



POLITECNICO
MILANO 1863

Modelica-based Digital Twin for the Italian Natural Gas Network Infrastructure

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- Problem setting and motivation
- Methodology used
- FMU model
- Filtering (Discrete Time Extended Kalman Filtering)
- Results
- Conclusion and future work



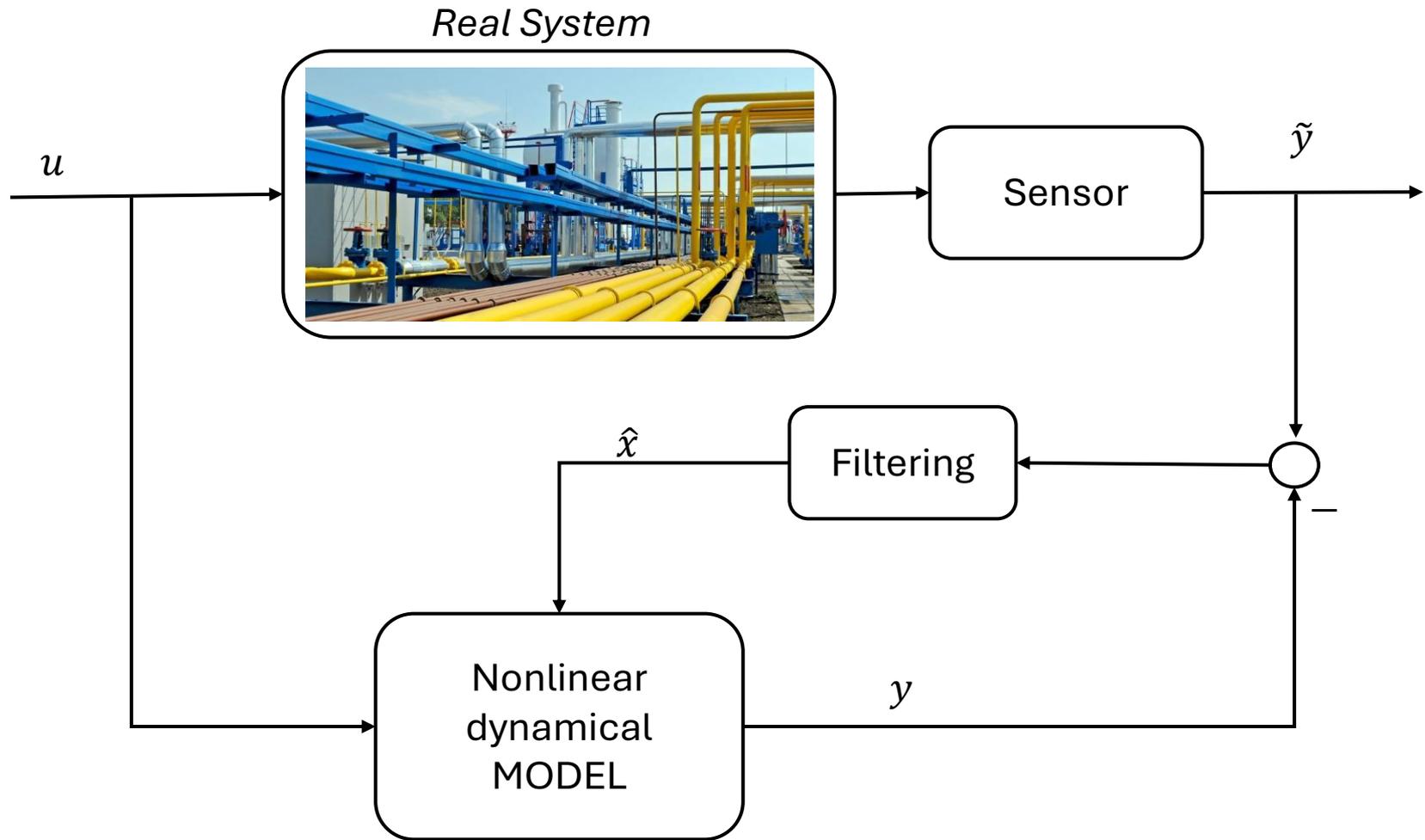
- ~ 10 000 km of high pressure network (40 000 km total)
- 13 compression stations for a total 960 MW
- ~ 2000 valves
- ~ 130 control valves
- 62 billion of Scm of gas transported in a year ([Snam, 2026](#))
- Natural gas is 40% of total energy supply in Italy ([IEA, 2024](#))

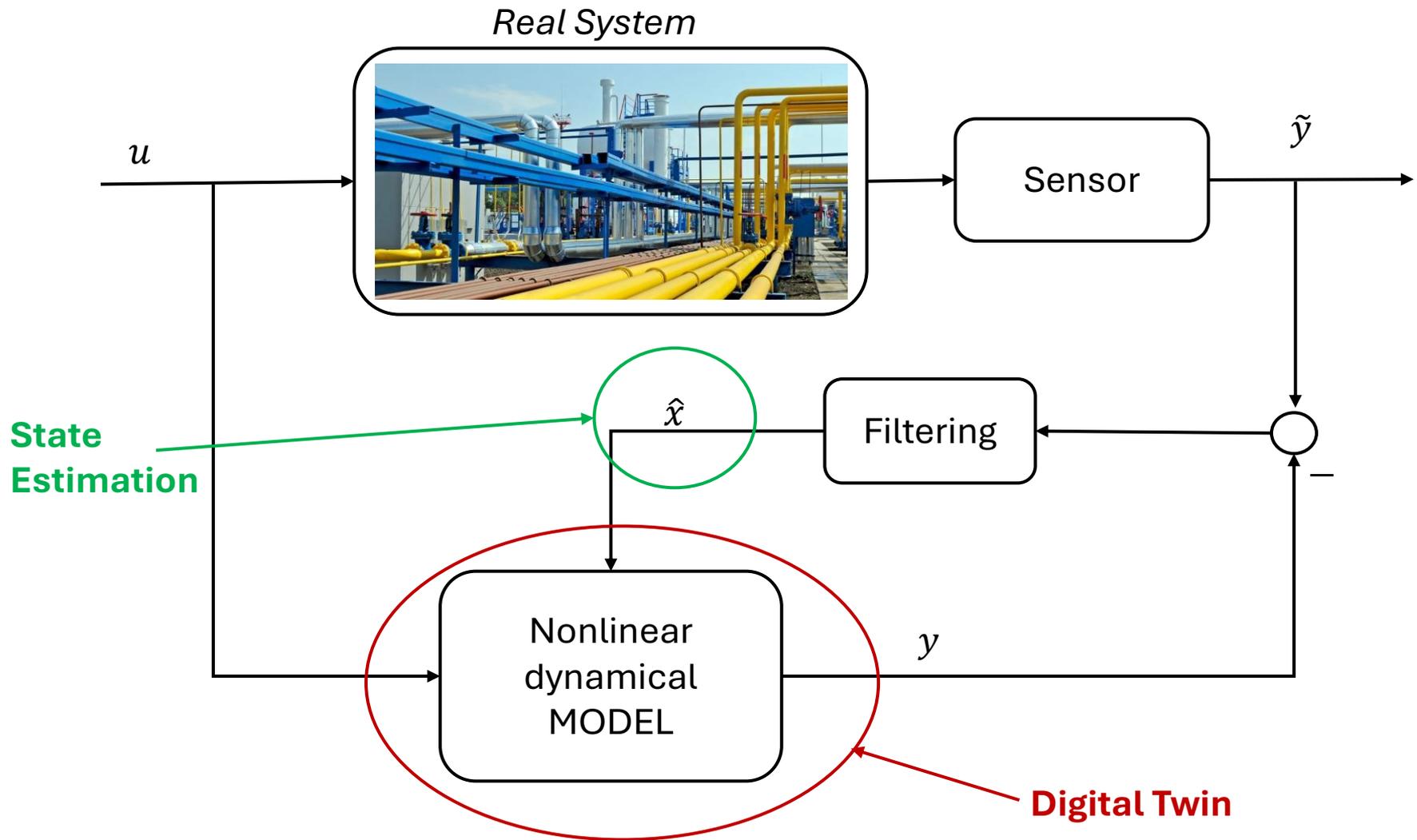


Snam S.p.A. is the Italian Transmission System Operator (TSO) for Natural Gas

The objective:

Development of a system for measurement reconciliation, state estimation, and real-time monitoring (Digital Twin) capable of determining the presence of faulty sensors throughout the entire network.

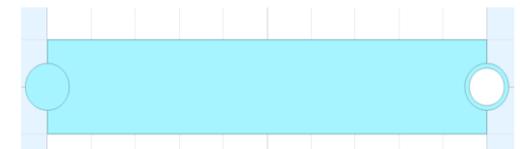
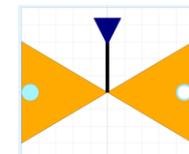
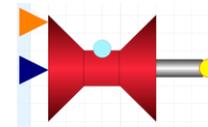
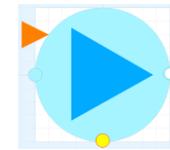




The Modelica simulation library “GasNetworks” has been developed ([De Pascali et al. \(2022\)](#)).

It contains the model of all components present in the network:

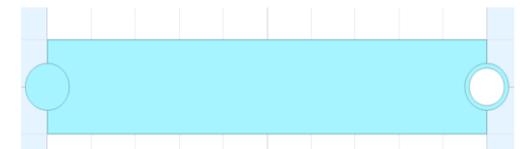
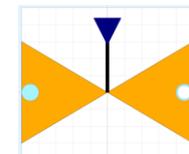
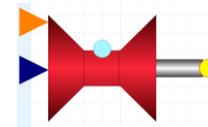
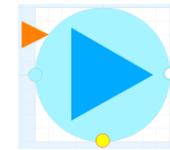
- Centrifugal Compressor
- Gas Turbine
- Control Valve
- Pipe



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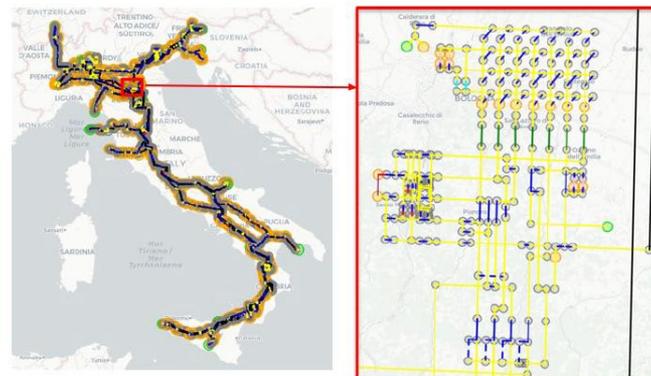
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Unfortunately, this library is not open-source yet 🤔

Snam's raw dataframe

Create a graph in Python with NetworkX



Reduction Algorithm

Automatic generation of .mo file defining the components topology



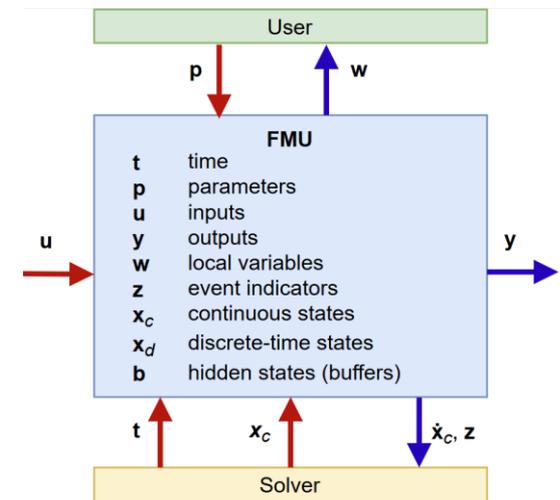
```
## write model declaration
pipeDecl = f' {pipeModel} pipe{edgeid:05}{{gasModelPipe}, {coefficients}, {initialization}};\n'
file.write(pipeDecl)
```

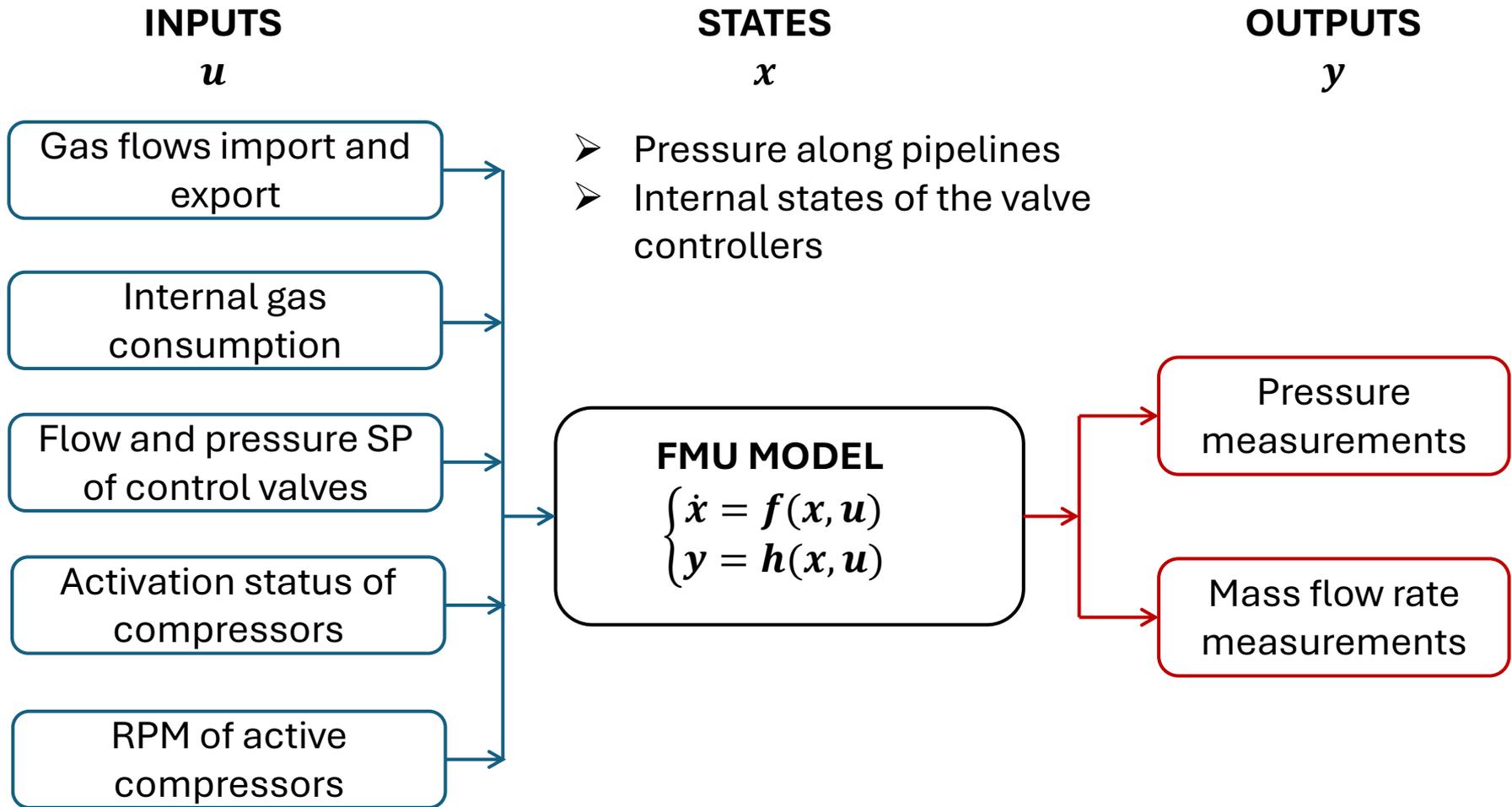
```
file.write(f' connect(pipe{edgeid:05}.inlet, node{inletNode:05}.port);\n')
file.write(f' connect(pipe{edgeid:05}.outlet, node{outletNode:05}.port);\n\n')
```

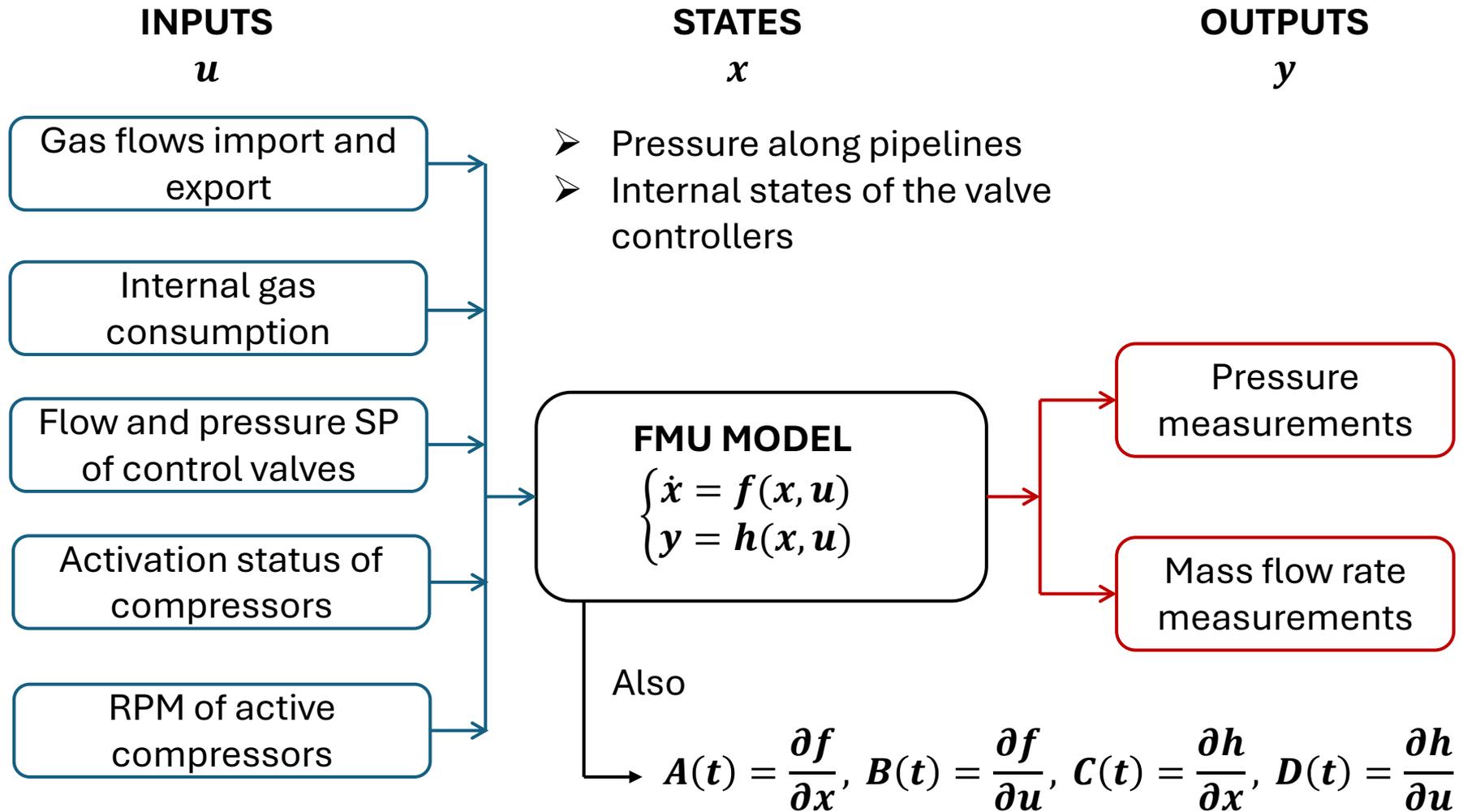
Two models:

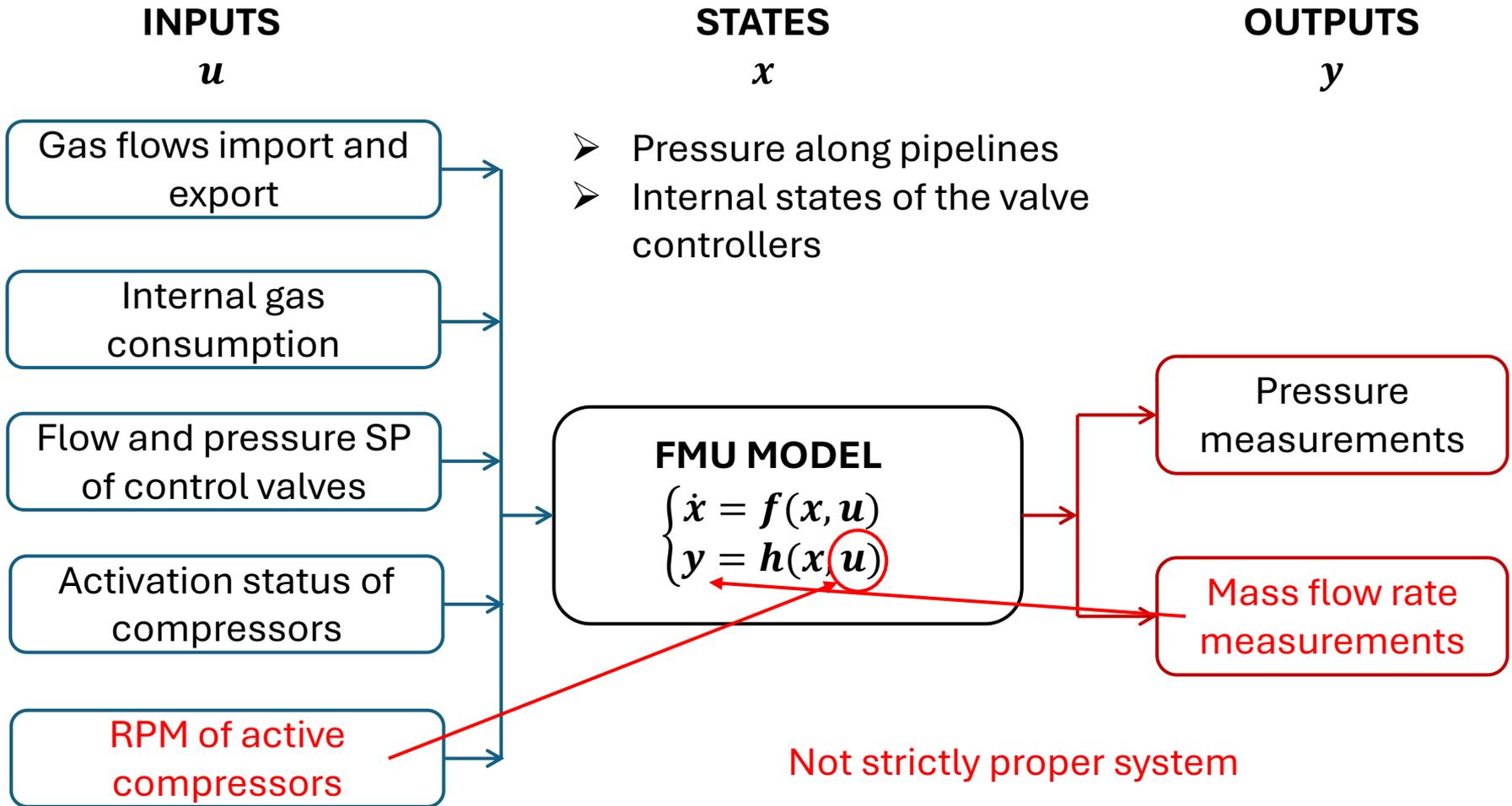
1. **Time invariant** → will be exported as FMU and used by the filter with external inputs
2. **Time variant** → will contain all the signals of the network and will serve as reference for the validation of the digital twin

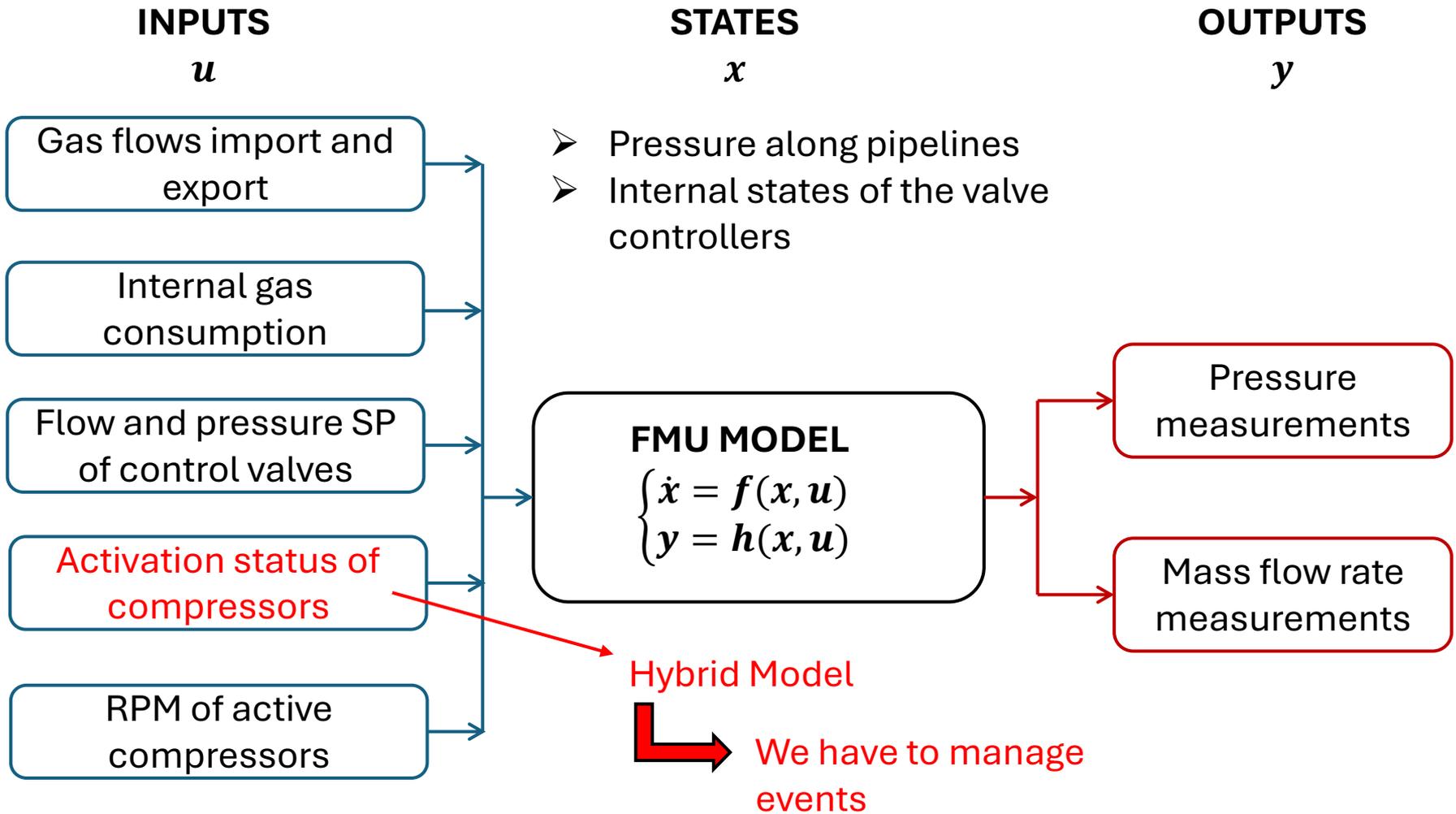
Discrete-time formulation is required so we chose **Model Exchange** to control the whole discretization loop and to access Jacobians needed for the Extended Kalman Filter.











Inside FMU it's continuous time but measured data are sampled every 4 minutes (240s)



we need a **Discrete Time** formulation for the dynamical model and the filter

To this end, a **backward Euler** discretization is applied, using Newton's method to solve the implicit formula for the next state value, with an upper limit on the number of iterations.

$$x_{k+1} - x_k - \Delta t f_c(x_{k+1}) = 0 \quad \text{fixed } \Delta t$$



We get: f_d, h_d, A_k, C_k



We can now apply the classical discrete time Extended Kalman theory!

Discrete Time Model:

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1}$$

$$y_k = h(x_k, u_k) + v_k$$

$$w_k \sim (0, Q_k)$$

$$v_k \sim (0, R_k)$$

Prediction:

$$P_k(-) = A_{k-1} P_{k-1}(+) A_{k-1}^T + Q_{k-1}$$

$$\hat{x}_k(-) = f(\hat{x}_{k-1}(+), u_{k-1})$$

Initialization:

$$\hat{x}_0(+) = x_0$$

$$P_0(+) = P_0$$

Update:

$$K_k = P_k(-) C_k^T (C_k P_k(-) C_k^T + R_k)^{-1}$$
$$\hat{x}_k(+) = \hat{x}_k(-) + K_k [y_k - h(\hat{x}_k(-), u_k)]$$
$$P_k(+) = (I - K_k C_k) P_k(-)$$

It is possible to estimate not only the network states but also additional variables



Bias Sensor Error Estimation

If we suppose that the bias error enters the output equation as an additive term:

$$y_k = h(x_k, u_k) + v_k + \beta_k \quad \text{Bias term } \beta_k$$

with

$$\beta_k = \beta_{k-1} + w_{k-1}^\beta$$

then

$$x_k^{en} = \begin{bmatrix} x_k \\ \beta_k \end{bmatrix}$$

$$A_k^{en} = \begin{bmatrix} A_k & 0 \\ 0 & I \end{bmatrix},$$

$$C_k^{en} = [C_k \quad I]$$

Physical network dynamic are very slow: the pressure distribution within the pipelines has time constants on the order of several hours. [Hammelmann et al. \(2023\)](#)



A natural choice would be $\Delta t = 240s$ in the Euler discretization since measurement data are collected every 4 minutes (240s)

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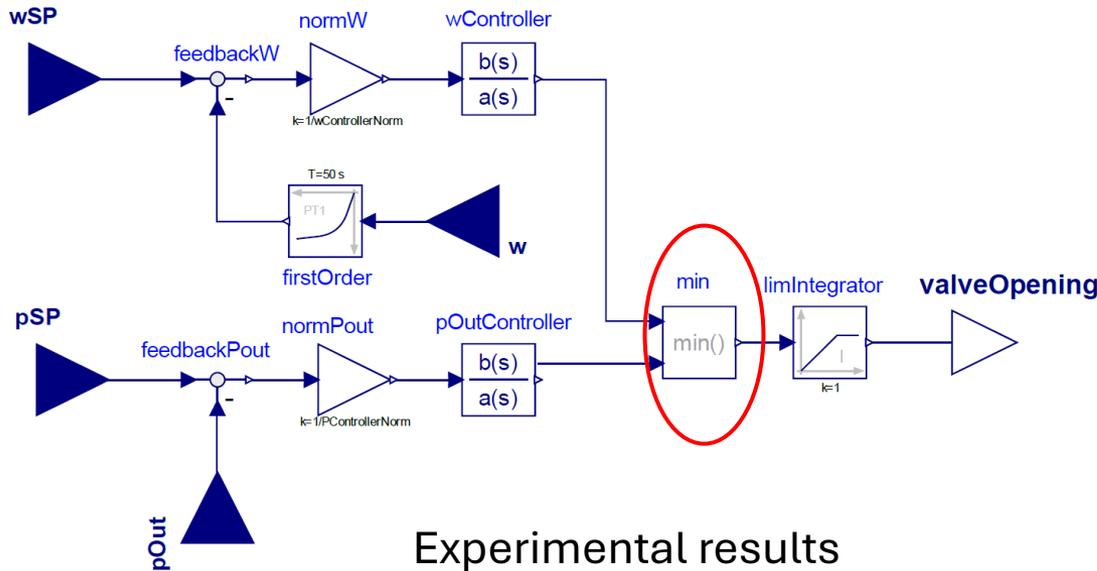
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BUT SOLVER FAILS

Newton's iterations fail to converge. Why?

Controls of control valves



Fast dynamics and very nonlinear



Problem for the numerical integration if Δt is too large

Experimental results

- $\Delta t = 240s$ Simulation failure
- $\Delta t = 120s$ Convergence limit
- $\Delta t = 80s$ **Robust convergence**



Three points per measurement

Validation up to now has been performed **only on synthetic data** suitably modified to introduce (known!) error sources, mimicking those expected in reality. We considered:

White Noise

$\mathcal{N}(\mu, \sigma^2)$ with $\mu = 0$ and $\sigma = 0.2 * 10^5$ Pa (0.2 bar) for pressure measurements
with $\mu = 0$ and $\sigma = 1$ Kg/s for mass flow rate measurements

Constant Bias Error

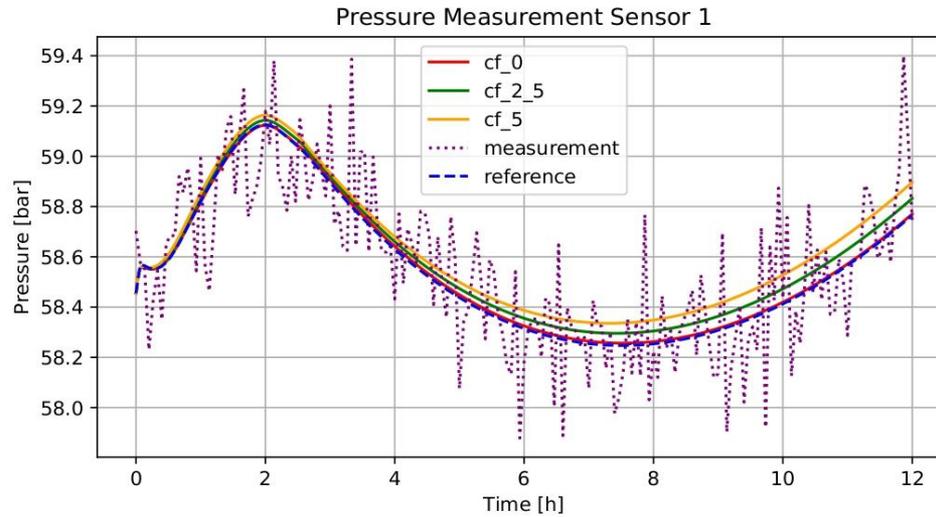
$\beta = 1 * 10^5$ Pa (1 bar) in specific pressure measurement sensors

Parametric error on friction coefficient

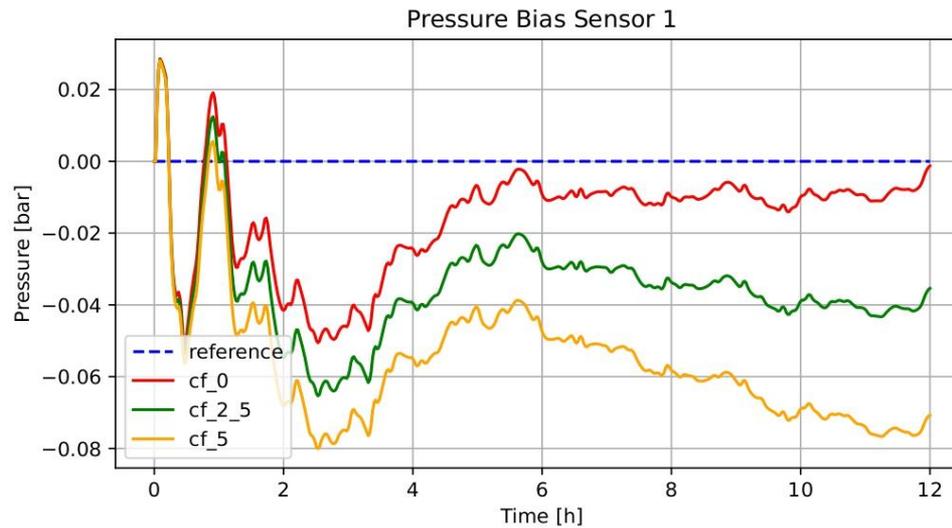
$$p_{out} - p_{in} = c_f \rho \omega \frac{u^2}{2} LA - \rho g (z_{out} - z_{in})$$

Error on c_f of 0% , 2.5% and 5%

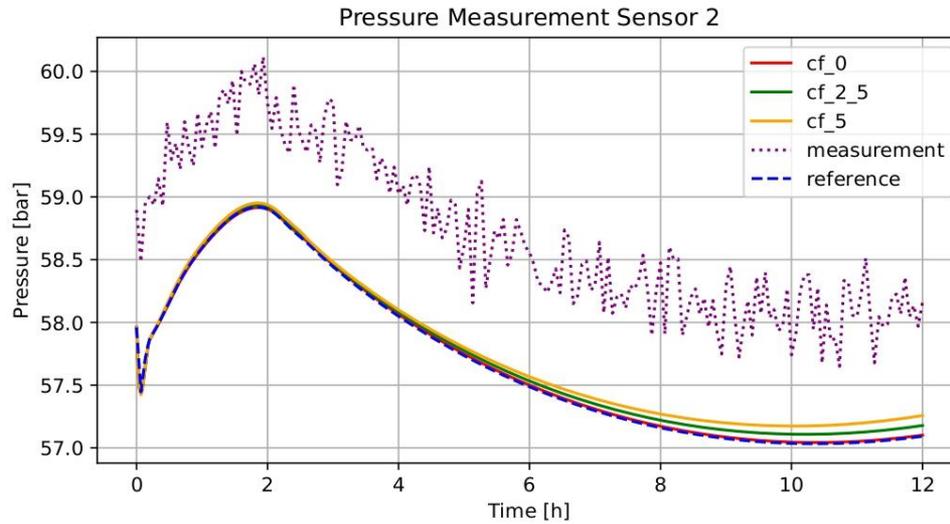
Pressure Estimation



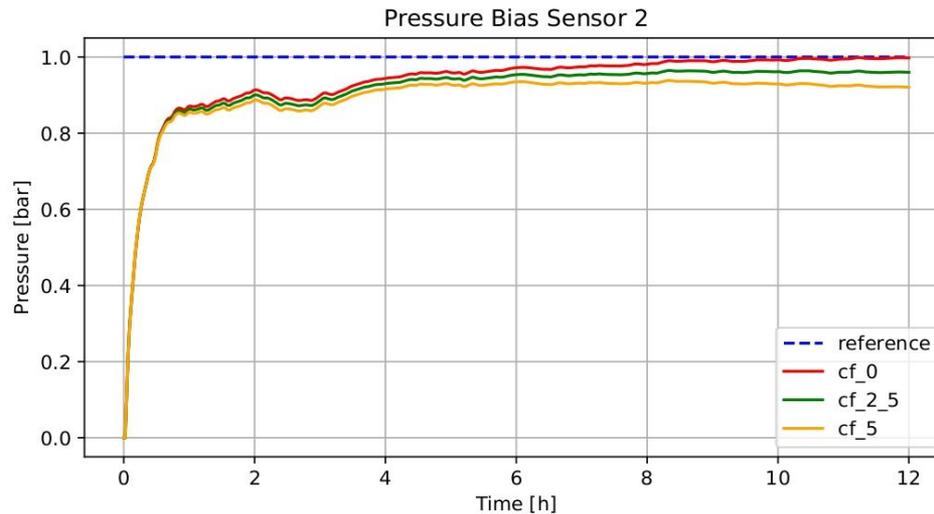
Bias Estimation



Pressure Estimation

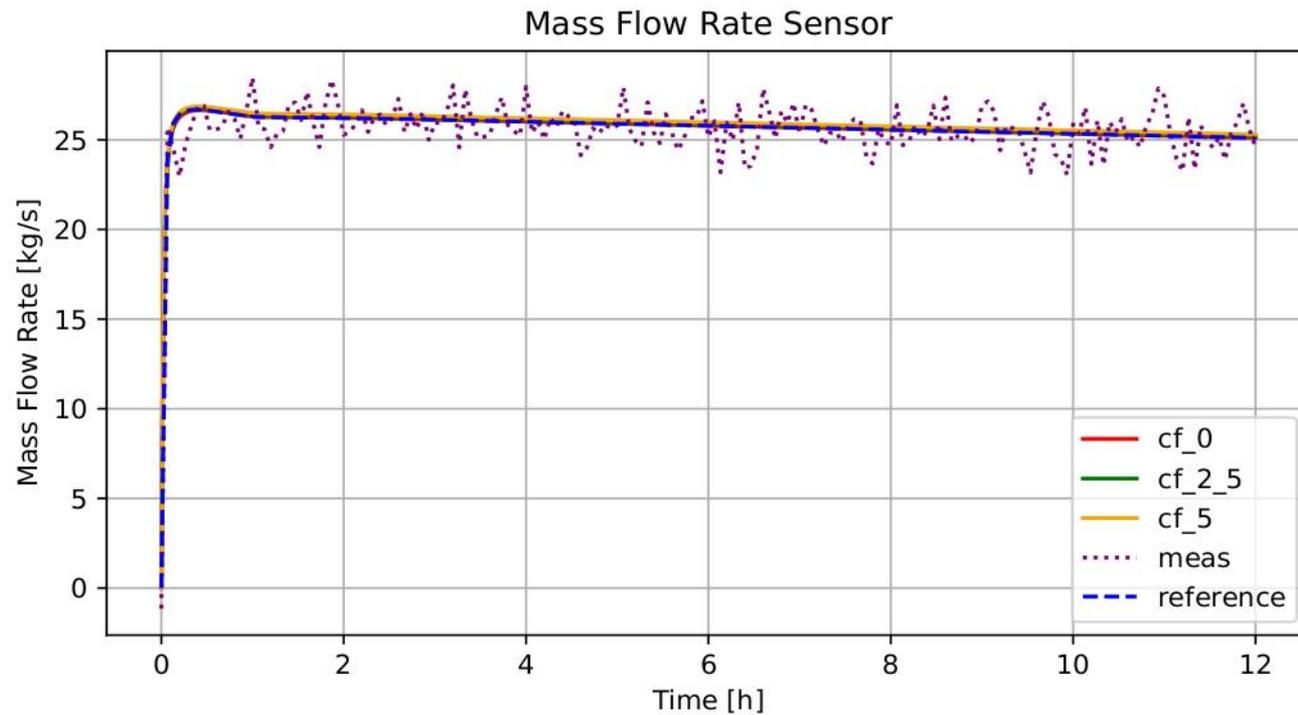


Bias Estimation



Fault detection and fault estimation!

Mass flow rate Estimation



- The proposed methodology can generate a digital twin of a real gas network to filter noisy field measurements and reconstruct the system state, with the possibility, through state augmentation, of detecting sensors that have an offset.
- It has been shown that the digital twin behaves robustly even in the presence of model uncertainties.
- Potential for real-time applications
- So far, validation has been performed only on synthetic data.
- Future work will focus on testing the methodology with real SCADA data (every 4 minutes).
- Other types of state augmentation could be considered based on the operator's needs.

This work has been submitted to IFAC WC 2026



The project is conducted using only open-source software

OpenModelica



CATIA-Systems/
FMPy



Simulate Functional Mock-up Units (FMUs) in Python

7 Contributors 120 Issues 555 Stars 139 Forks

1. FMU export in C → memory leaks problems
2. FMU export in C++ → Initialization problem, the event iteration during `when initial()` cannot handle more than one iteration
3. FMU C++ was not working with PyFMI
4. Now the FMU C++ runs smoothly in FMPy with the correct initialization 😊

**Thank you for your
attention!**