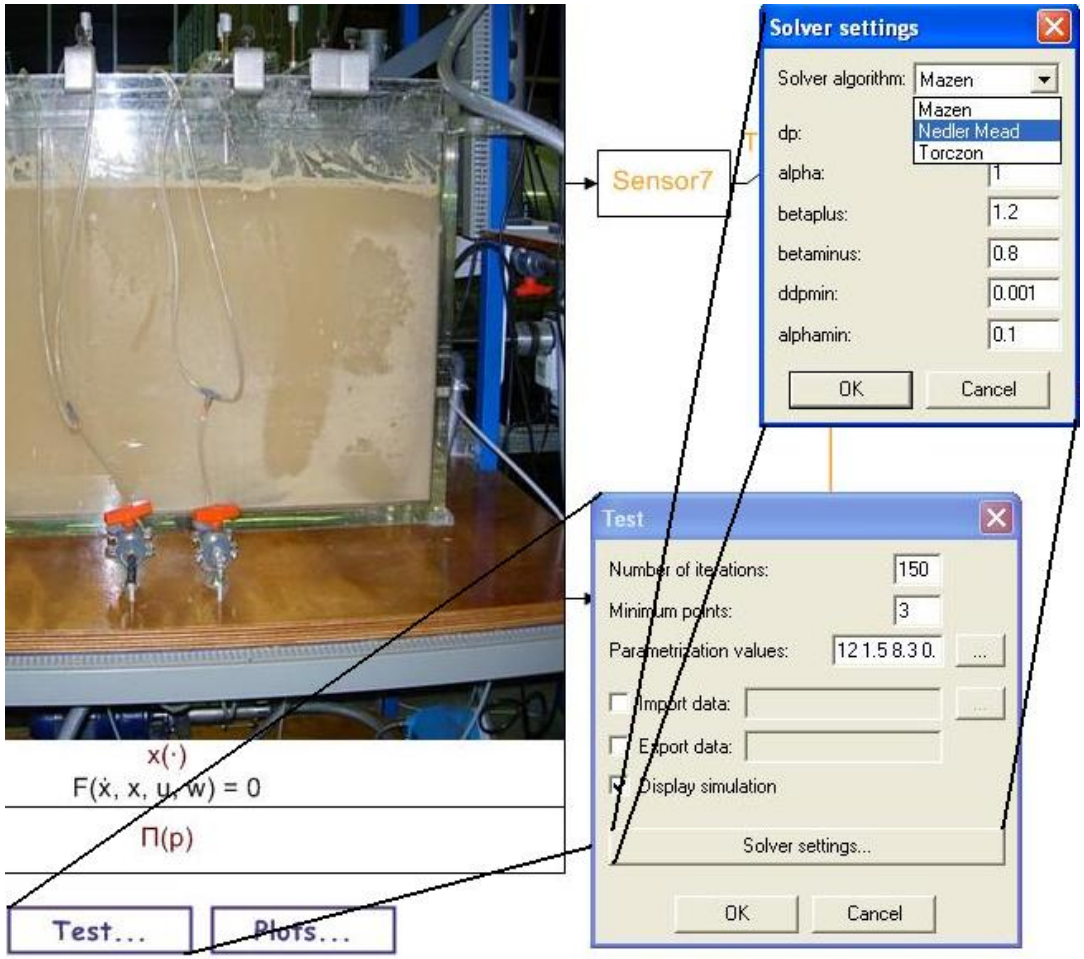
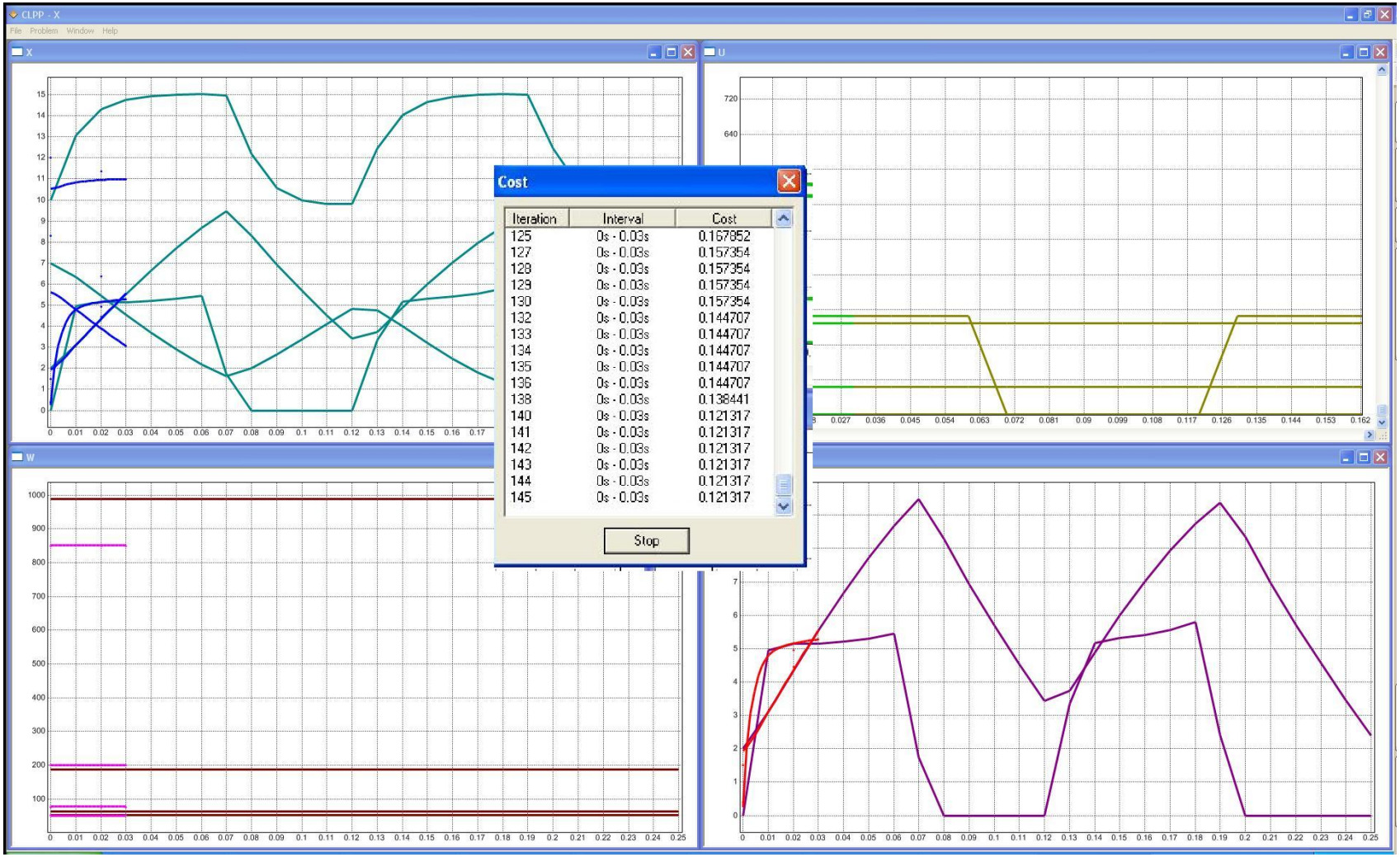


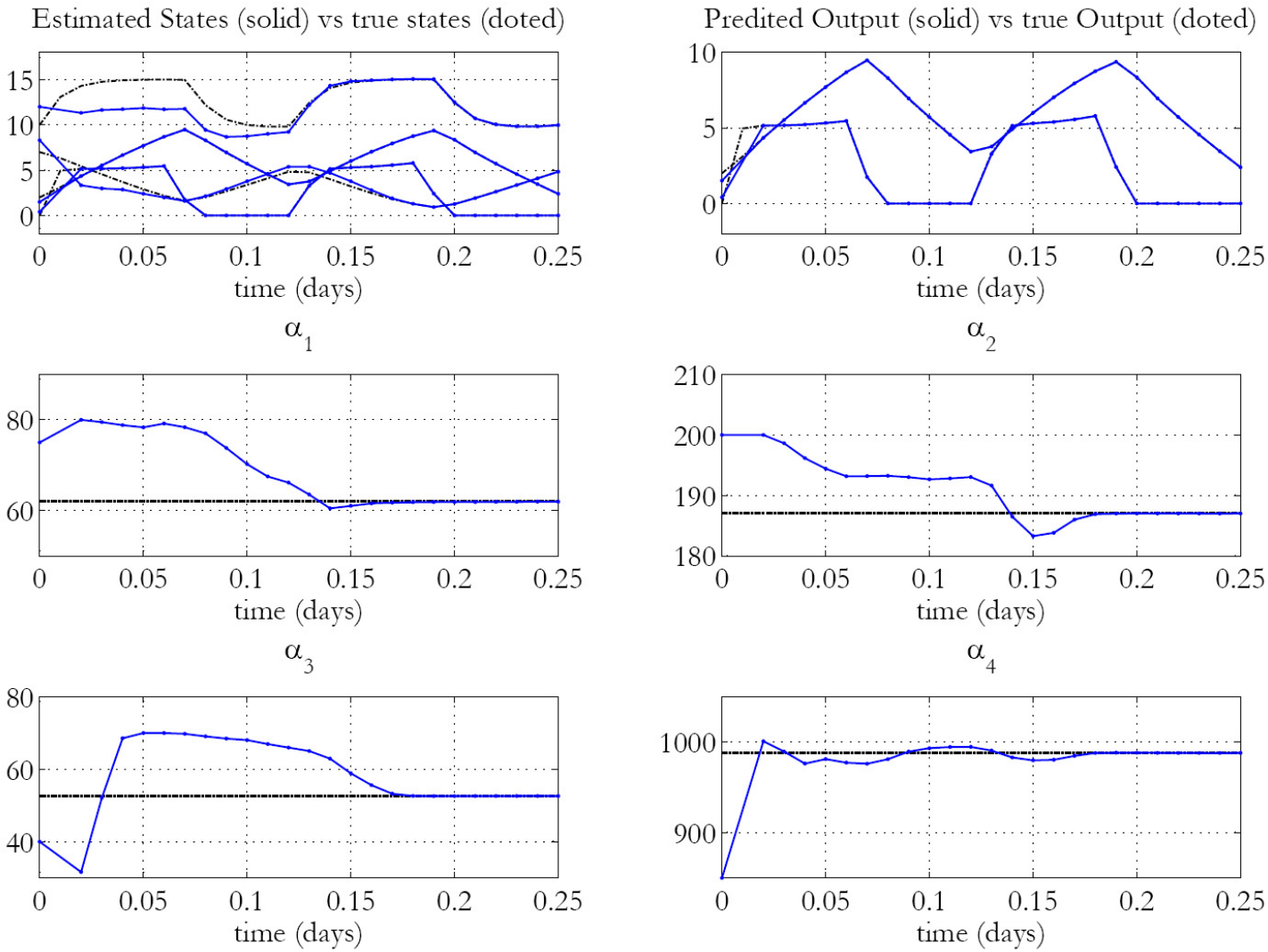
Test the observer performance : Choose the on-line iteration parameters

A Typical Working Session



Test the observer performance : check the convergence

A Typical Working Session



Convergence of the observer for the waste-water case study

Further Interesting Features of CLPP

- synchronous and non uniform measurement acquisition
- Easy use experimental data
- Can be used to detect badly posed inverse problems
- Optimize the process measurement choices
- Automatic creation of a MATLAB/SIMULINK bloc

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n1  t1  v1
n2  t2  v2
.   .   .
ni  ti  vi
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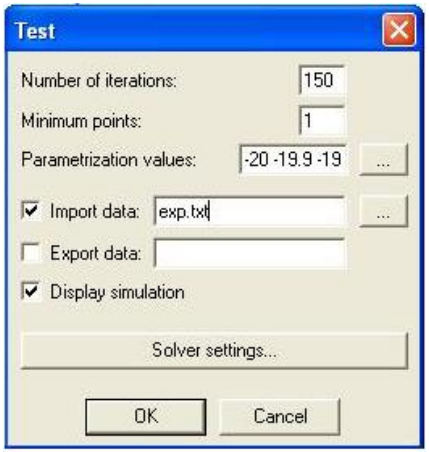


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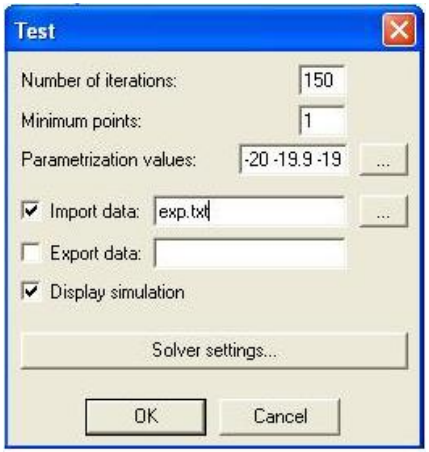
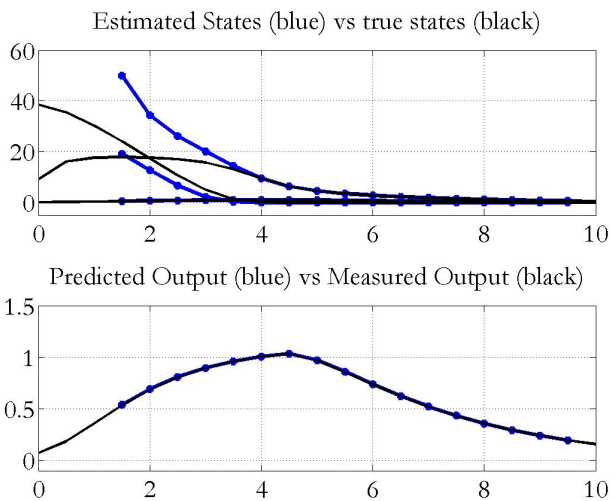




[Fouchard et al. Biotechnology and Bioengineering, 2009]

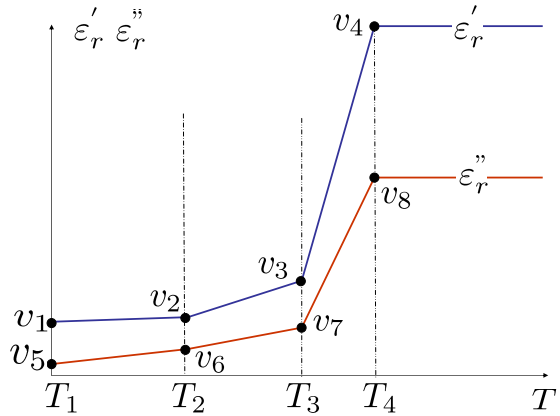
Micro-Wave Tempering

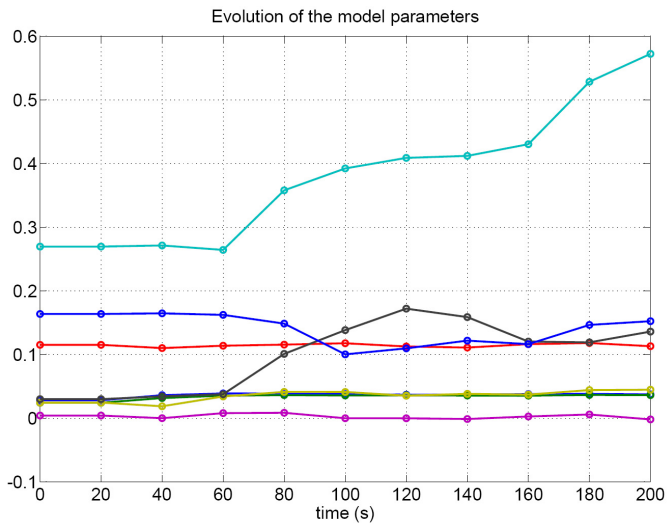
Physics $\longrightarrow$

$$\frac{\partial T}{\partial t} = F(T, T_z, u, \underbrace{\varepsilon_r^{'}(T), \varepsilon_r^{"}(T)}_{??})$$

Discretization $\longrightarrow$

$$\dot{x} = f(x, u, p) \quad (x, p) \in \mathbb{R}^{21} \times [0, 1]^8$$





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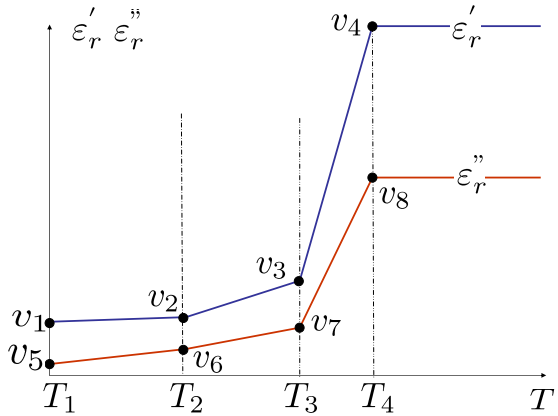

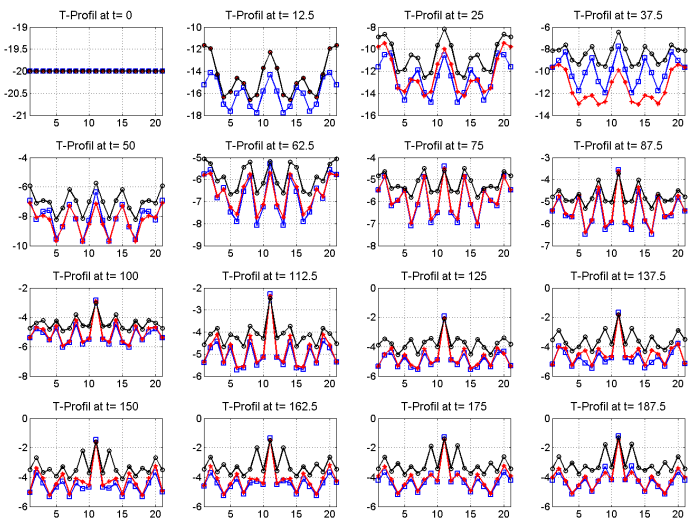

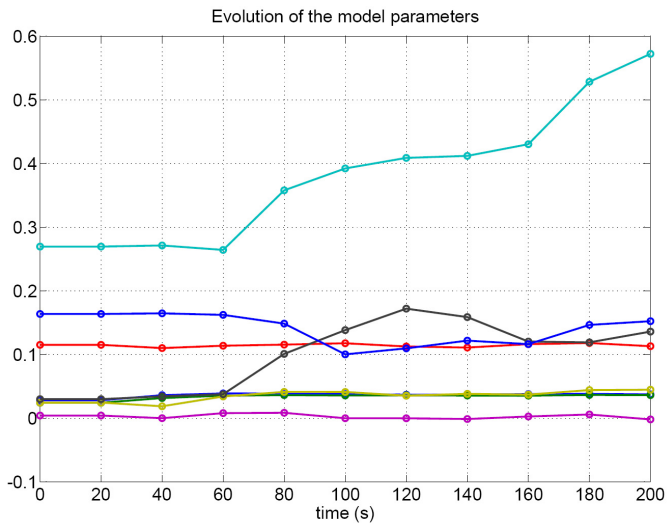

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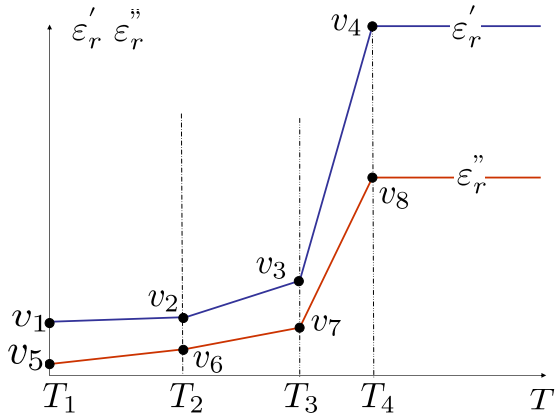
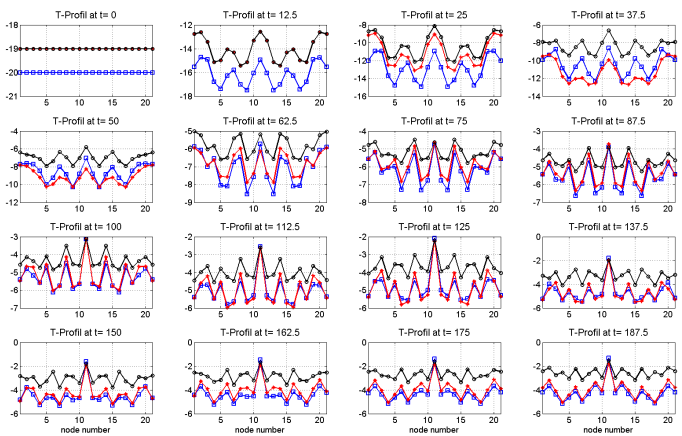
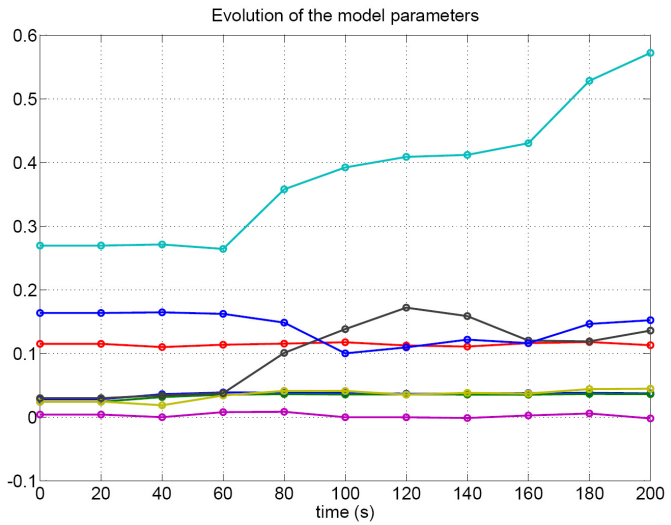




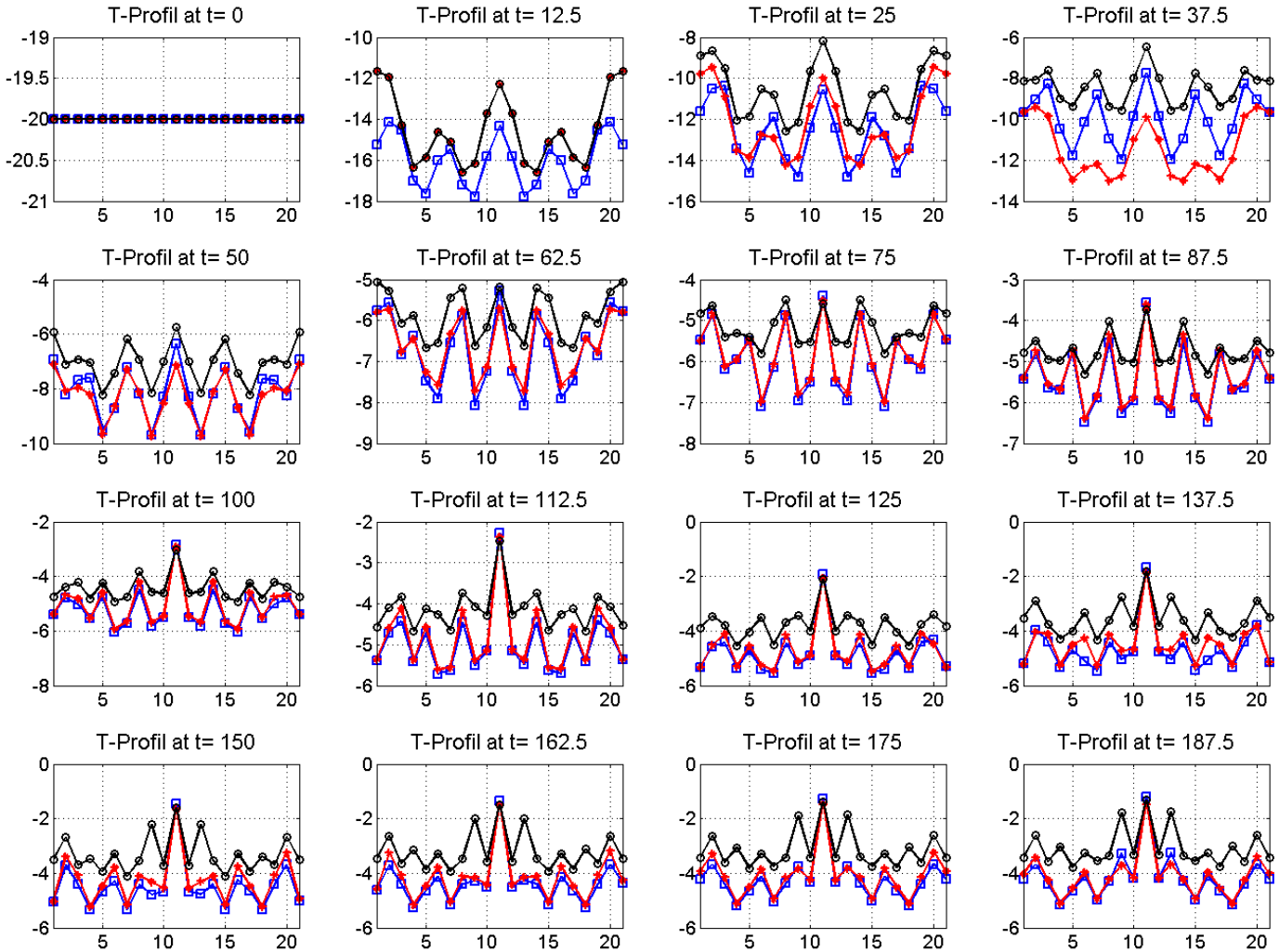


Release

Freely available (for academic) at

www.gipsa-lab.fr/projects/ANR_CLPP

very soon (autumn 2010 !)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T-Profil at t= 12.5
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T-Profil at t= 50
T-Profil at t= 62.5
T-Profil at t= 75
T-Profil at t= 87.5
T-Profil at t= 100
T-Profil at t= 112.5
T-Profil at t= 125
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T-Profil at t= 175
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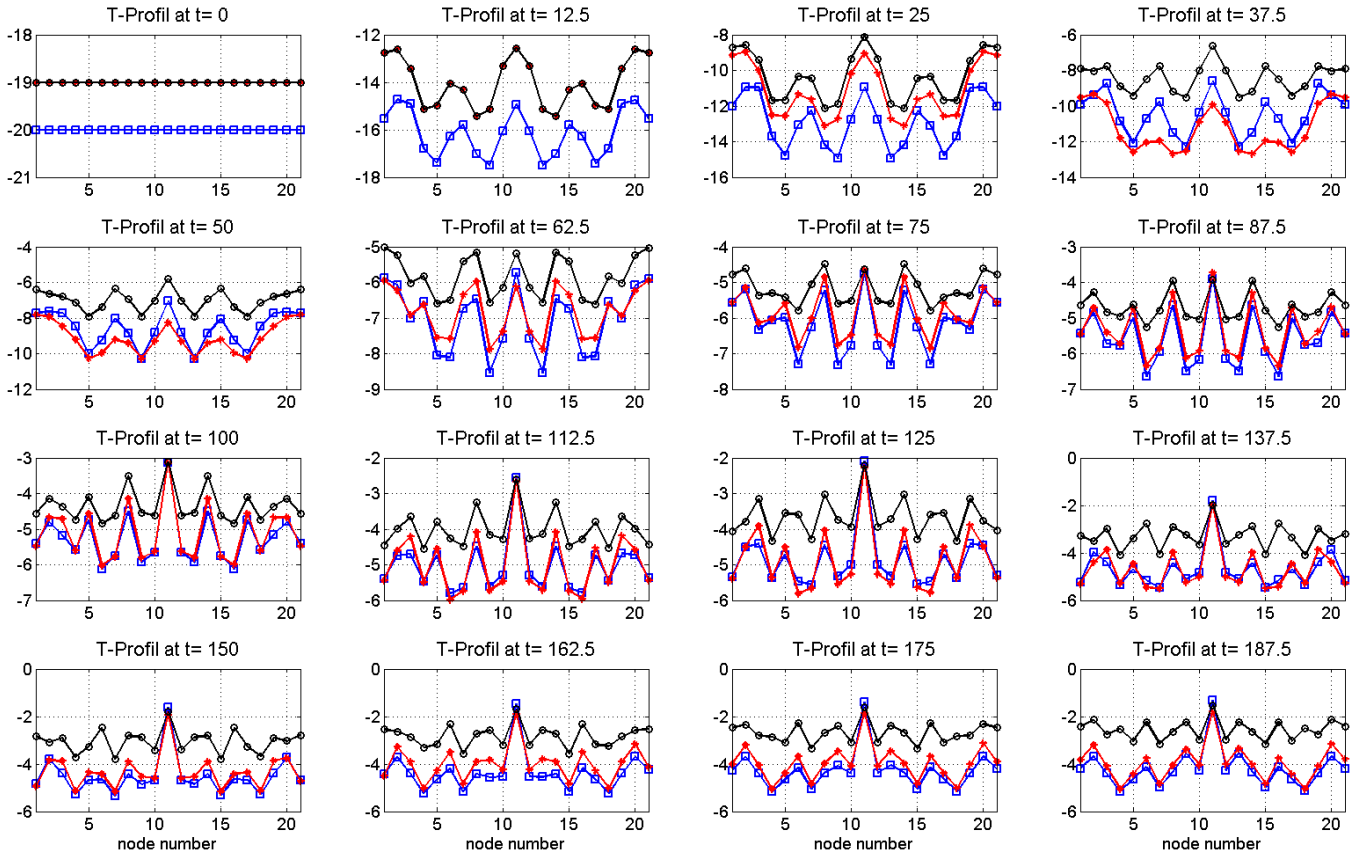
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