Unsupervised Fault Detection in a Controlled Conical Tank

J. Ortega, C. Ramírez, T. Rojas,
F. Tamssaouet, M. Orchard, and J. Silva

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IDS Information and Decision System Group

FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS UNIVERSIDAD DE CHILE

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Presenter: Marcos Orchard

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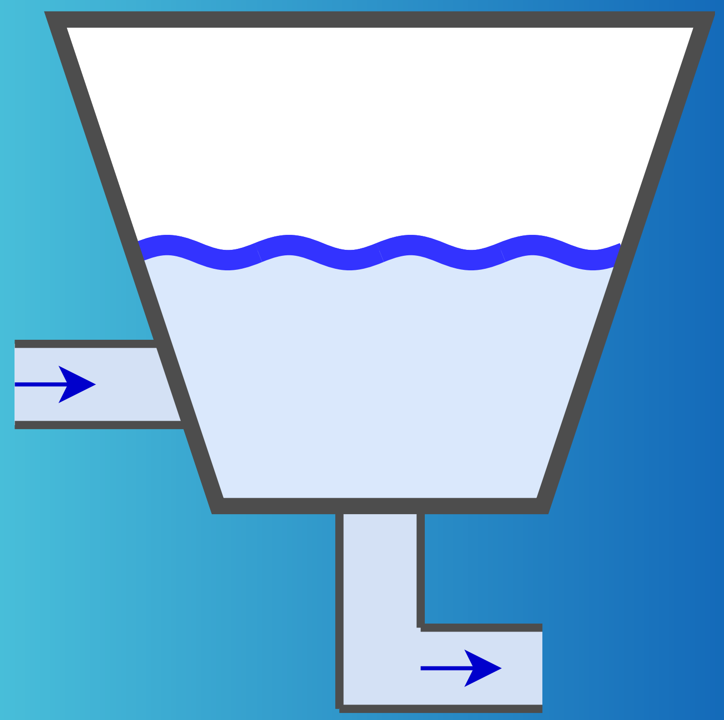
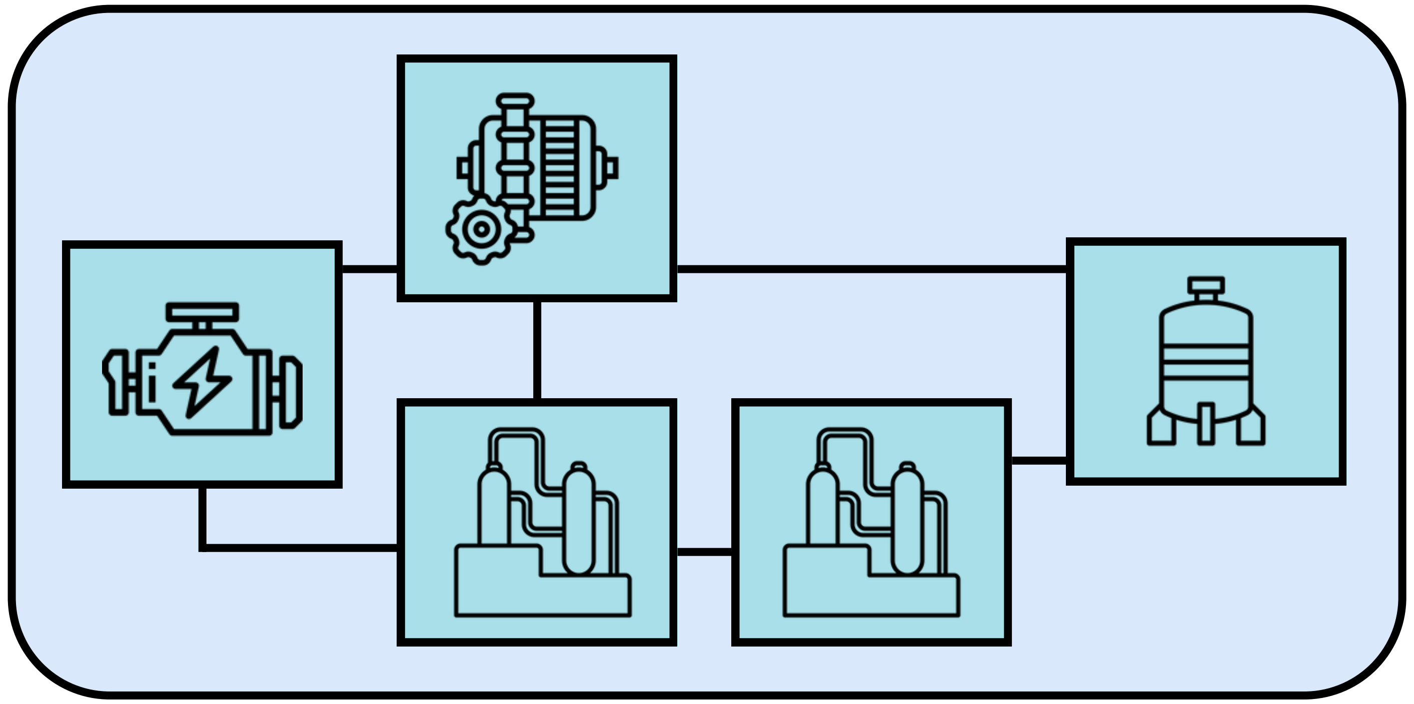
Motivation and FDI	**01**
Controlled Conical Tank	**02**
MI-based Fault Detection Methodology	**03**
Study Case — Black-Box Model	**04**
Complementary White-Box Analysis	**08**
Conclusion and Future Work	**11**



Motivation and FDI

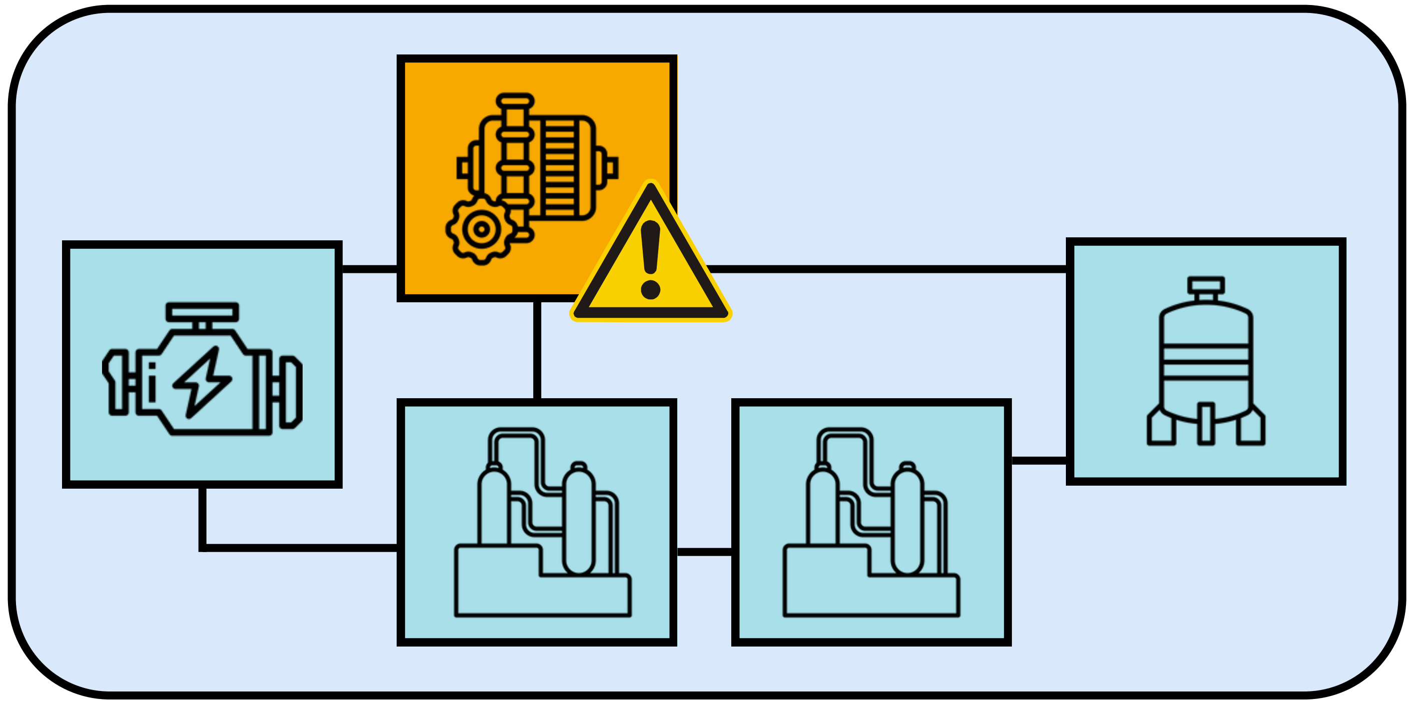
Fault Detection and Identification (FDI)



Motivation and FDI

Fault Detection and Identification (FDI)

Provides information regarding process and sub-process failure, enabling predictive maintenance



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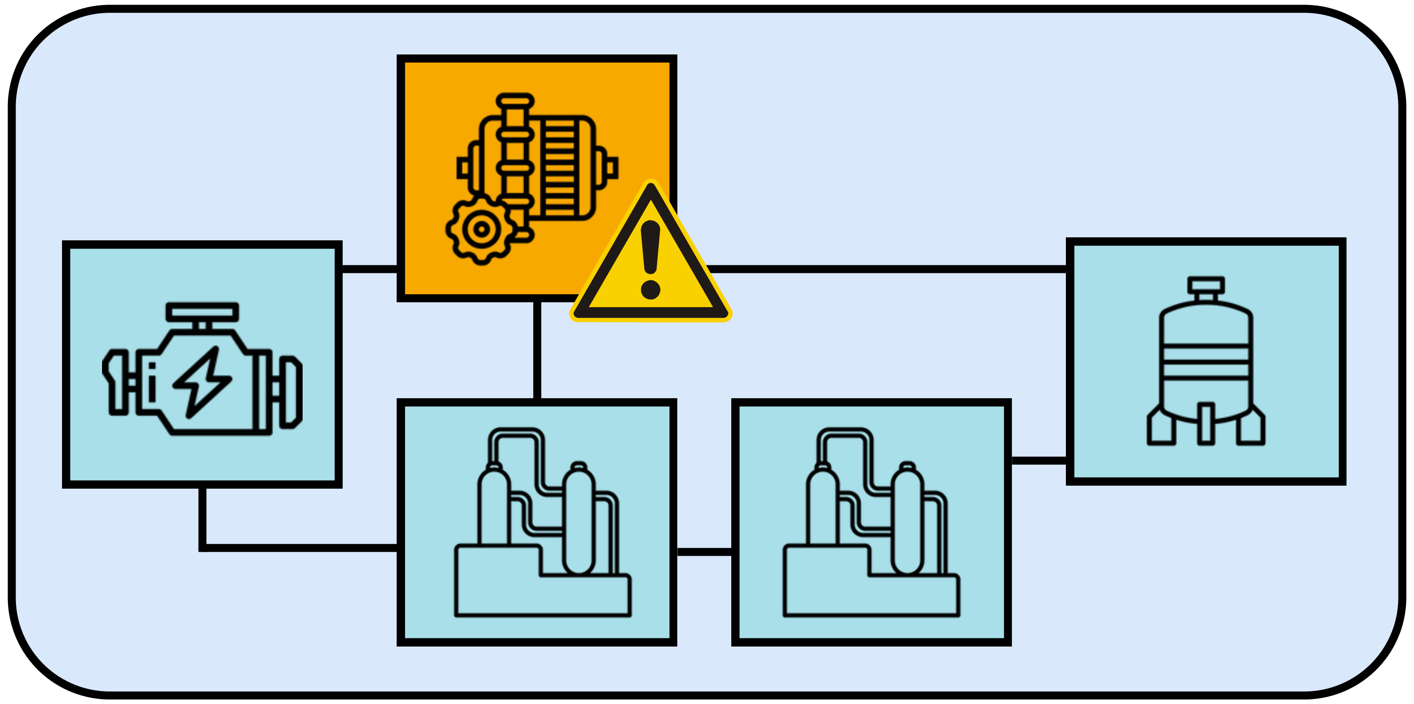


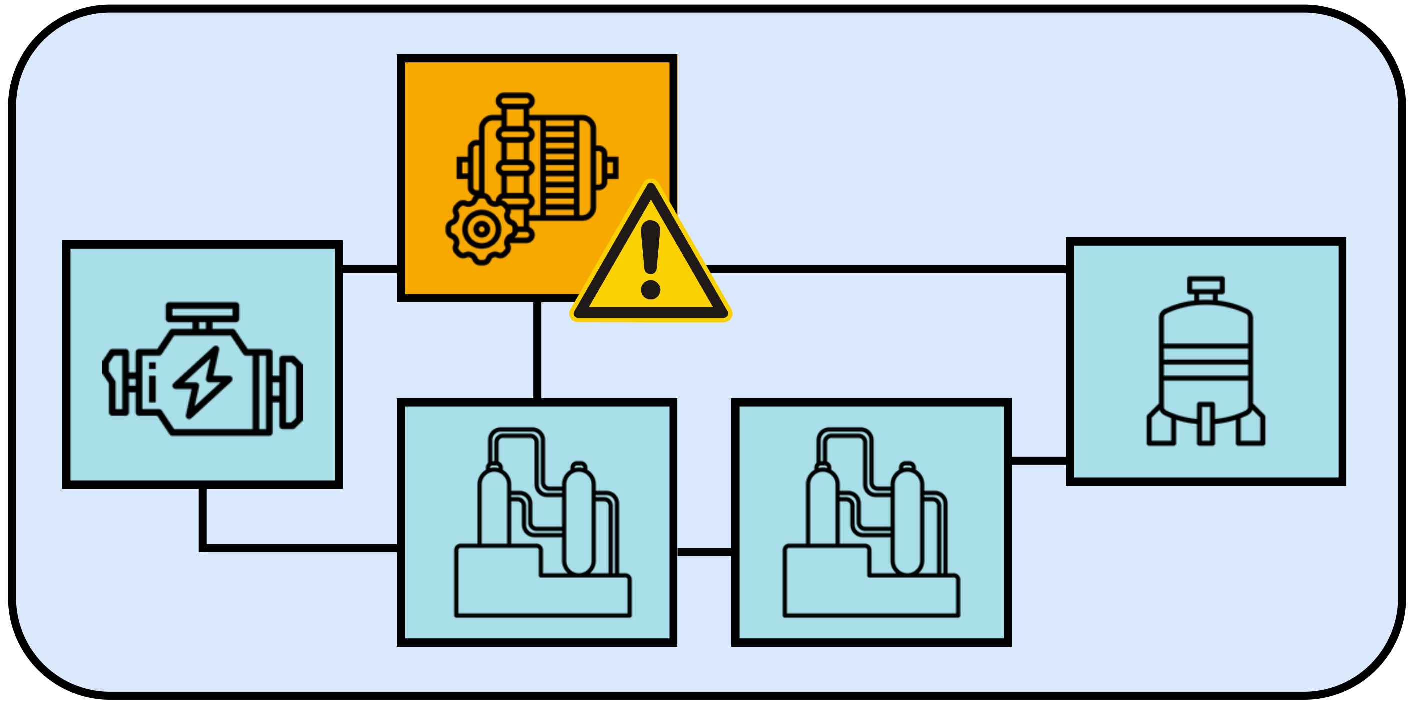
Challenges

- Non-linear systems
- Controlled systems

Motivation and FDI

Fault Detection and Identification (FDI)

Provides information regarding process and sub-process failure, enabling predictive maintenance



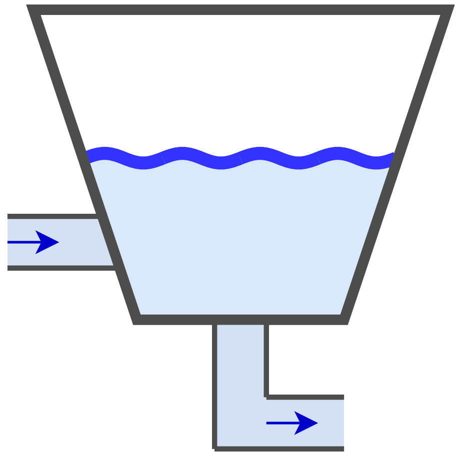
Challenges

- Non-linear systems
- Controlled systems

Our contribution

MI-based unsupervised FDI scheme

Study case: controlled conical tank



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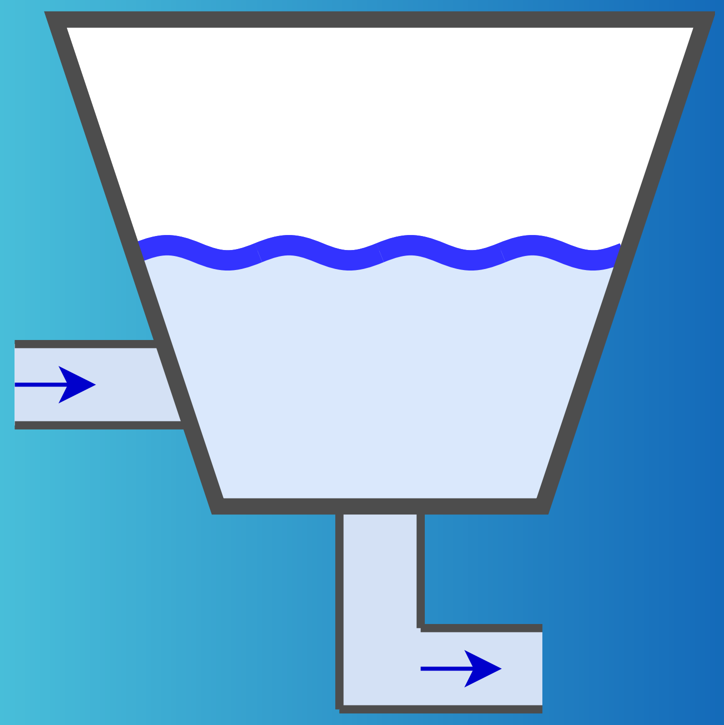
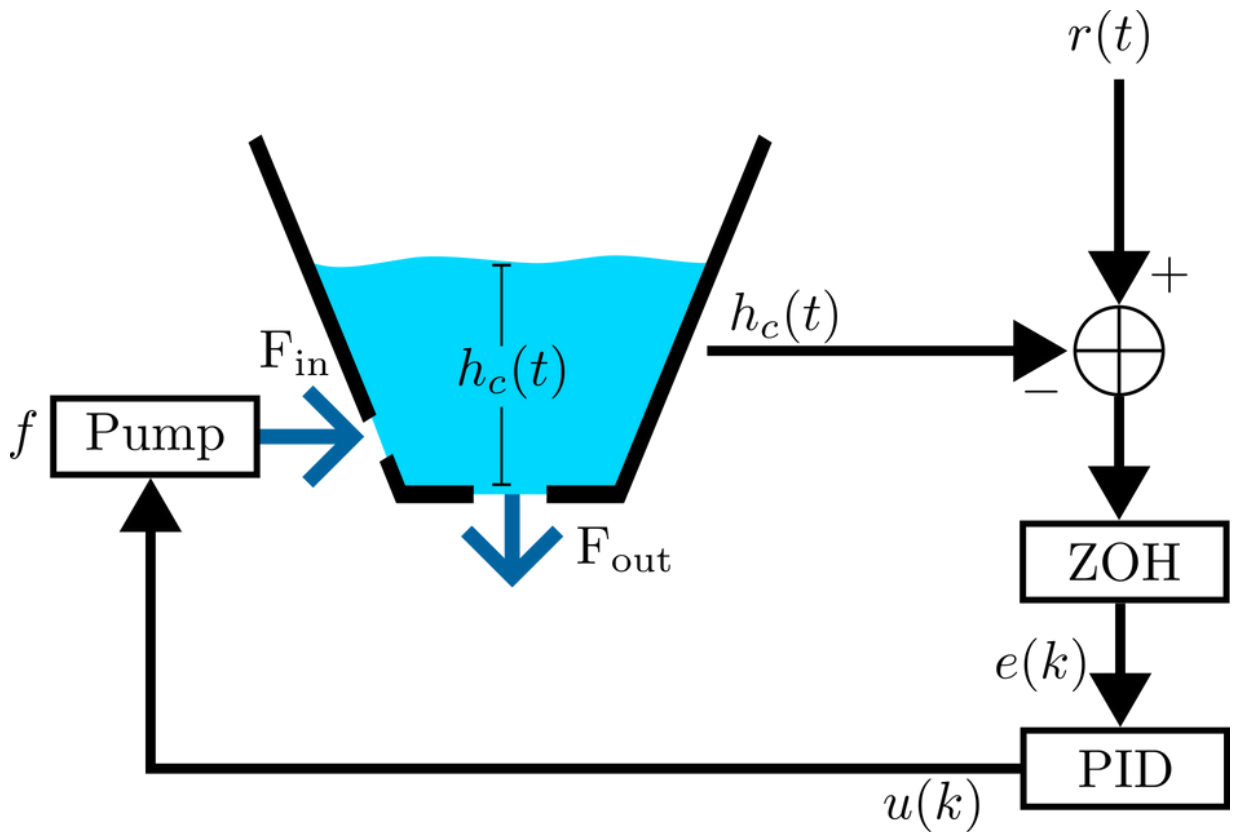


Controlled Conical Tank

Proportional–derivative–integral (PID) controller tuned with particle swarm optimization (PSO)

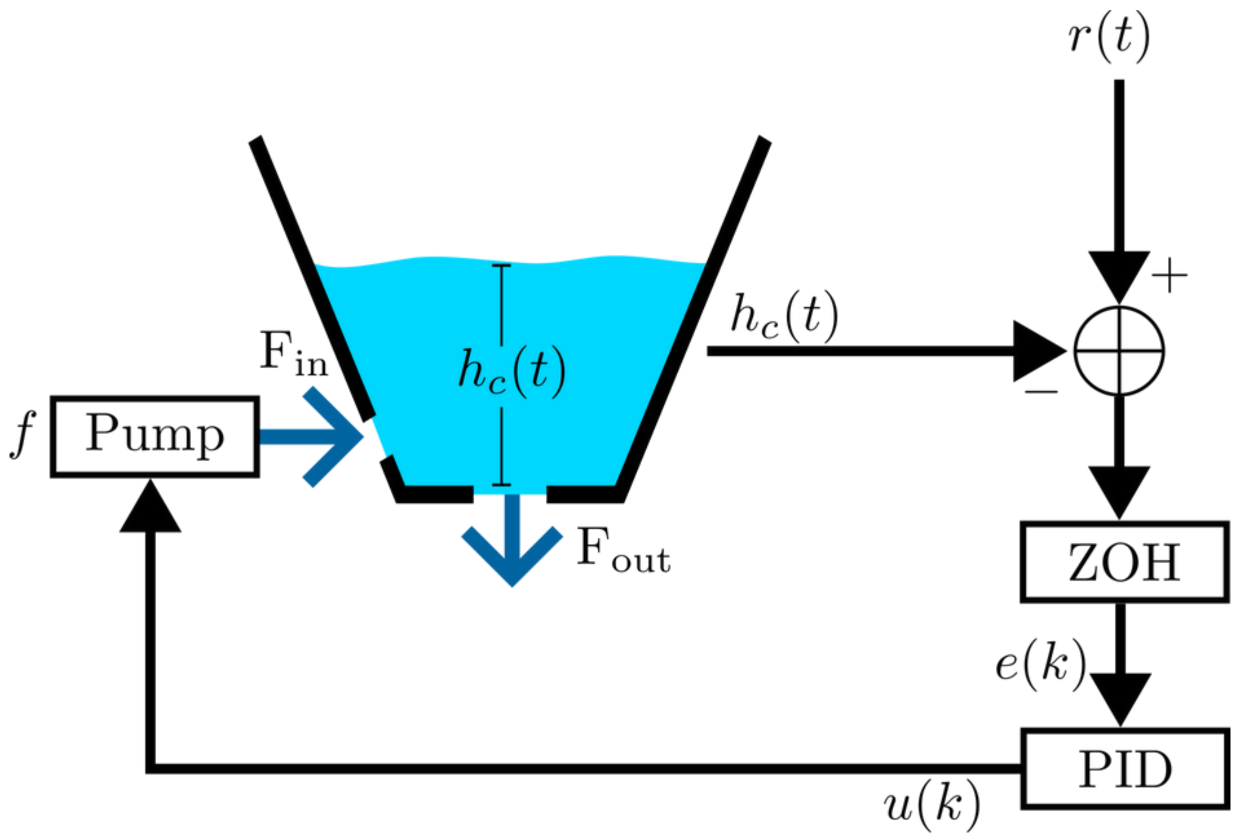
Controlled Conical Tank

Proportional–derivative–integral (**PID**) controller tuned with particle swarm optimization (**PSO**)



Controlled Conical Tank

Proportional–derivative–integral (PID) controller tuned with particle swarm optimization (PSO)



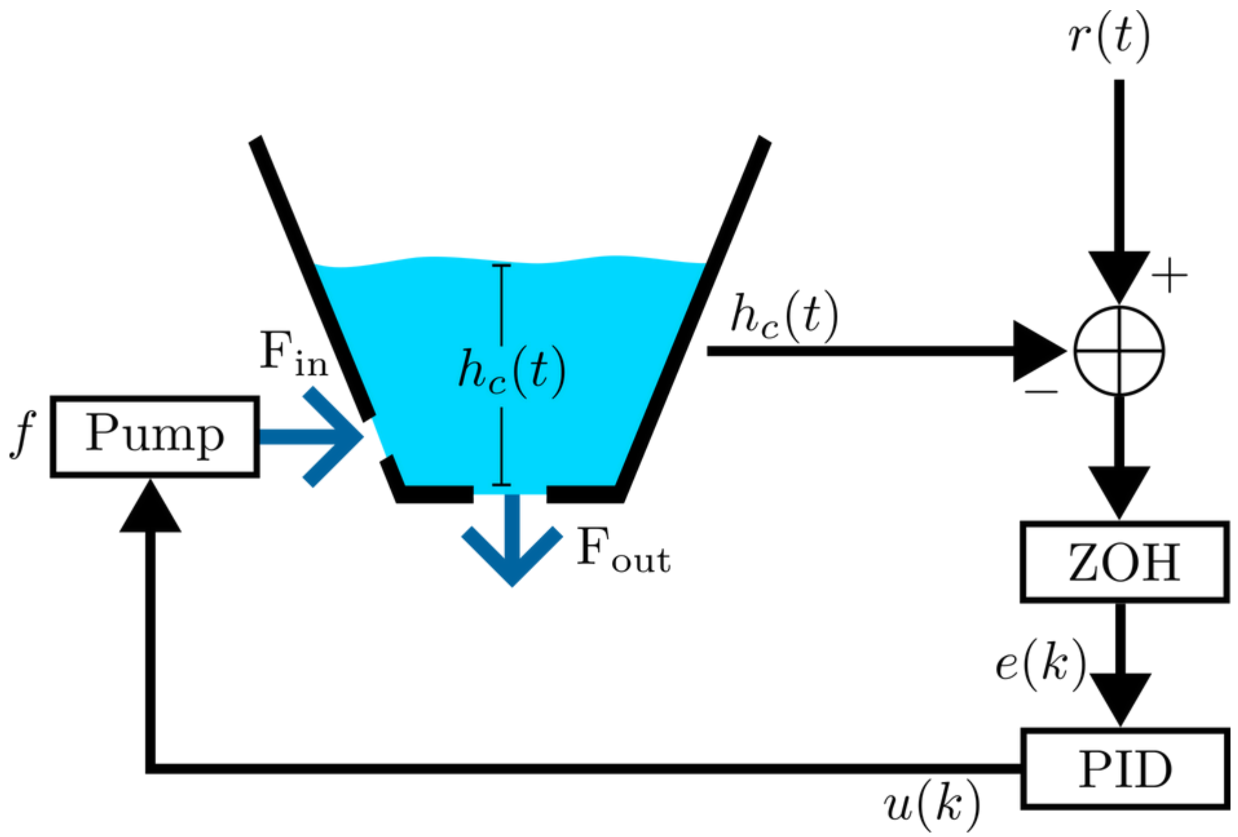
Model of Jáuregui (2016)

$$\frac{dh_c}{dt} = \frac{\alpha_1 \cdot f + \alpha_2 - \beta\sqrt{h_c}}{0.63 h_c^2 + 11.4 h_c + 17.1}$$

$$\alpha_1 = 543\ \mathrm{cm^3 s^{-1}}$$
$$\alpha_2 = -78.23\ \mathrm{cm^3 s^{-1}}$$
$$\beta = 20.21\ \mathrm{cm^{5/2} s^{-1}}$$

Controlled Conical Tank

Proportional–derivative–integral (PID) controller tuned with particle swarm optimization (PSO)



Model of Jáuregui (2016)

$$\frac{\mathrm{d}h_c}{\mathrm{d}t} = \frac{\alpha_1 \cdot f + \alpha_2 - \beta\sqrt{h_c}}{0.63h_c^2 + 11.4h_c + 17.1}$$

f : pump usage percentage (%)
h_c : water height (cm)

Zero-order hold (ZOH) samples each 15 s

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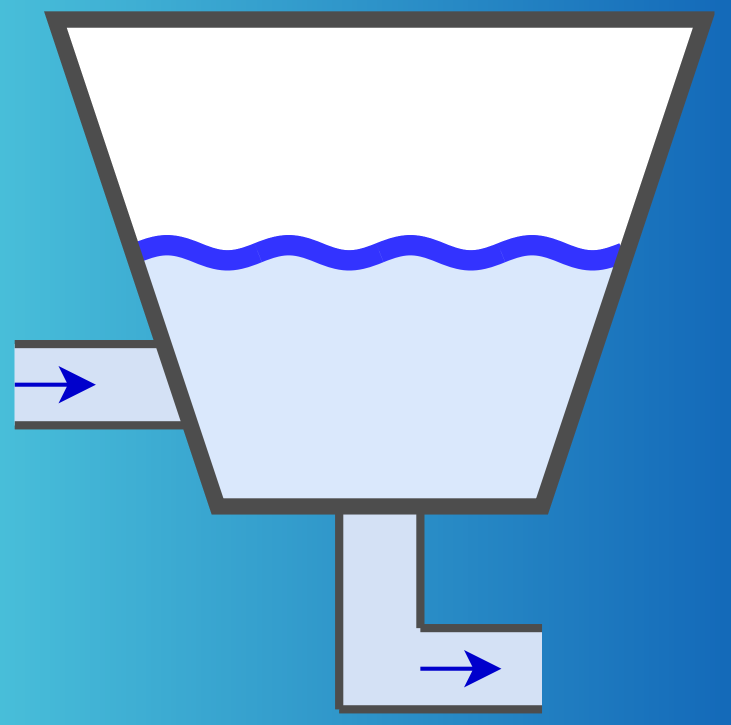
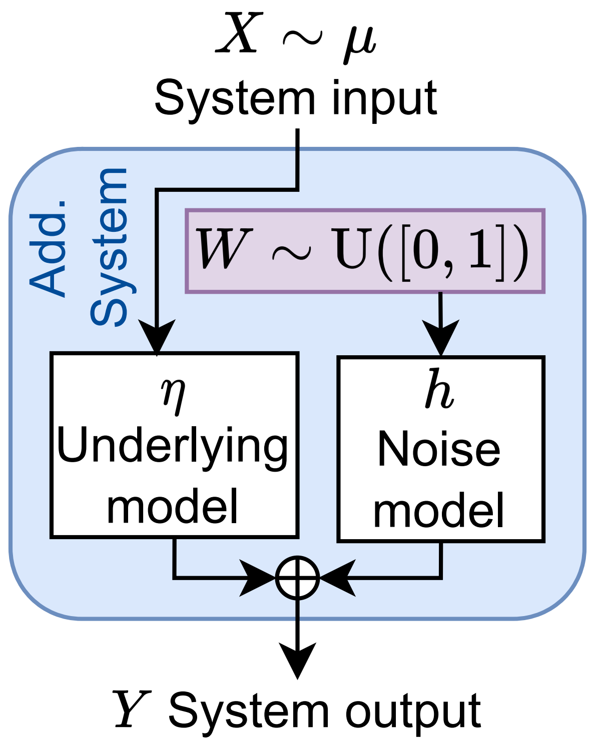


MI-based Fault Detection Methodology

Method by Ramírez et al. (2024)



Additive noise system

MI-based Fault Detection Methodology

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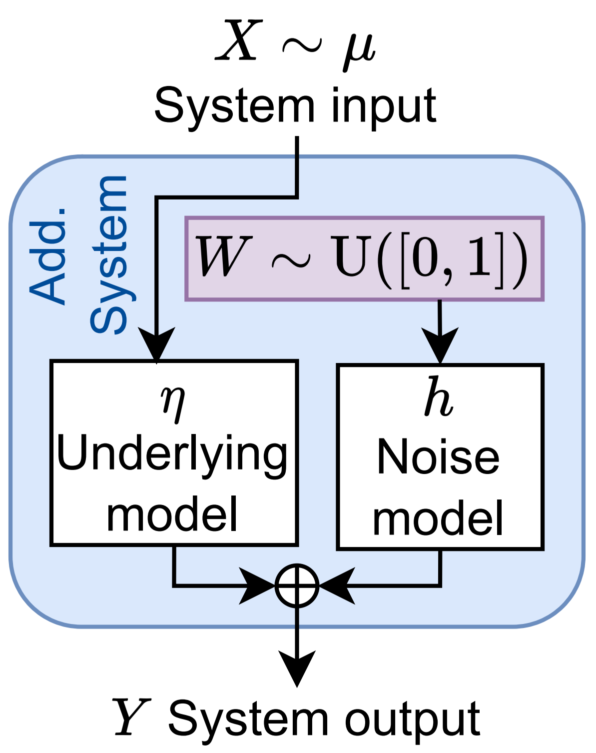

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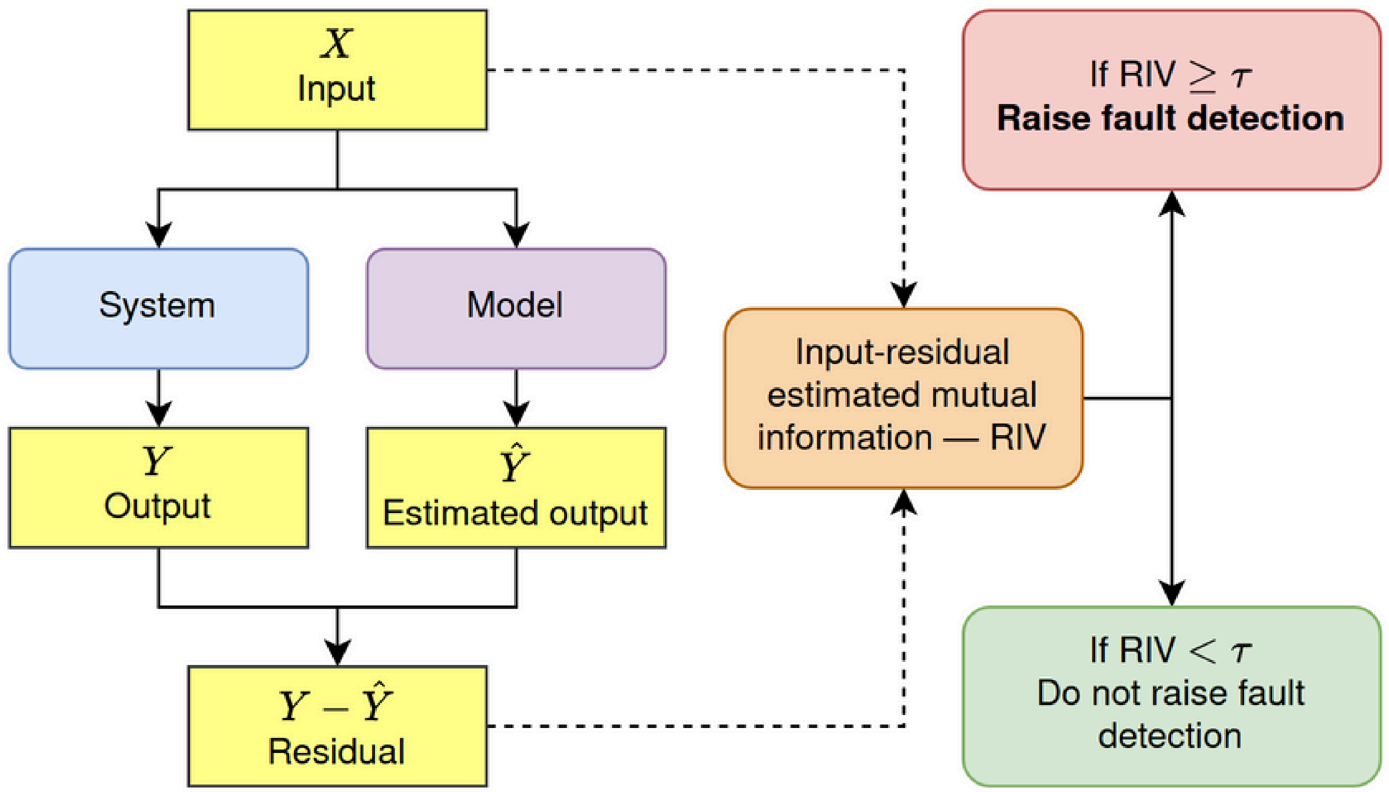

Fault detection scheme

MI-based Fault Detection Methodology

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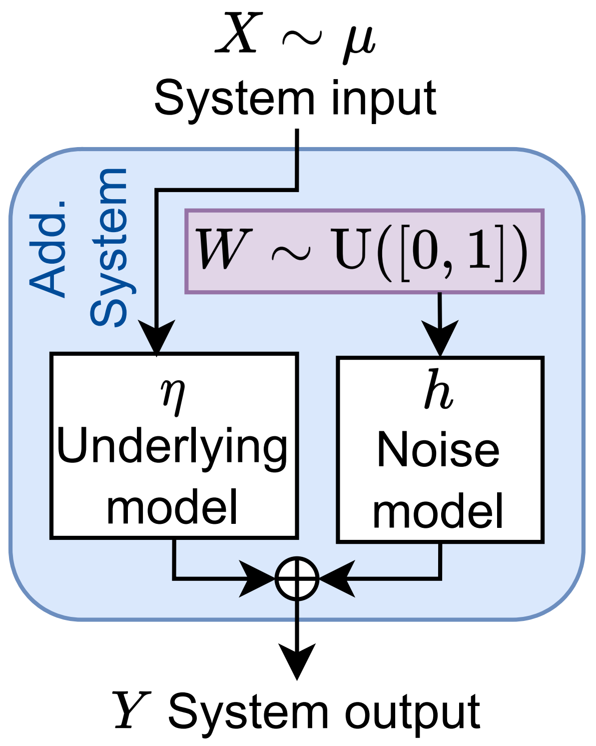

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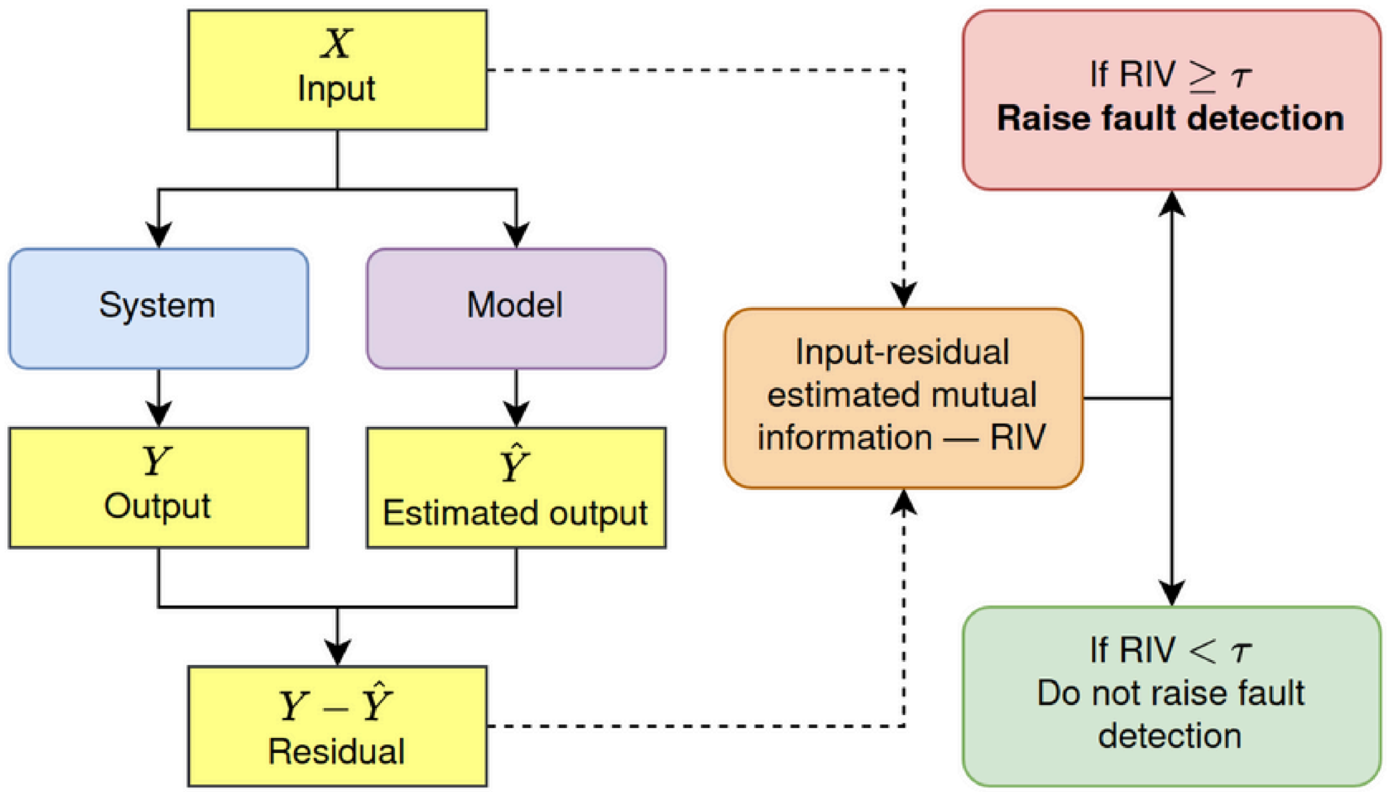

Fault detection scheme

System sampling
(data acquisition)

MI-based Fault Detection Methodology

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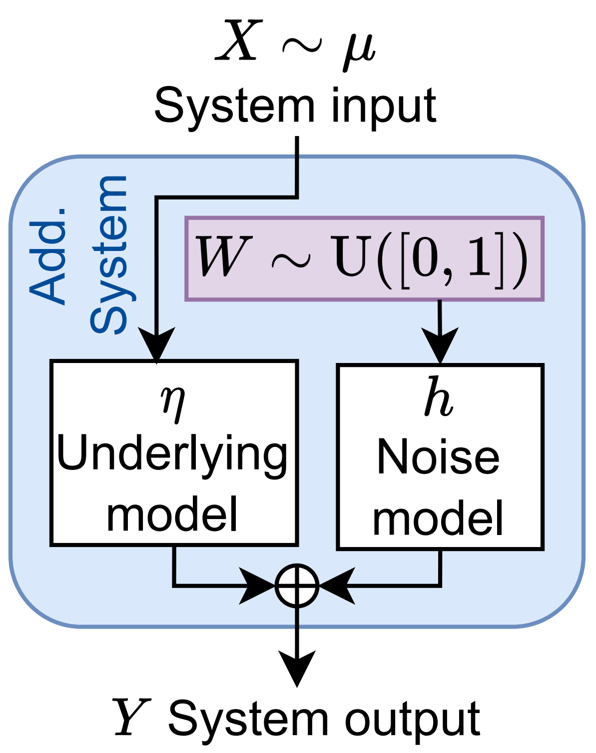

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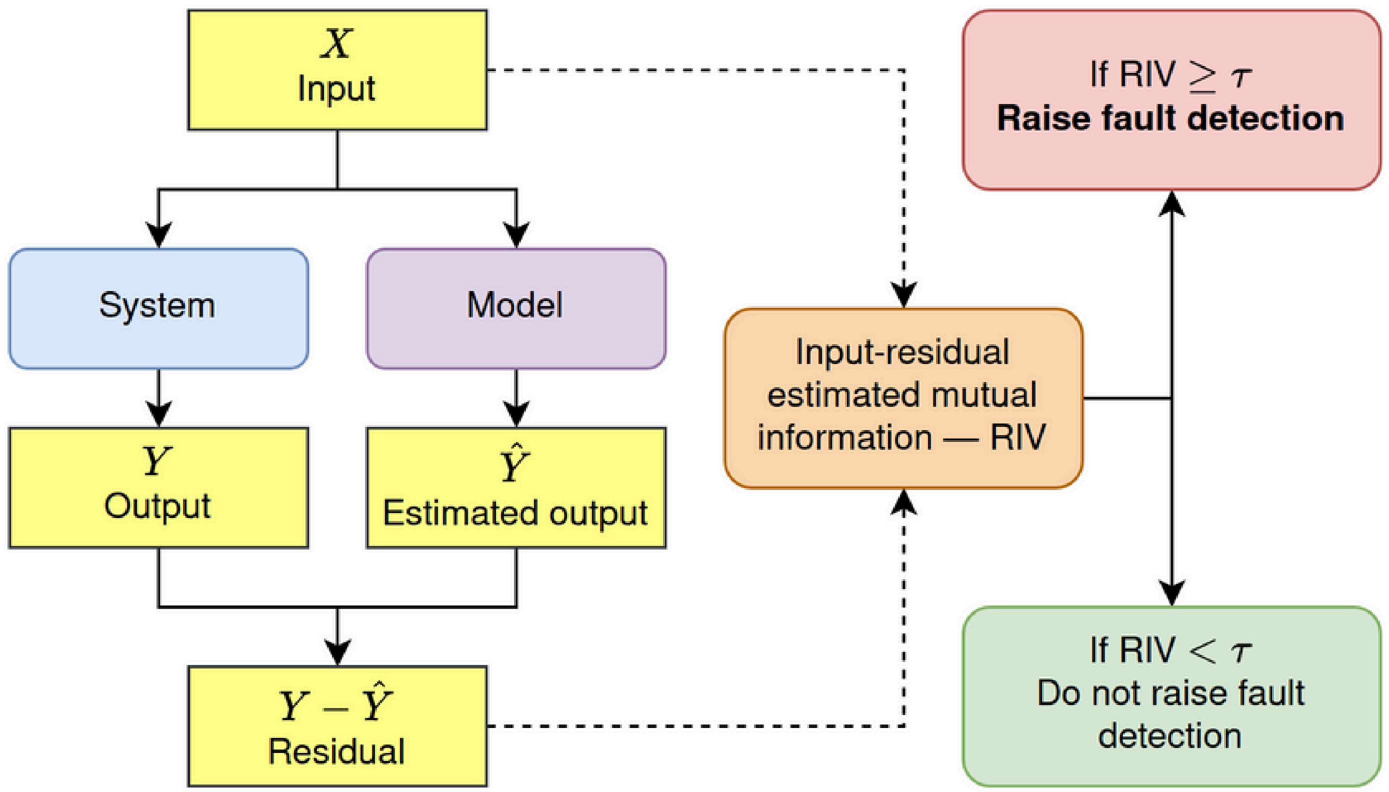

Fault detection scheme

System sampling (data acquisition) → Twin model estimations

MI-based Fault Detection Methodology

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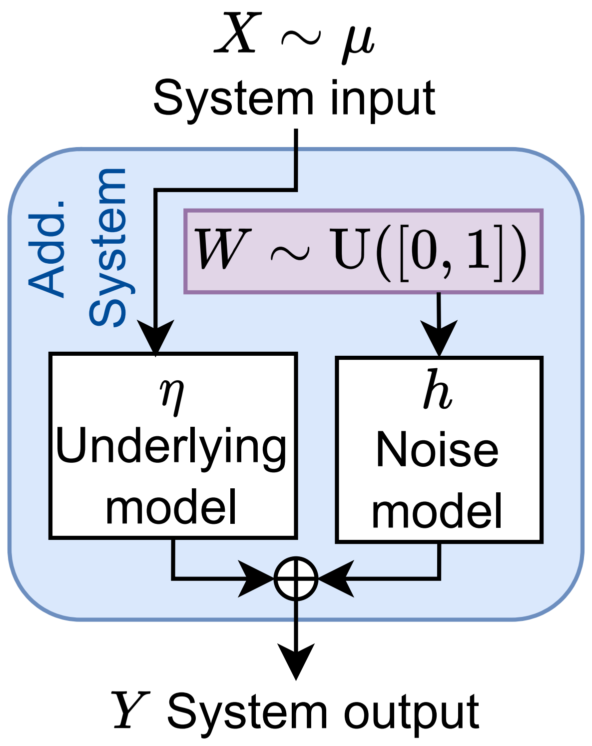

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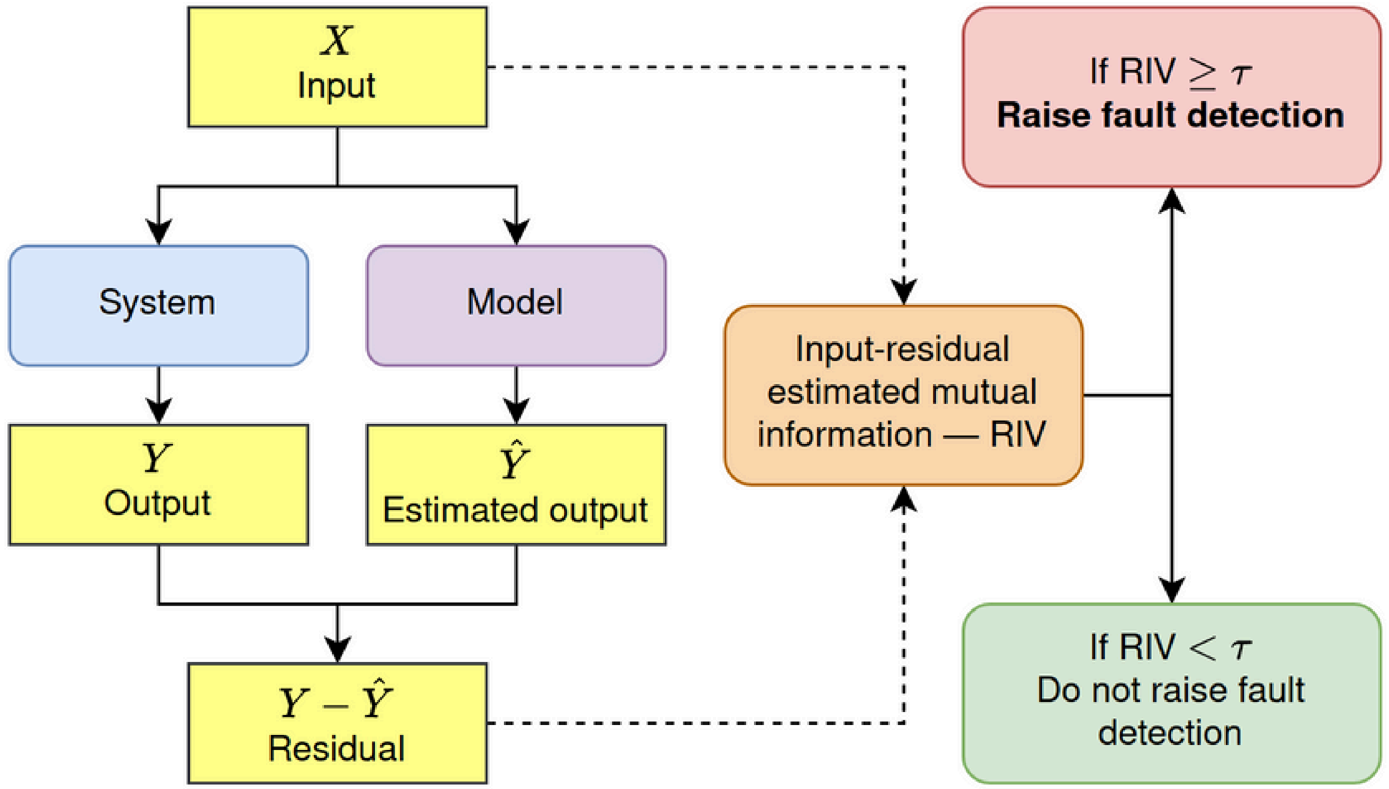

Fault detection scheme

System sampling (data acquisition) → Twin model estimations → Residuals (estimation errors) computing

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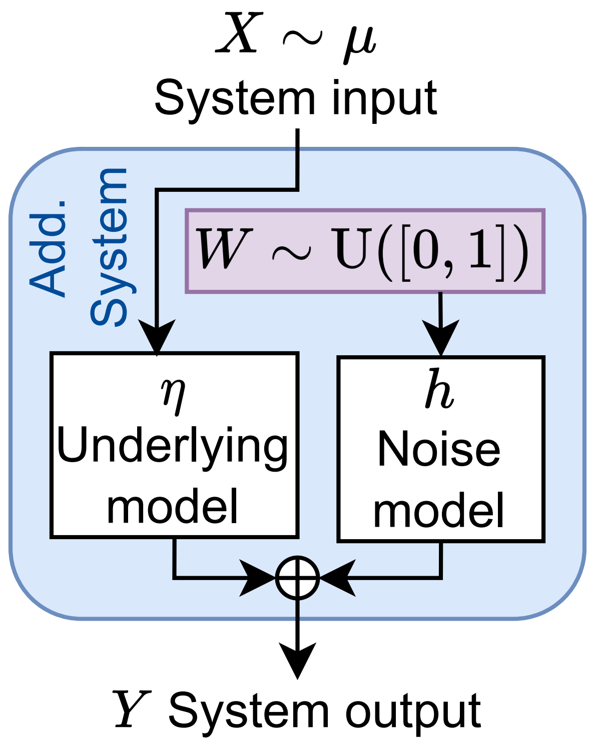

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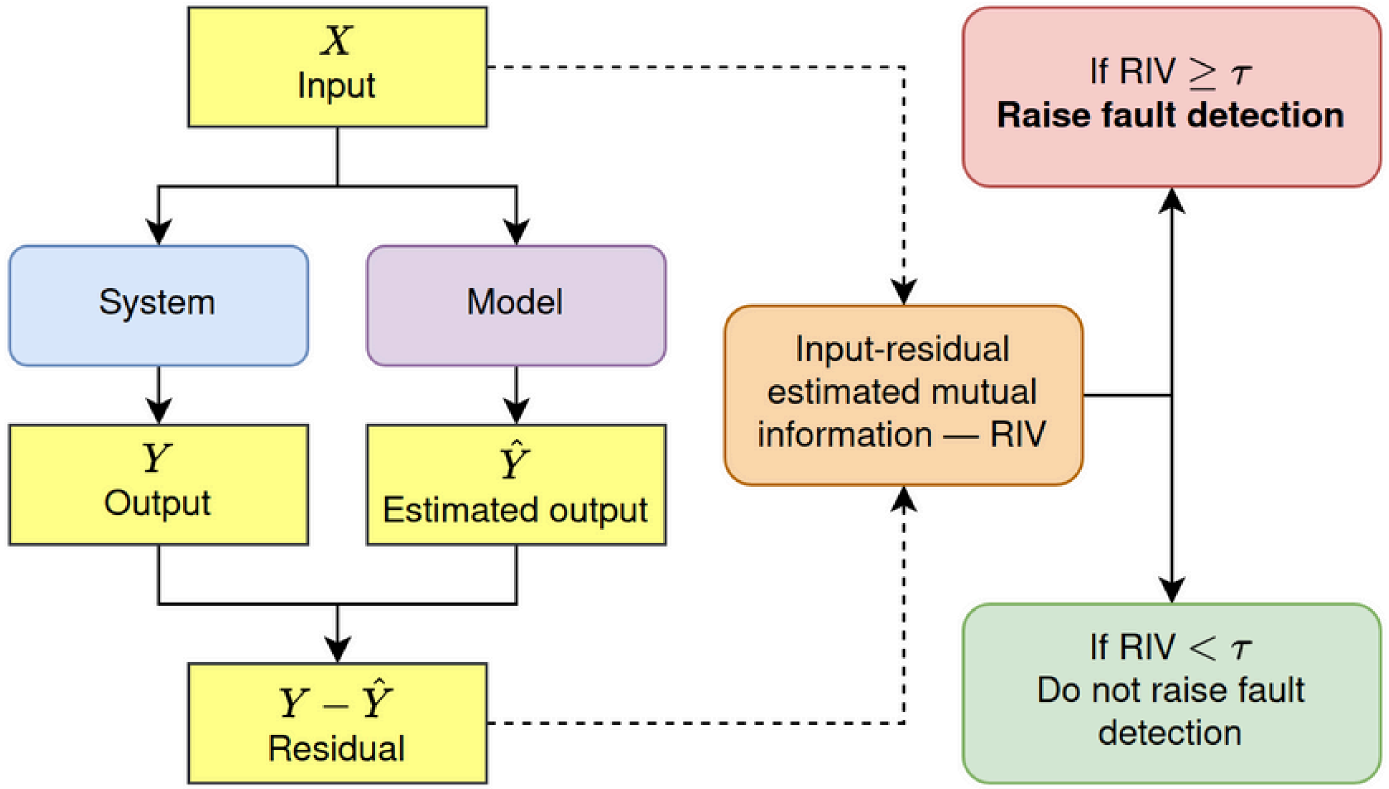

Fault detection scheme

System sampling (data acquisition) → Twin model estimations → Residuals (estimation errors) computing → Input-residual mutual information (MI) estimation

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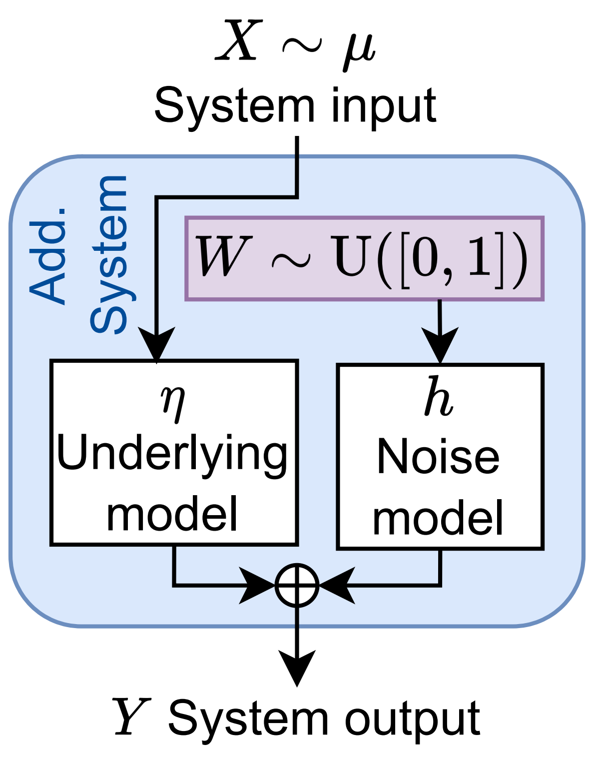

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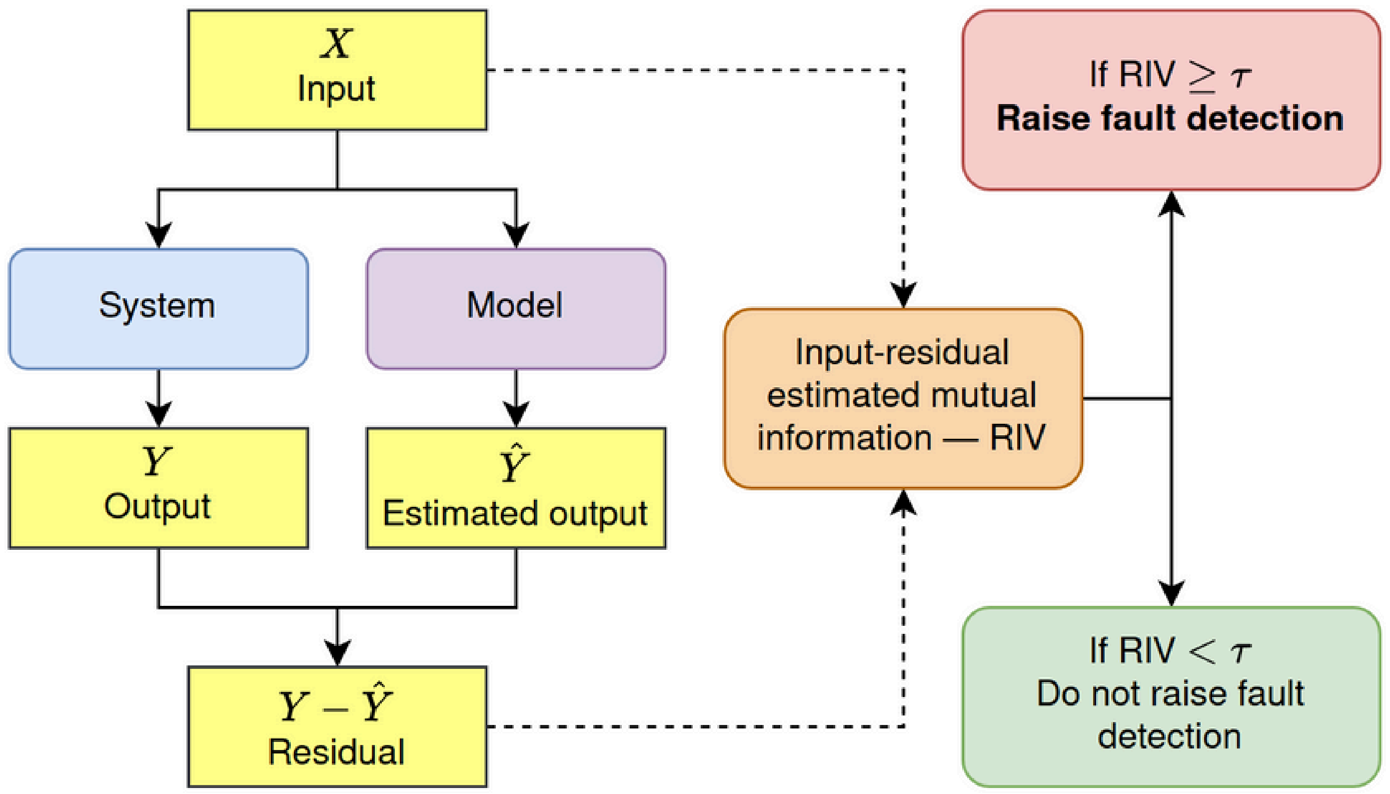

Fault detection scheme

System sampling (data acquisition) → Twin model estimations → Residuals (estimation errors) computing → Input-residual mutual information (MI) estimation → Thresholding of MI estimation

MI quantifies statistical dependency

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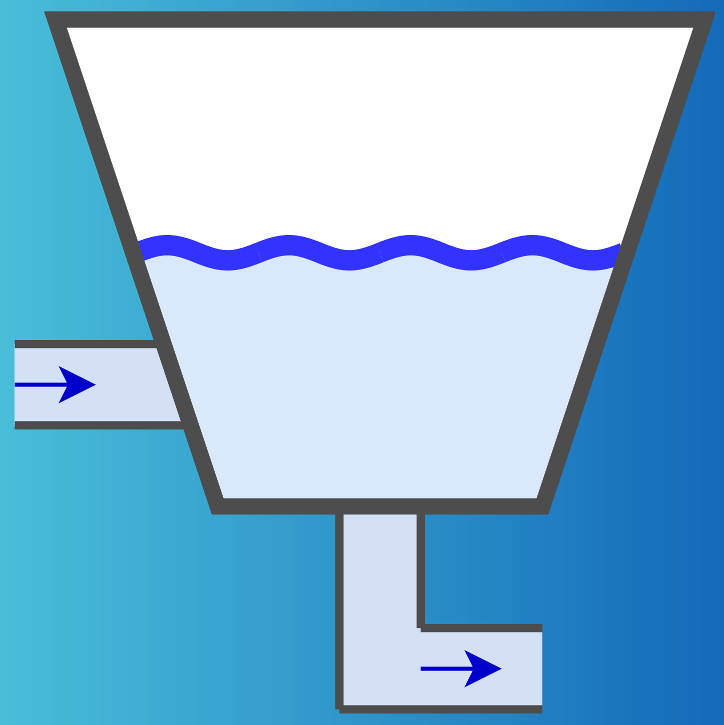
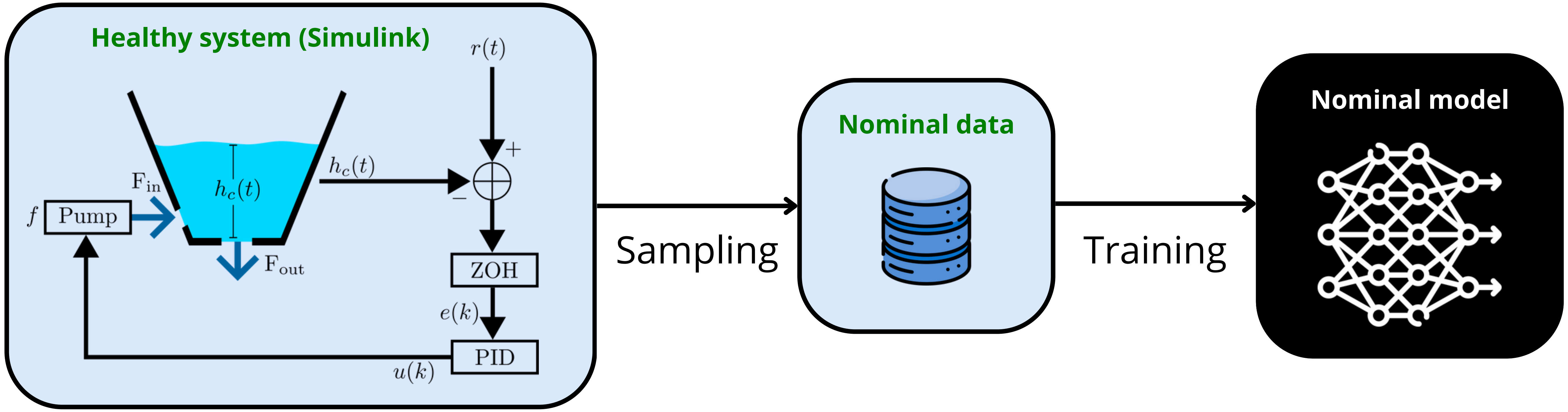


Study Case — Black-Box Model

Model: Multilayer perceptron (MLP) trained using nominal data



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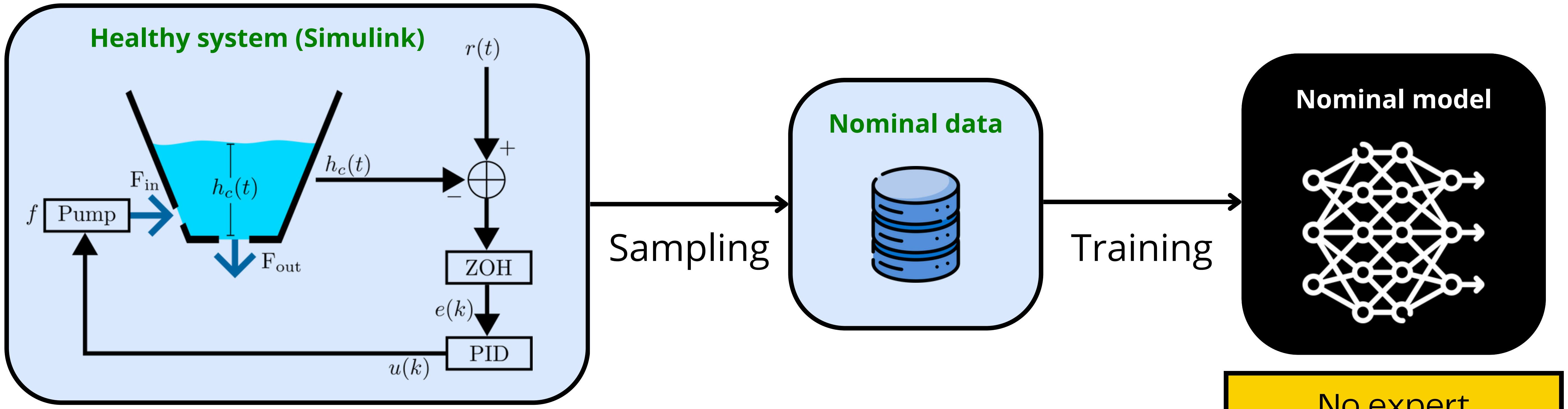
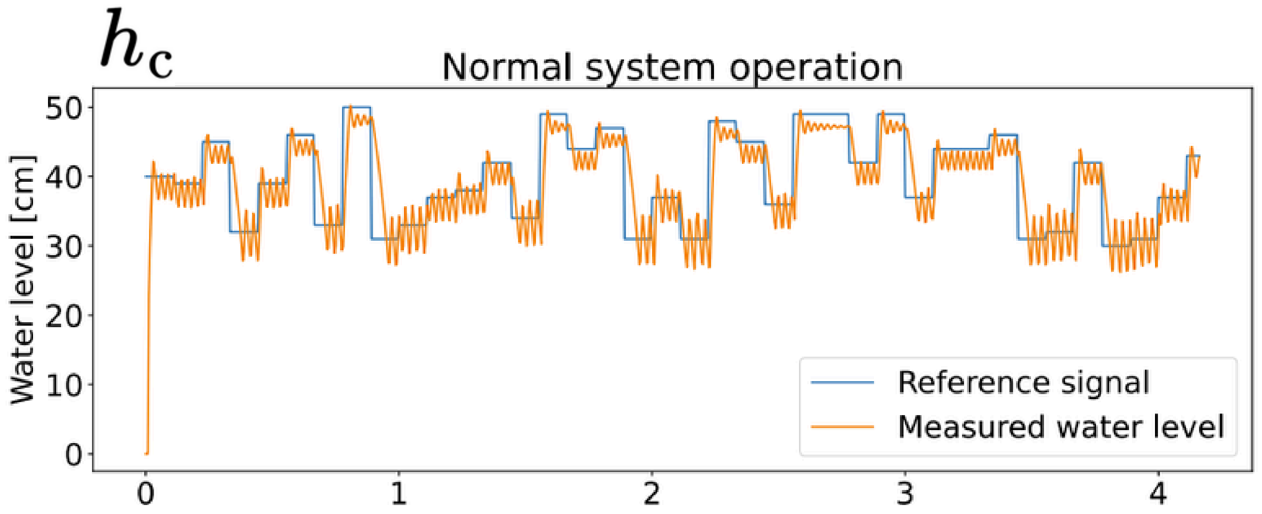
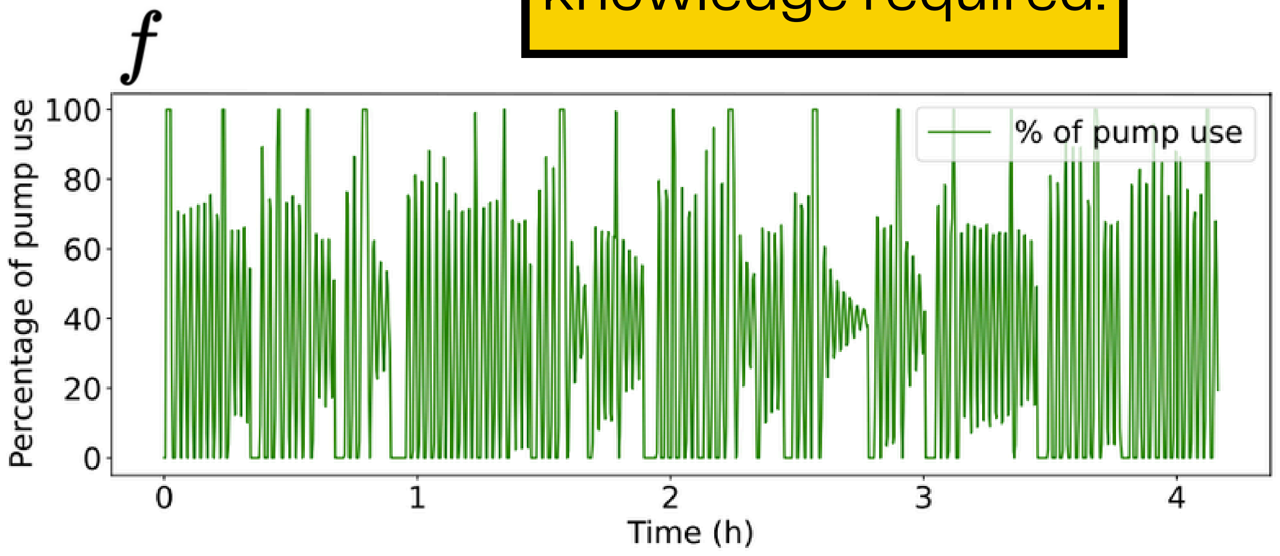


No expert knowledge required!

Data

90 hours of nominal operation





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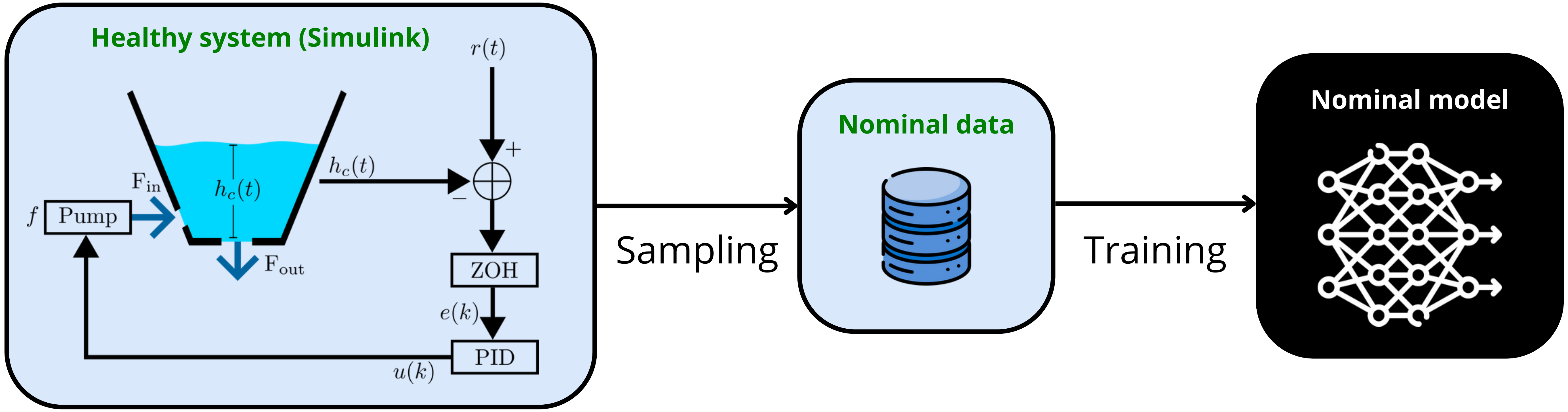


Model inputs

$h_c(t-1), f(t-1), h_c(t-2), f(t-2)$

Model output

$h_c(t)$

Architecture

2 hidden layers of 100 and 50 units

ReLU activation functions

Loss function

Mean sqaured error (MSE)

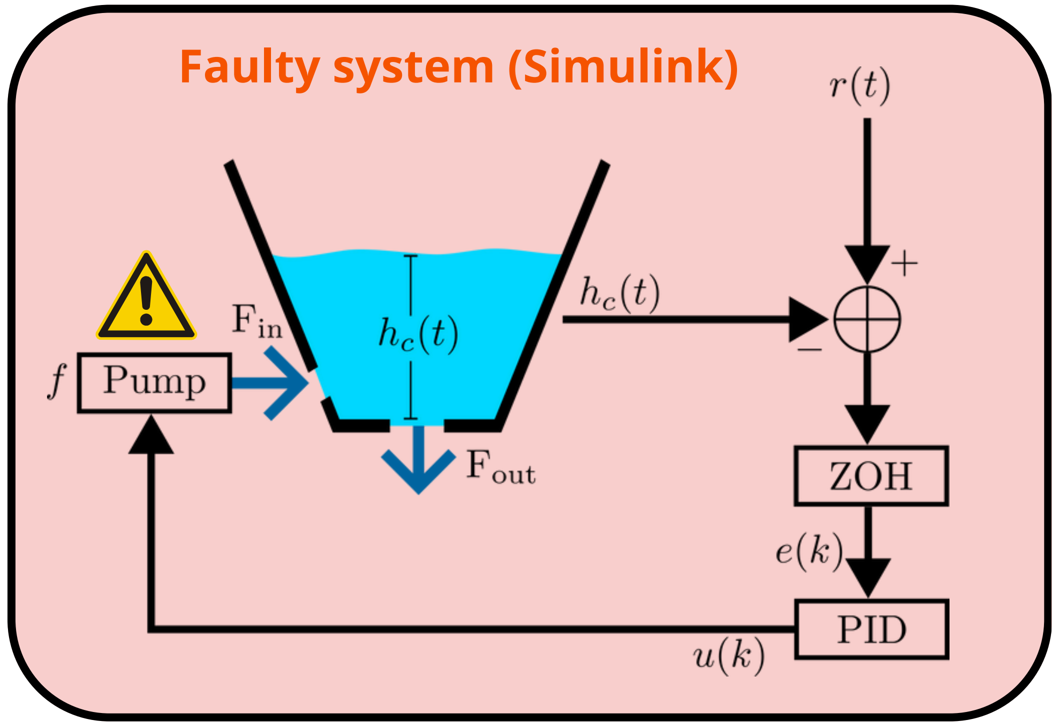
Hyperparameters

ADAM optimizer

Learning rate 1e-4

Study Case — Black-Box Model

Induced faults: pump failures

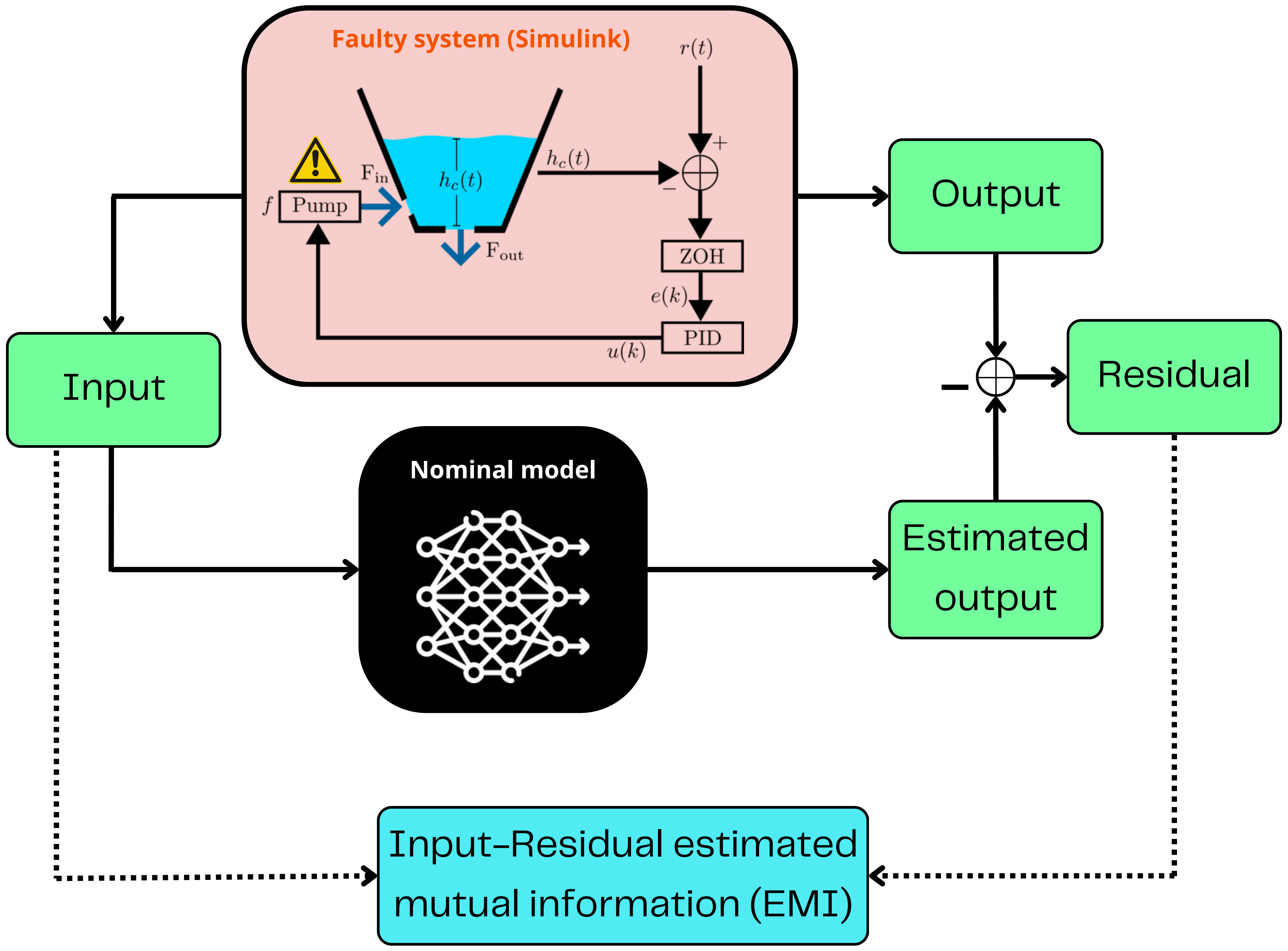


$$F_{\text{in}} = \alpha_1(1 - \delta \cdot s(t - T_{\text{fault}})) \cdot f + \alpha_2$$

δ quantifies the severify of the fault

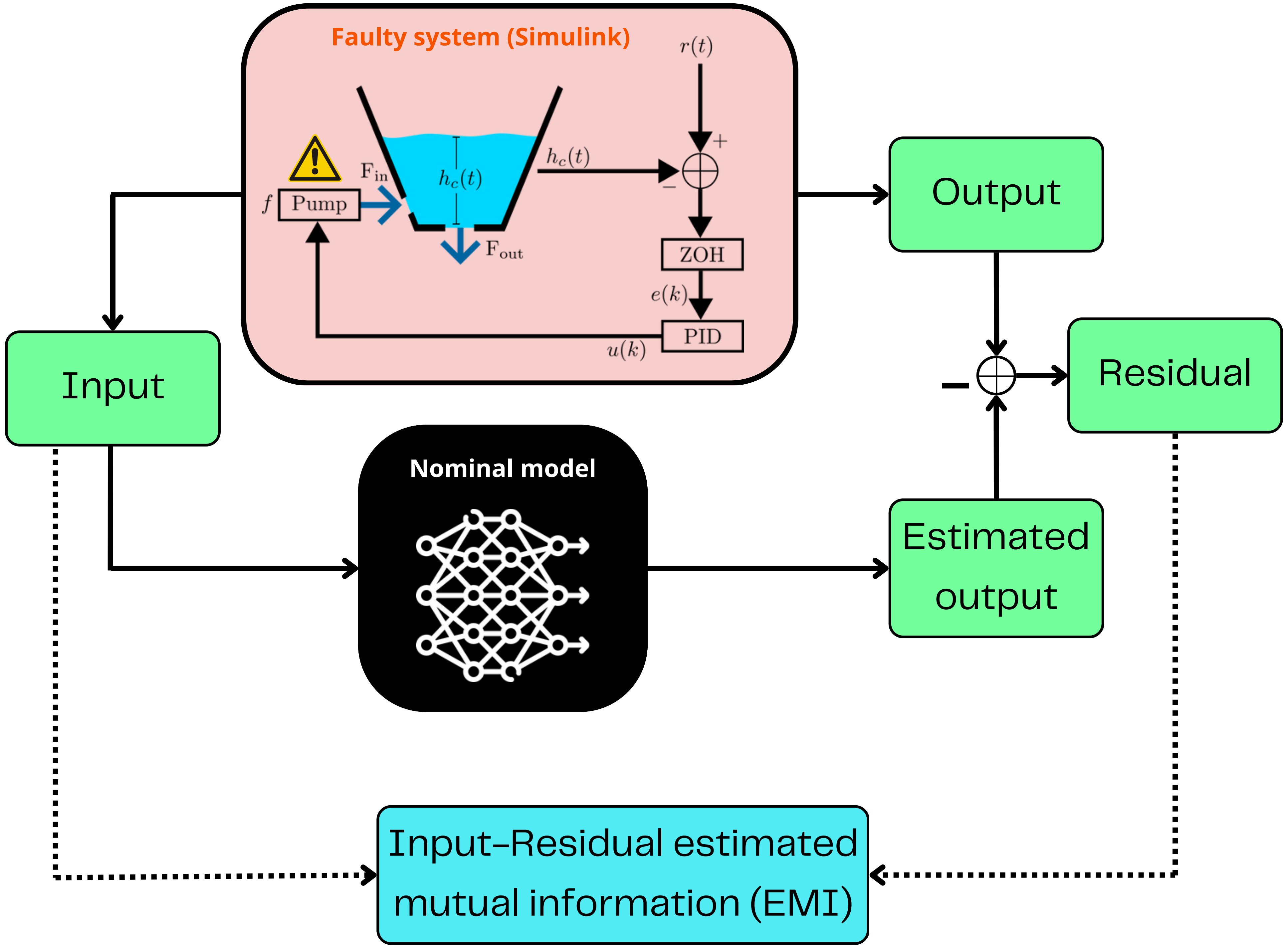
Study Case — Black-Box Model

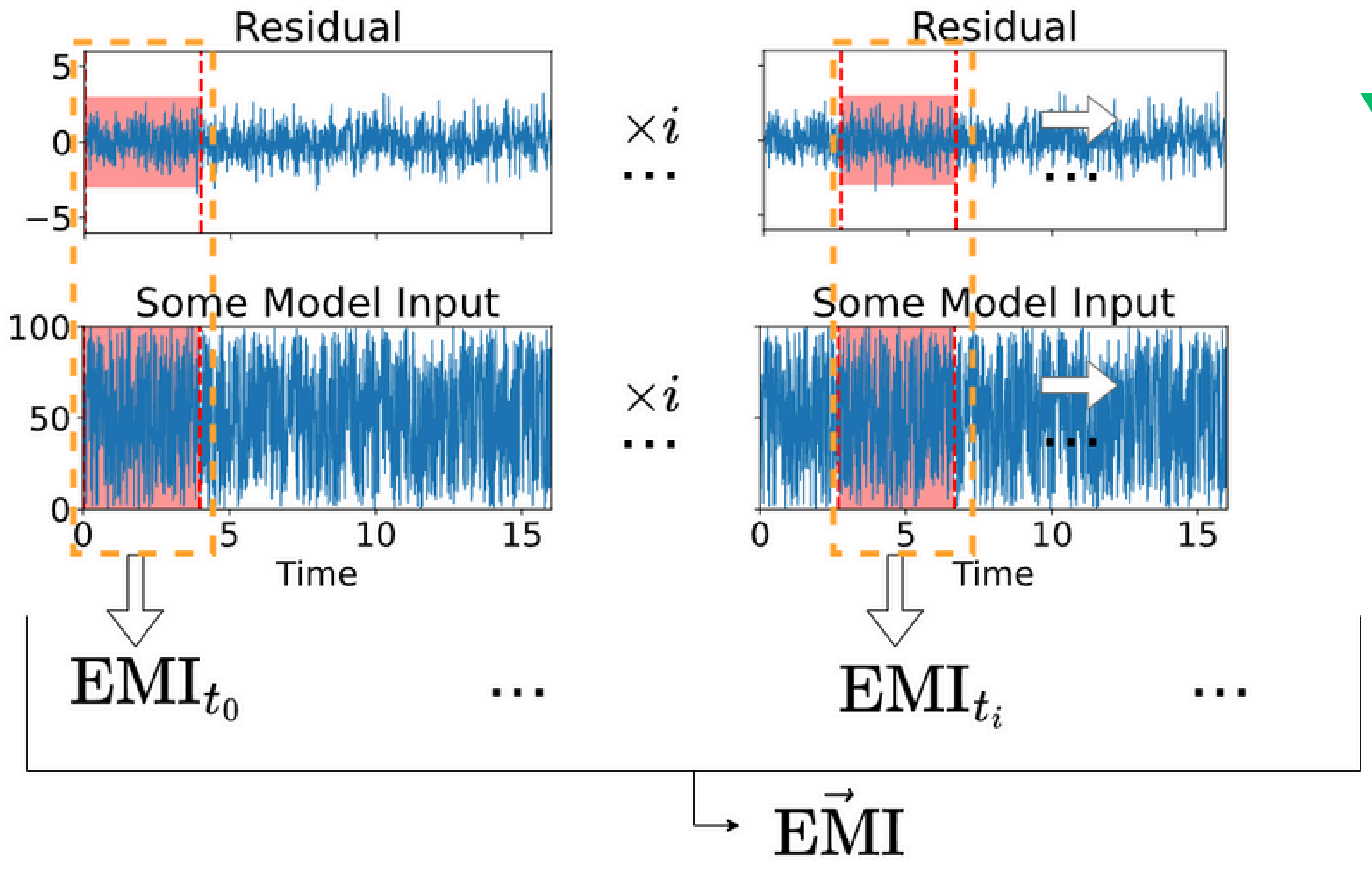
Monitoring pipeline



Study Case — Black-Box Model

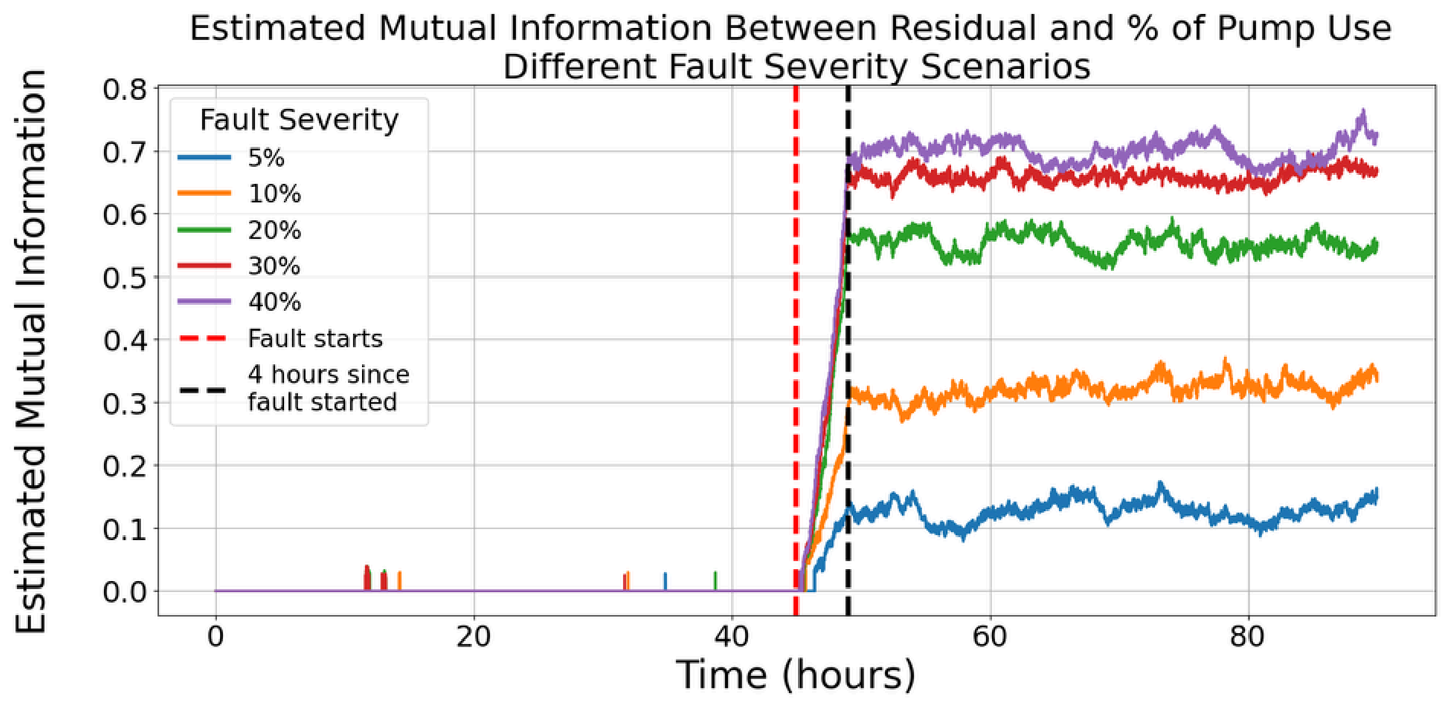
Monitoring pipeline: rolling window





Study Case — Black-Box Model

Results



Study Case — Black-Box Model

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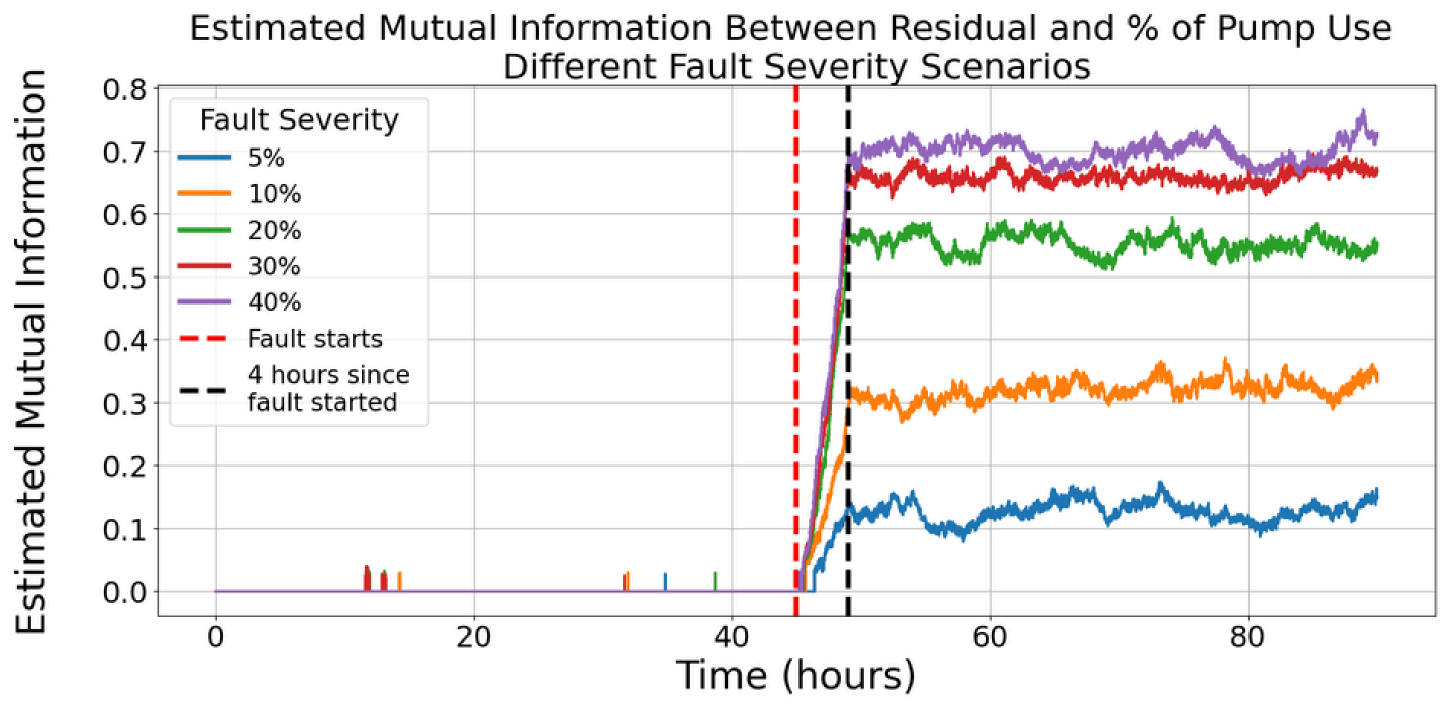

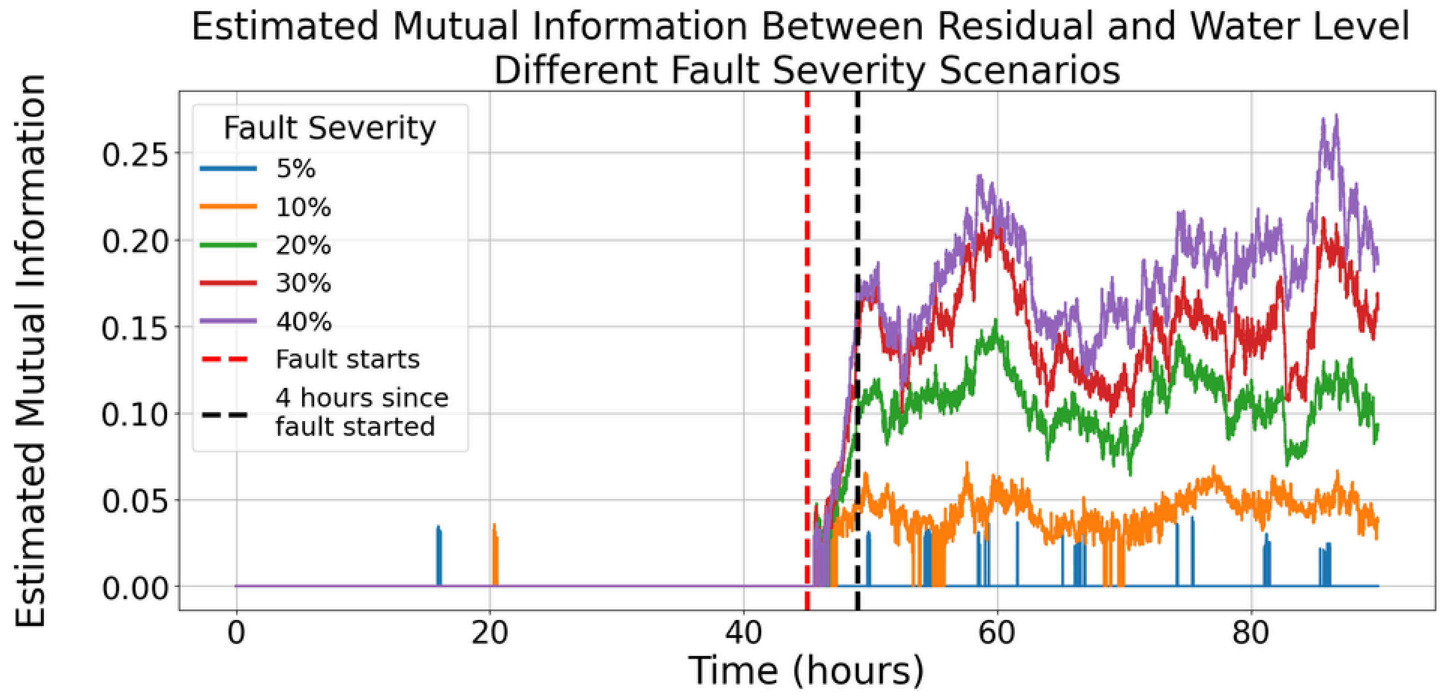

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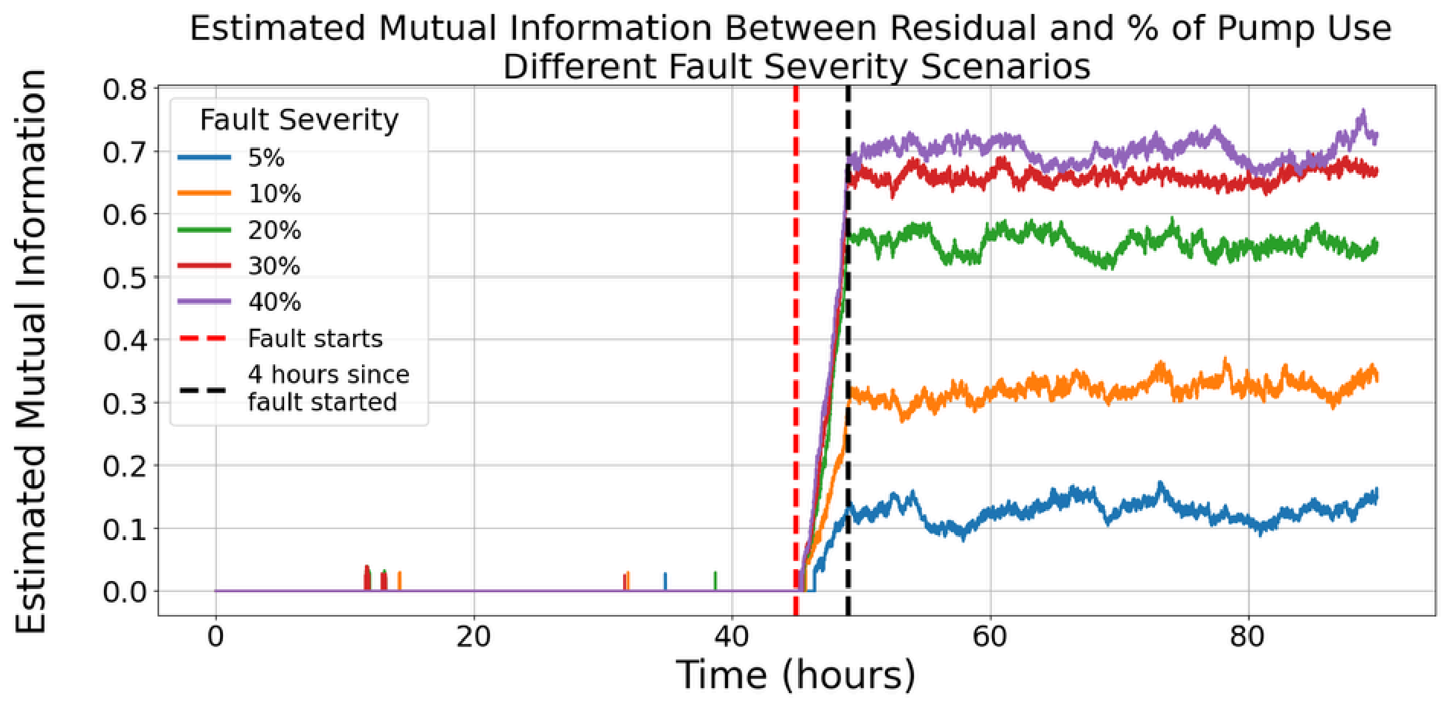

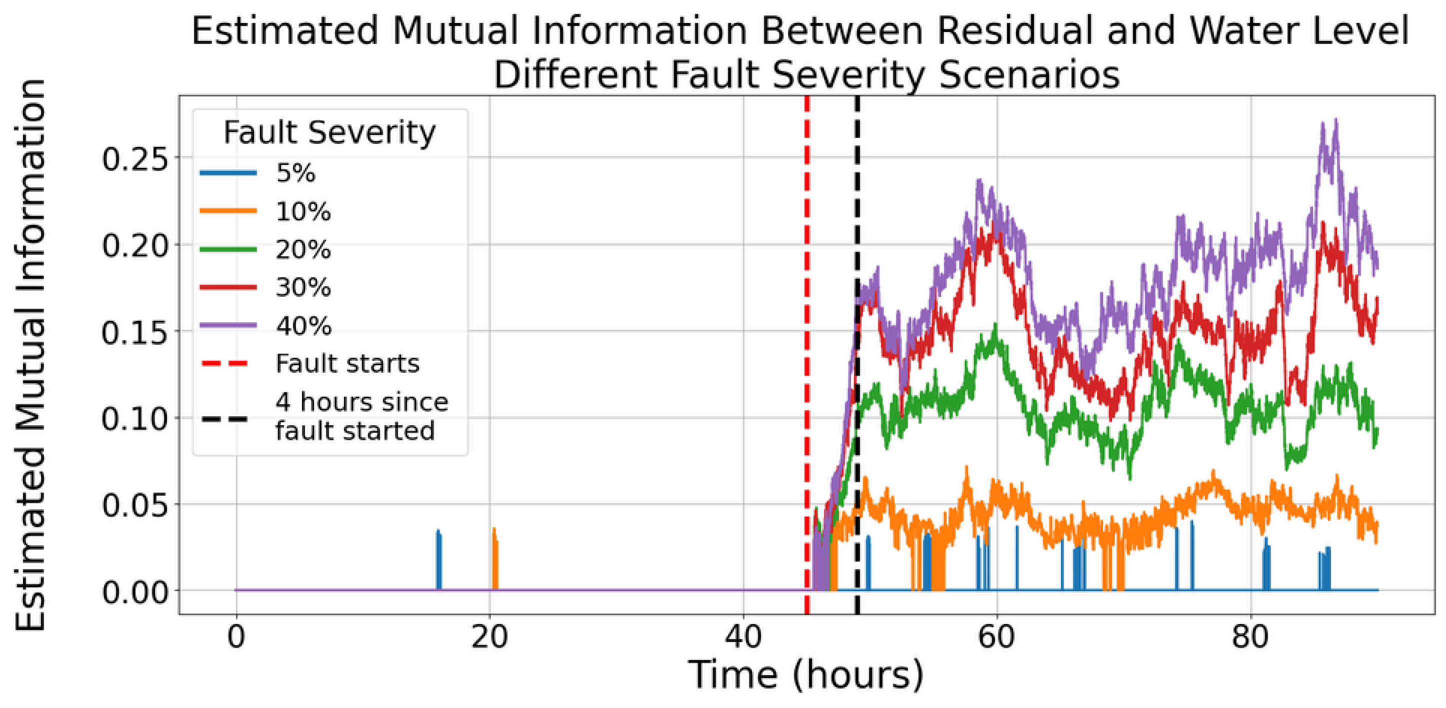

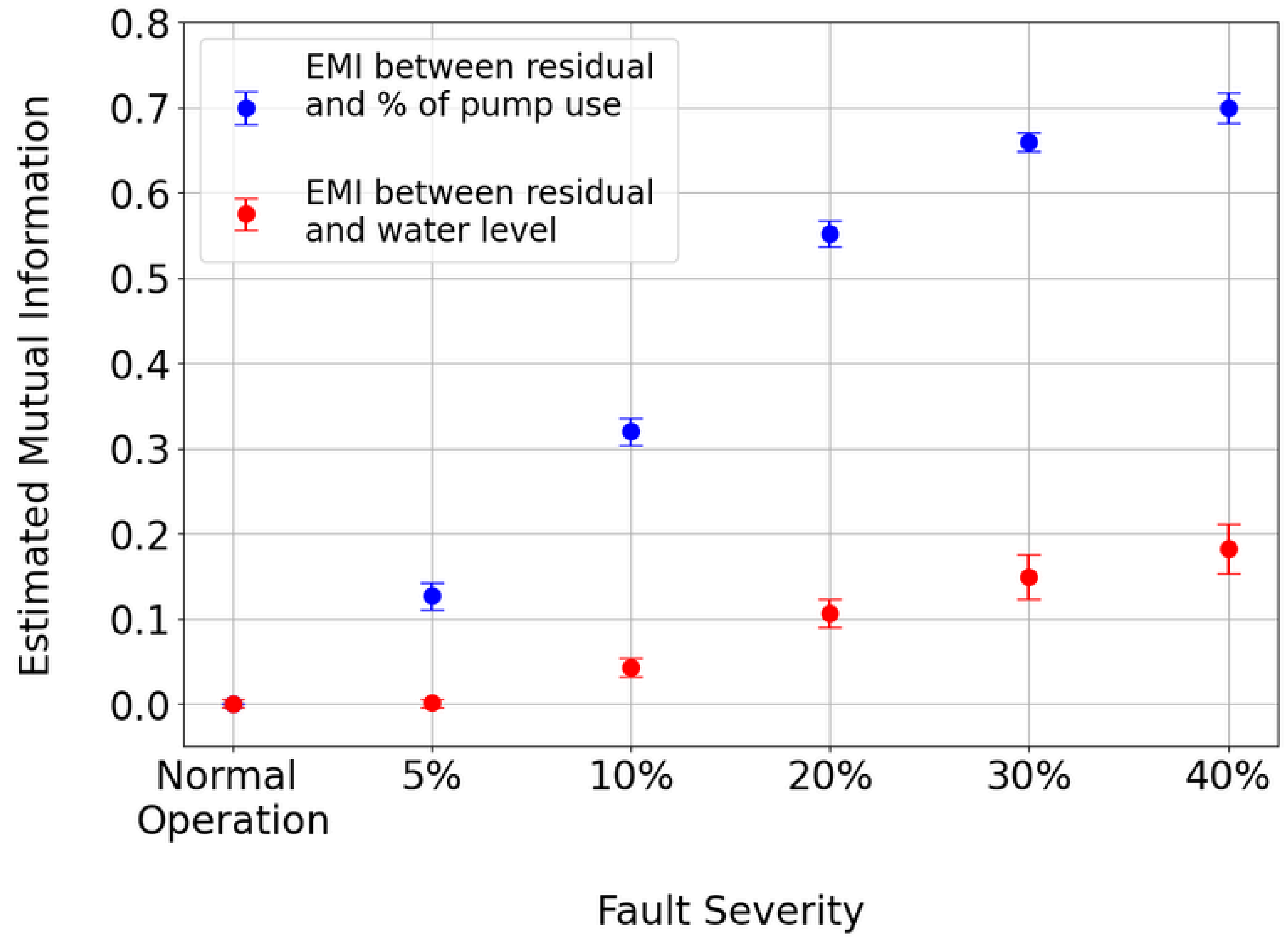

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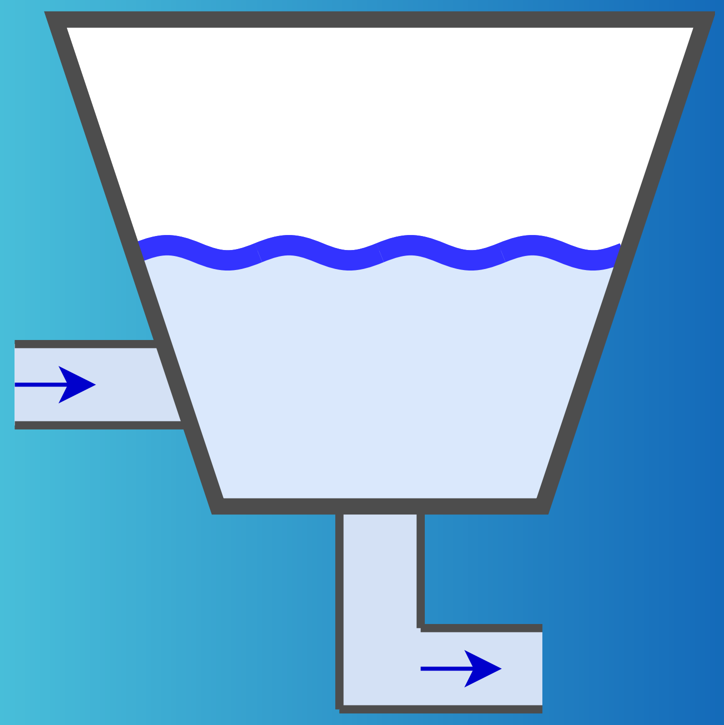
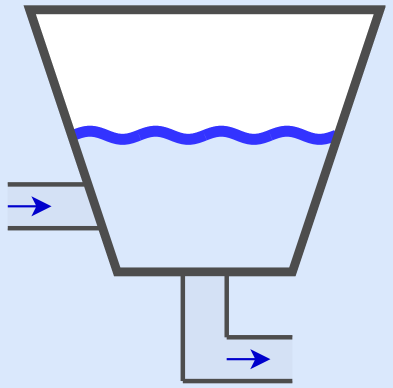


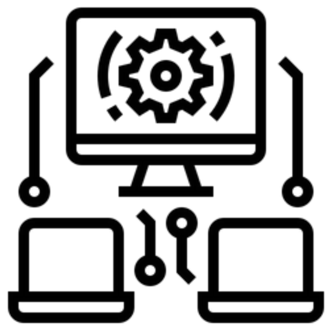
Complementary White-Box Analysis

Model: Twin healthy system build from expert knowledge

Open loop healthy system
(Euler's method)



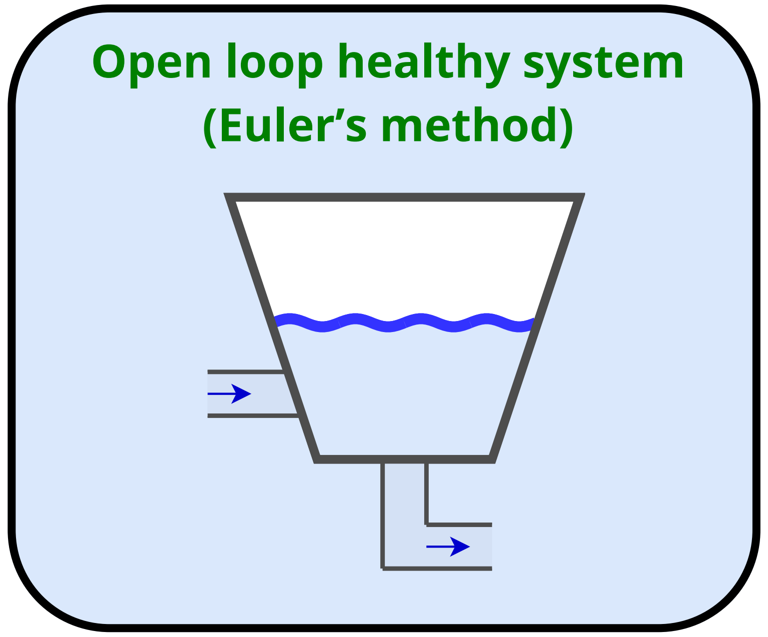
Nominal twin model

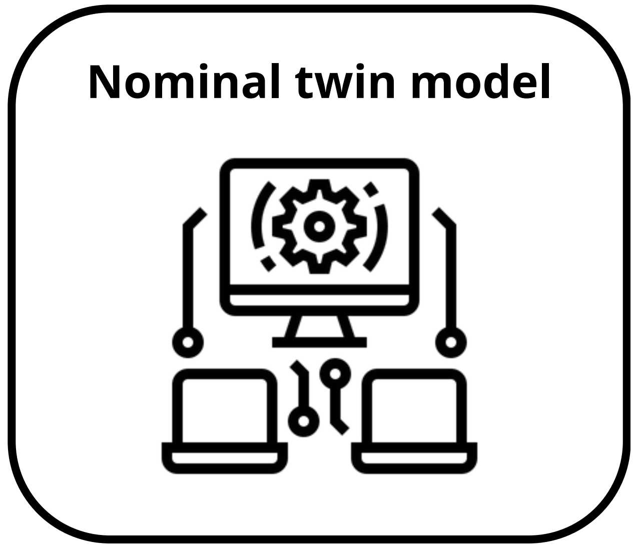


The white-box model (nominal twin model) replicates the ODEs that determine a healthy system.

Complementary White-Box Analysis

Model: Twin healthy system build from expert knowledge





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Model input

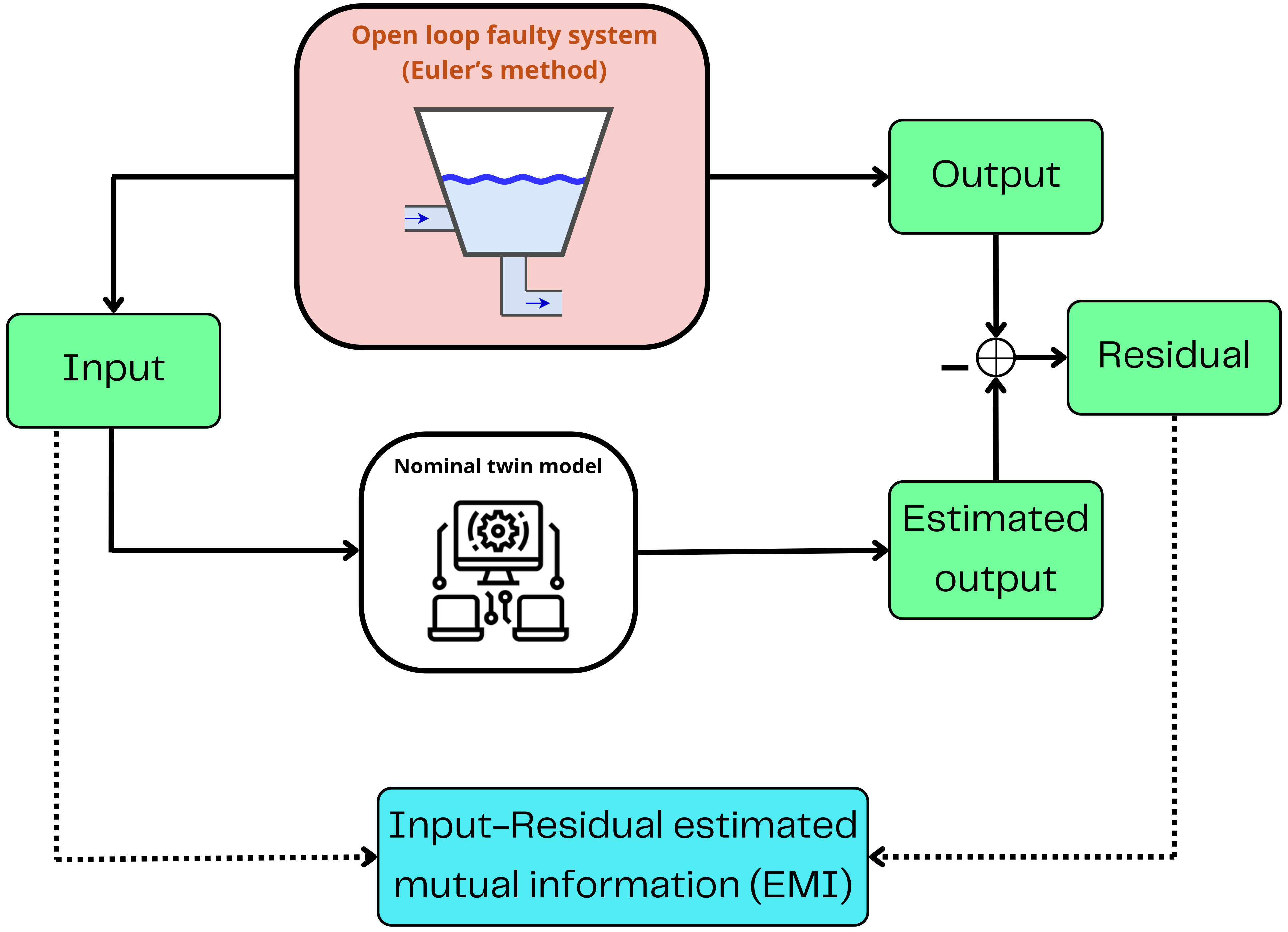
$f(t)$

Model output

$h_c(t)$

Complementary White-Box Analysis

Model: Twin healthy system build from expert knowledge



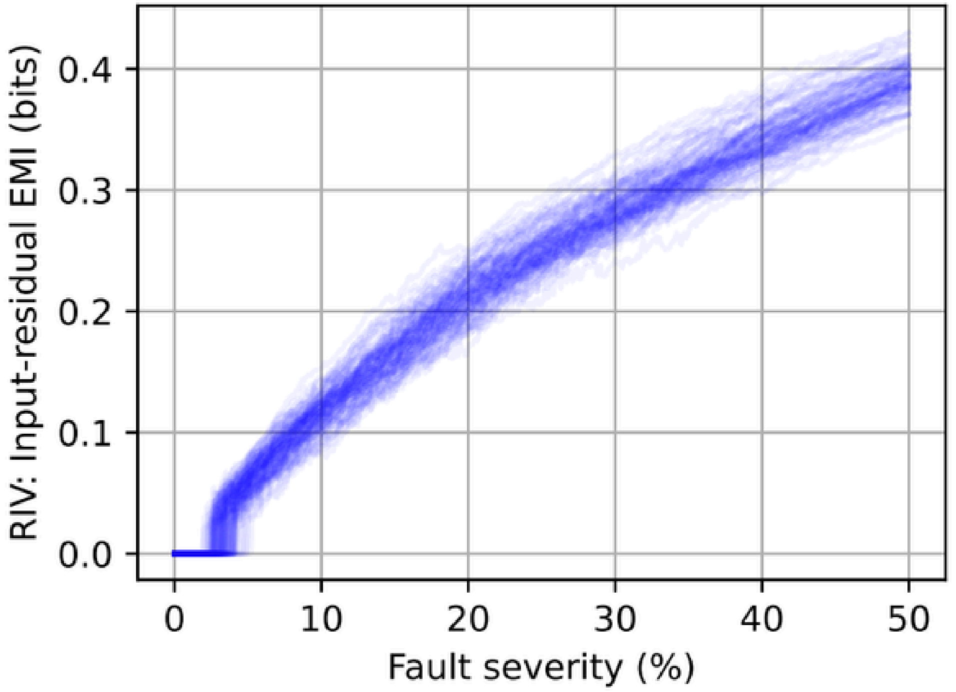
Data

5 hours from inputs sampled uniformly from [30%, 40%] each 15 s

No rolling window (all data is used)

Complementary White-Box Analysis

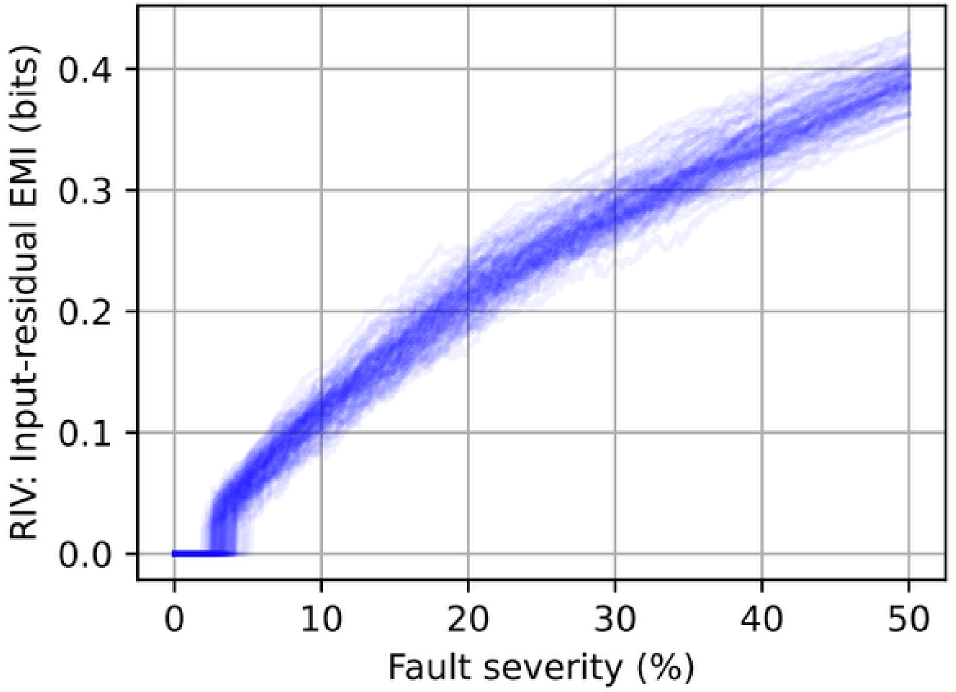
Results



100 simulations

Complementary White-Box Analysis

Results



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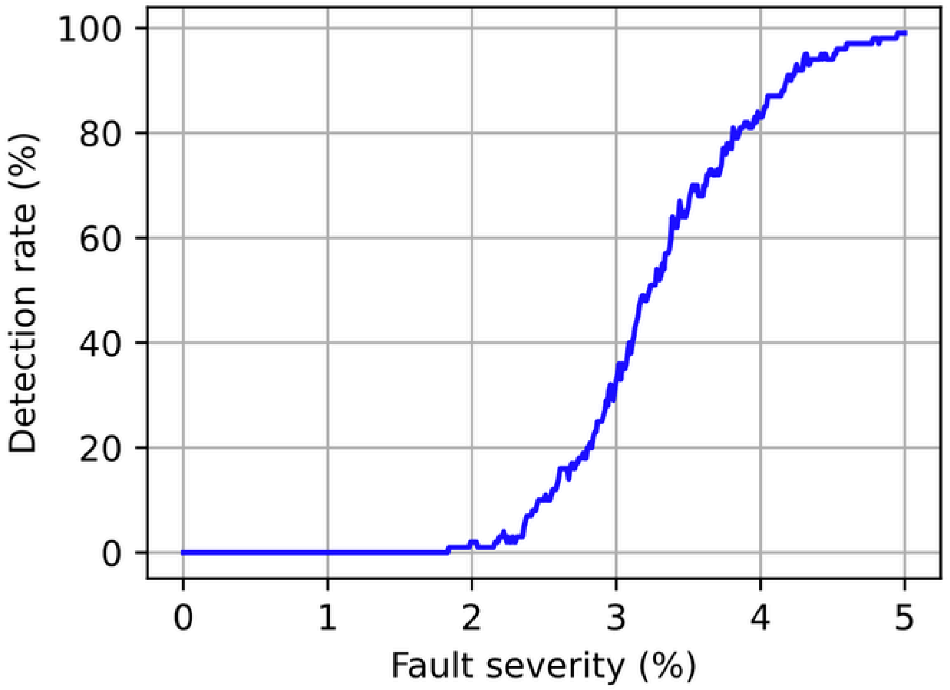

100 simulations

Complementary White-Box Analysis

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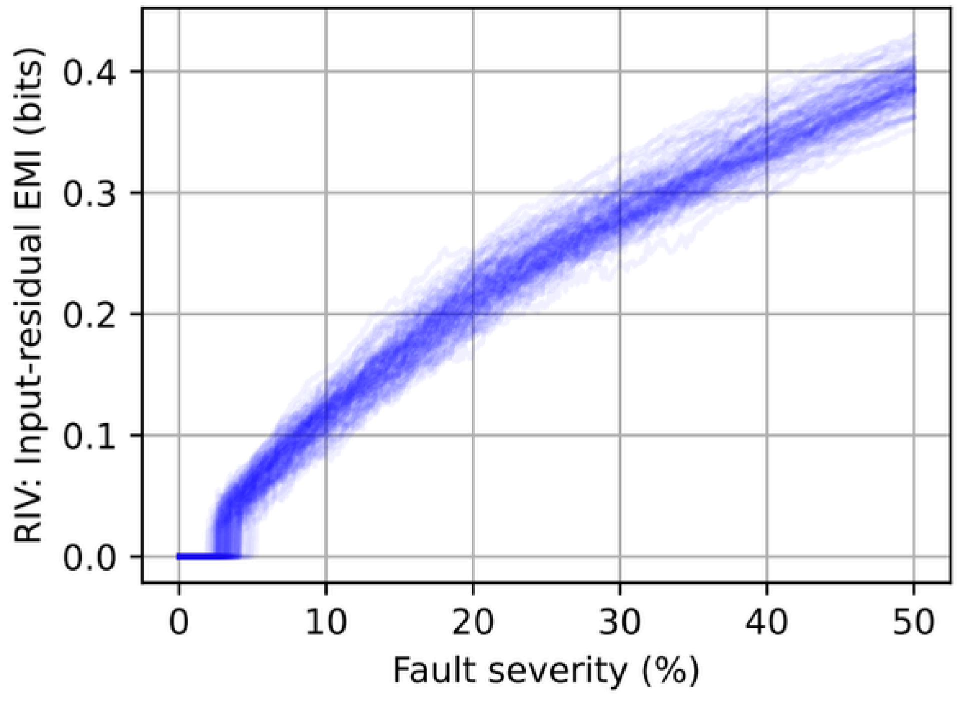

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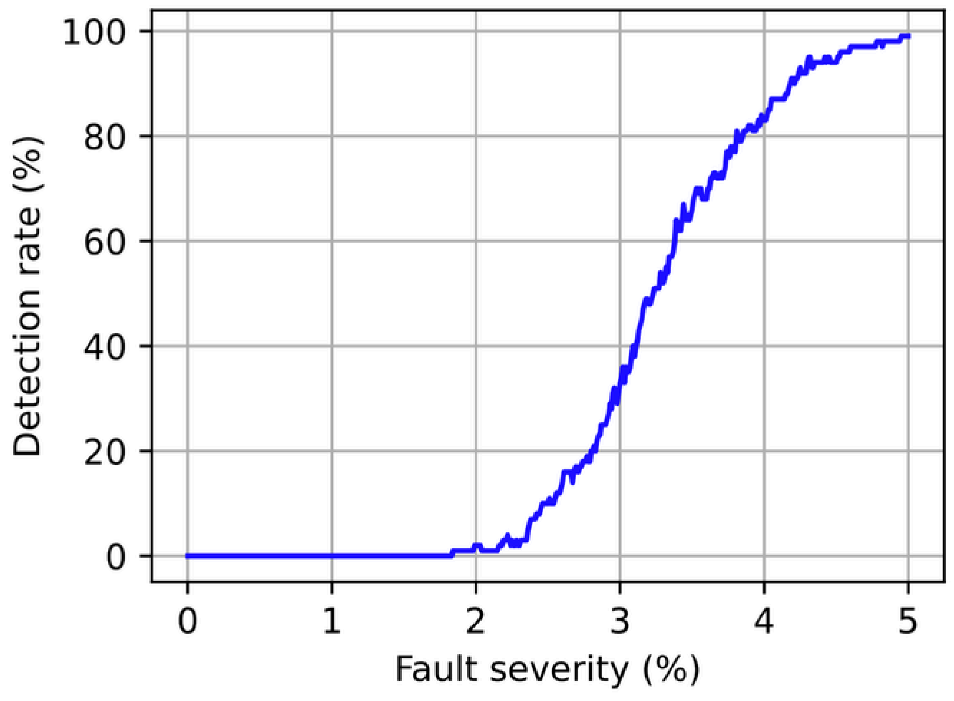

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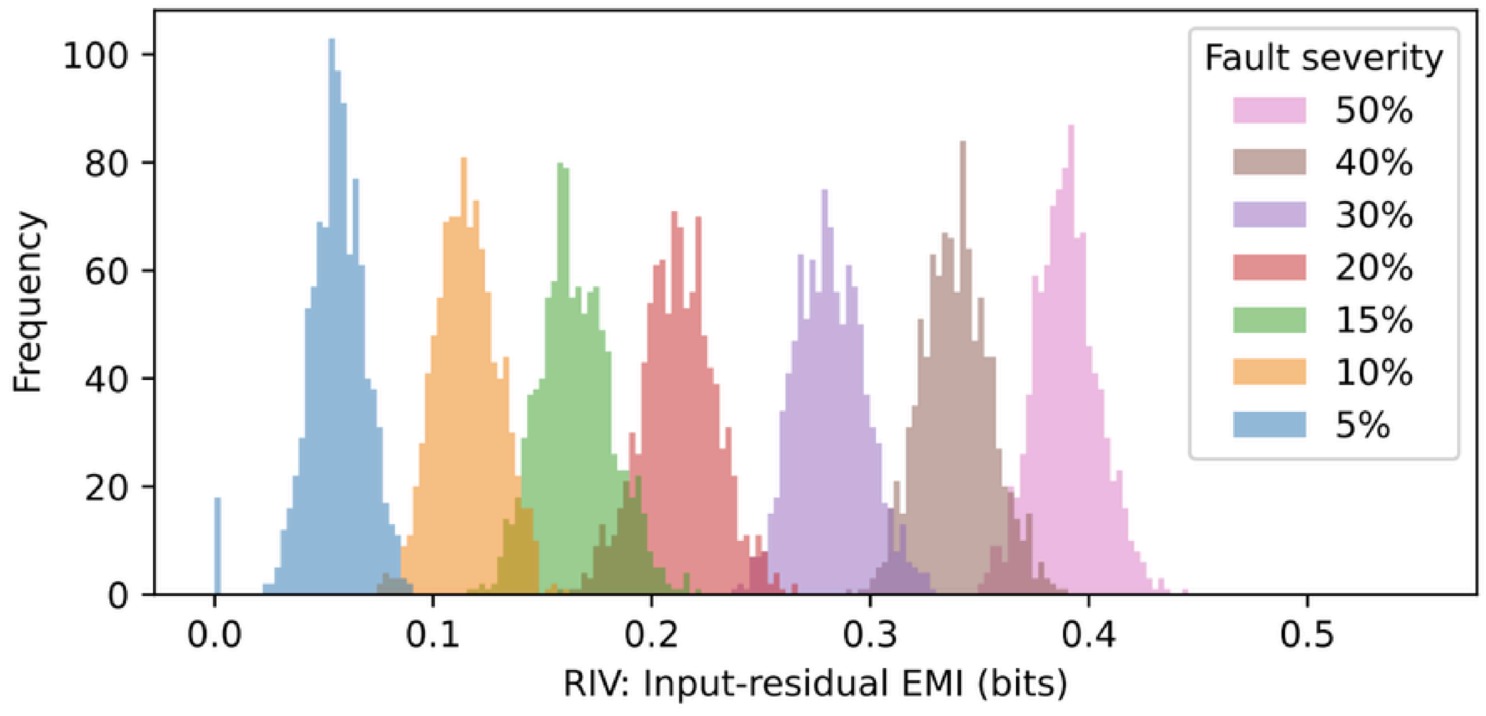

1000 simulations per fault severity

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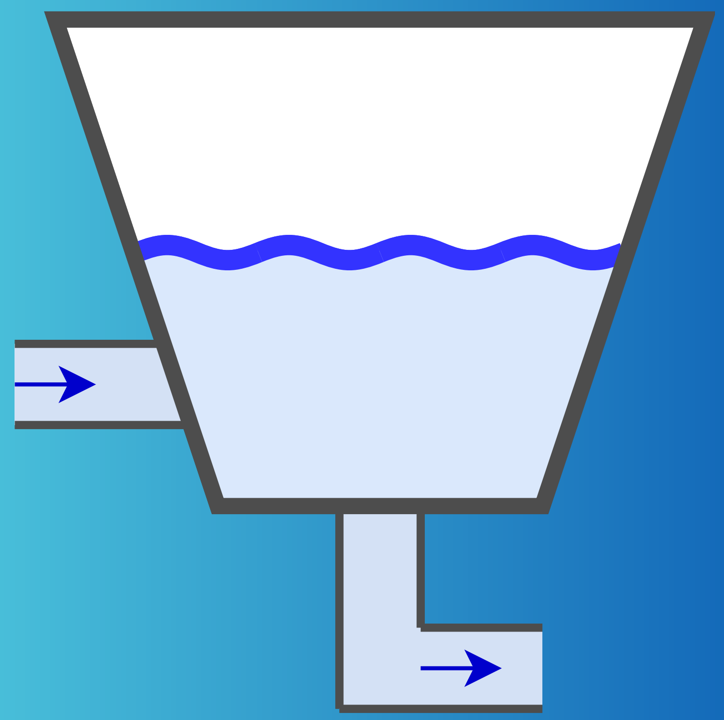

Conclusion and Future Work

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- **Our method does not require prior availability of faulty data (unsupervised).**

Conclusion and Future Work

- We provided a method that detects faults with no requirement of expert knowledge.
- In addition to detecting faults, our method quantify their severity.
- Expert knowledge enables a white-box analysis, which provide further insights of our indicator's behavior on system faults.
- **Our method does not require prior availability of faulty data (unsupervised).**
- More sophisticated models may be tested (i.e., closed-loop twin model) and comparison with other FDI methods in the same settings may be useful.

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Joaquín Ortega

Camilo Ramírez

Tomás Rojas

Ferhat Tamssaouet

Marcos Orchard

Jorge Silva

November, 2024

camilo.ramirez@ug.uchile.cl

IDS Information and Decision System Group

fcfm FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS UNIVERSIDAD DE CHILE

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