A Method to Evaluate the Performance of Predictors in Cyber-physical Systems

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Introduction

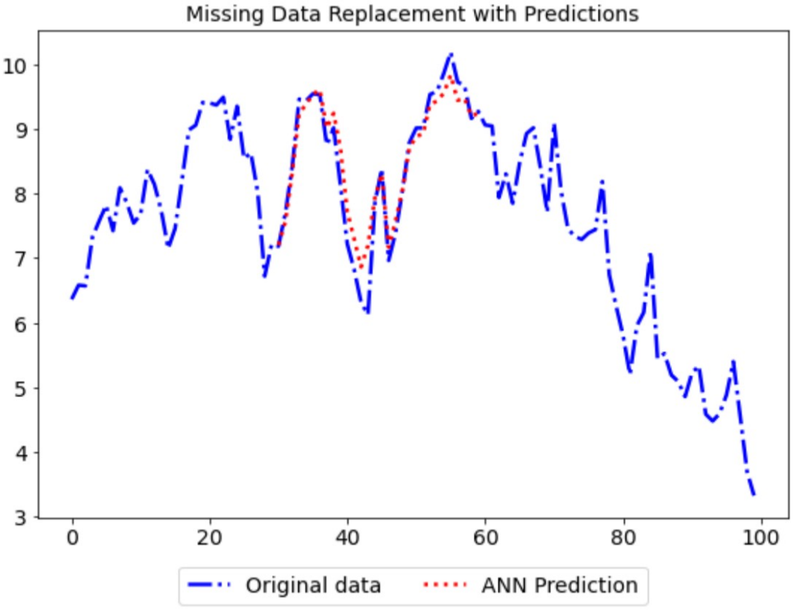
- Cyber-physical Systems are compositions of software and hardware components
  - Sensors, actuators, controllers, storage, processing units, etc
  - Outputs of some components are used as inputs of other components
    - Becoming data-driven designs
  - Behavior is sensitive to the quality of data
  - Sensing is subject to errors

- Predictors
  - Assess data quality
  - Derive new variables
  - Replace faulty data

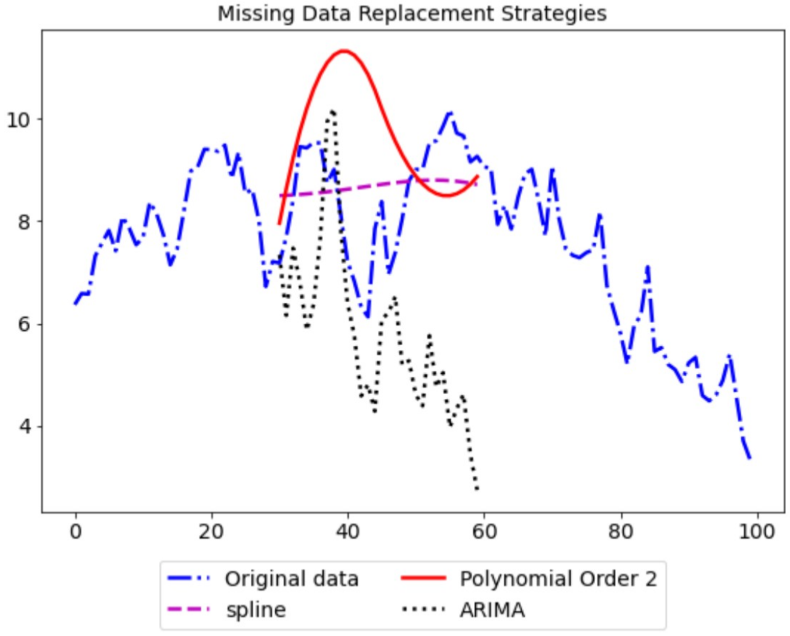
- Predictors can be interdependent
  - What are the impacts of prediction interdependence?

Predictors

- Multivariate ANN models

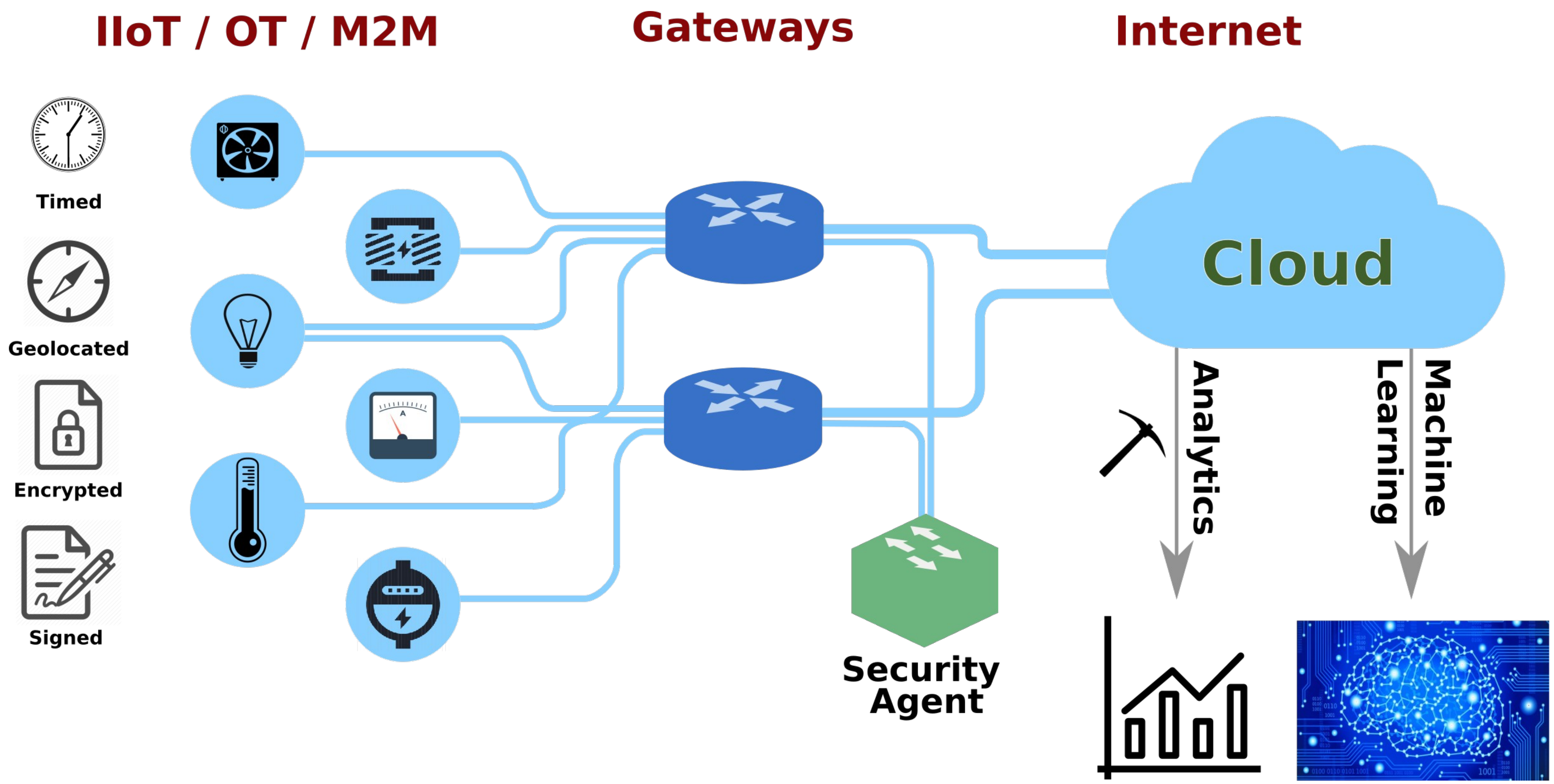


(a) ANN Replacement Method



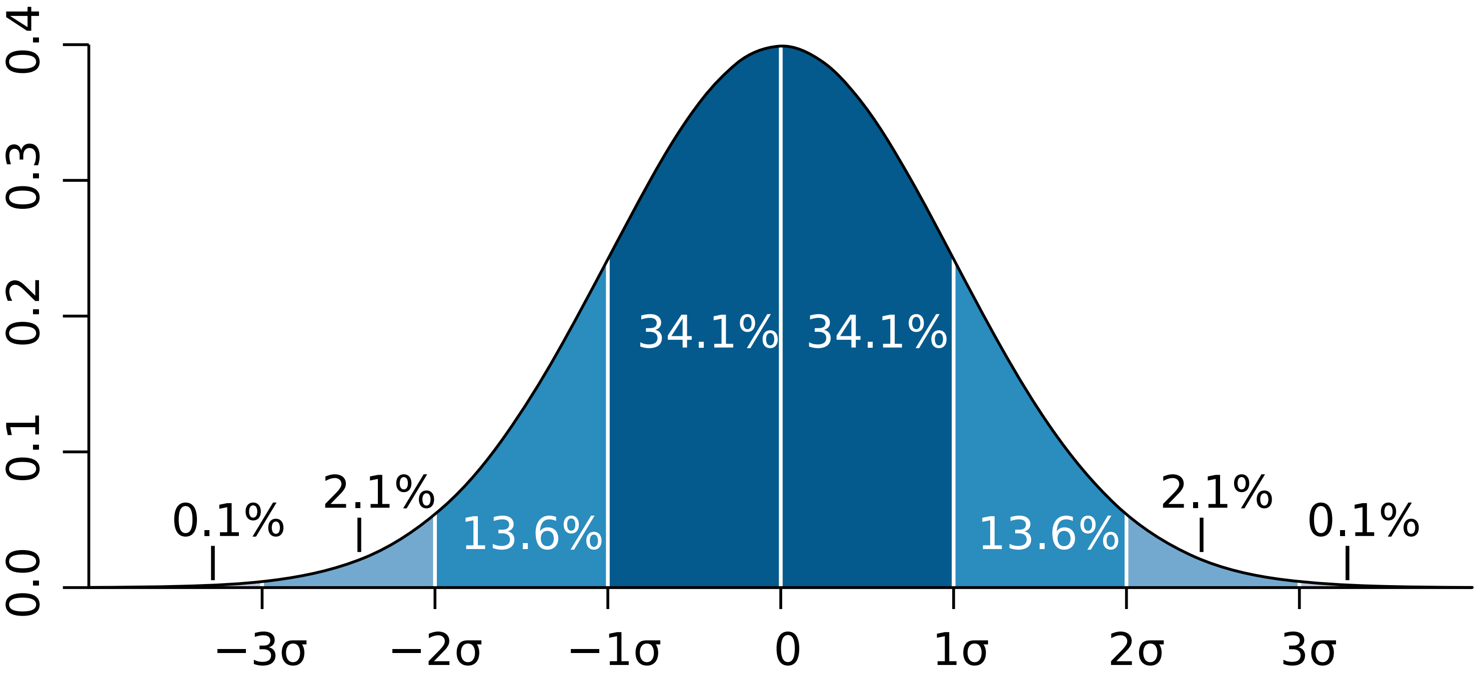
(b) Non-Linear Interpolation Methods

LISHA's Secure IoT+AI Platform



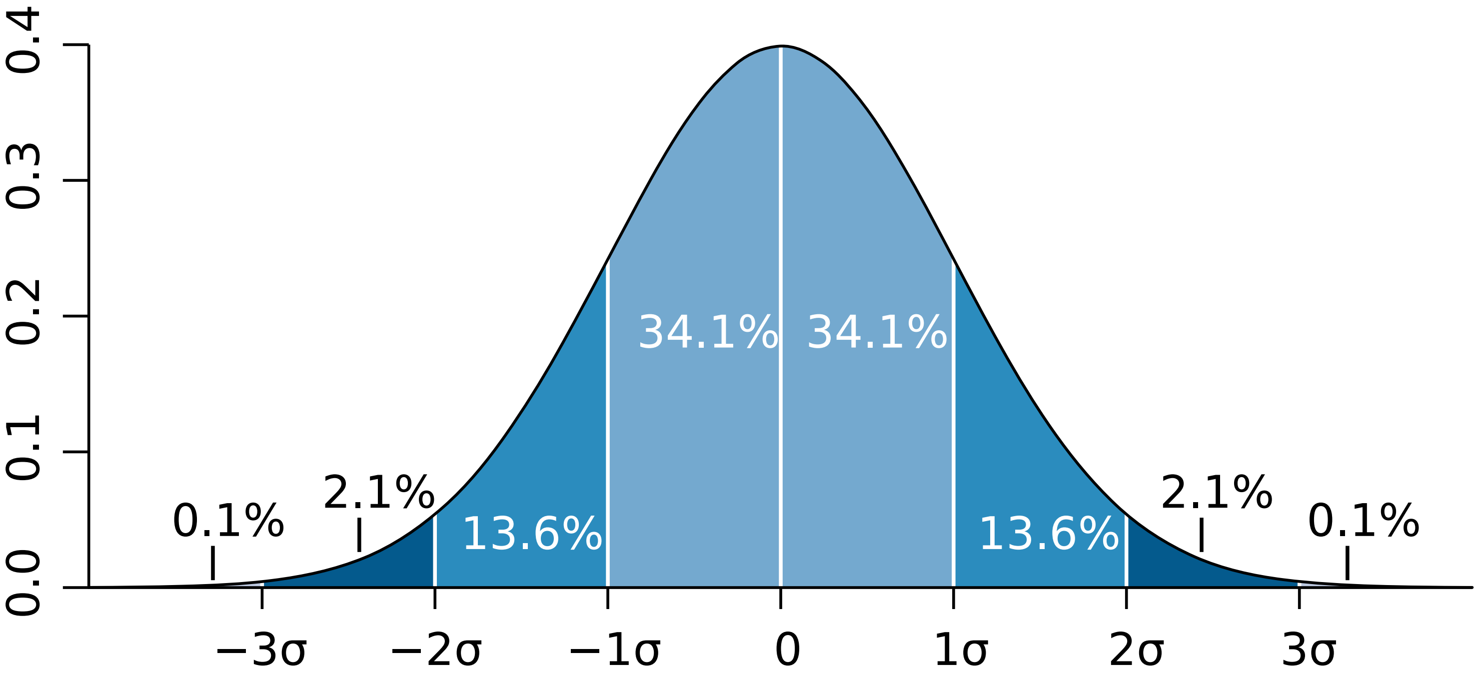
A Word on ML for CPS

The 2σ rule! Who cares for those 5% anyway?

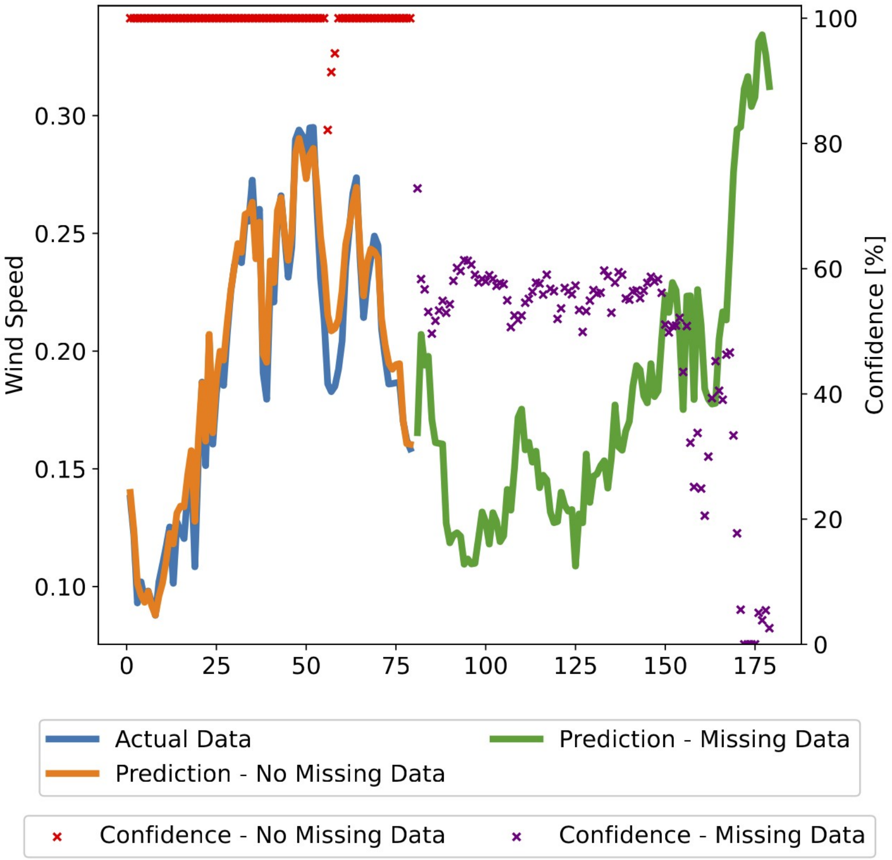


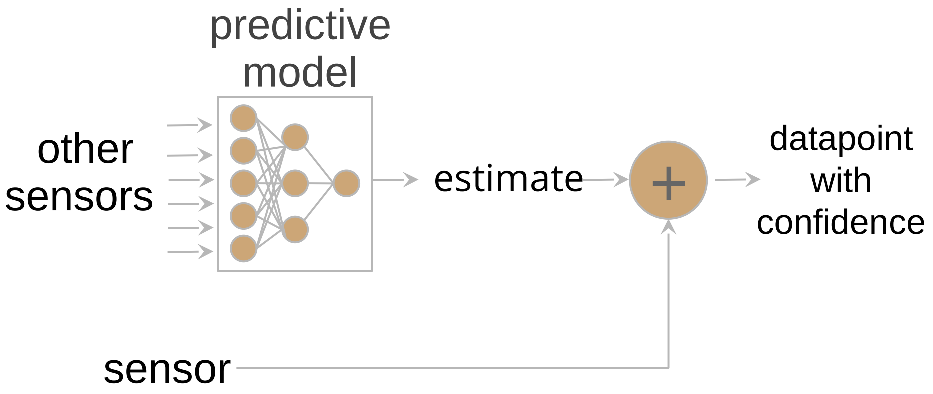
A Word on ML for CPS

We have v ML is often handling the missing cases! n the 3σ!



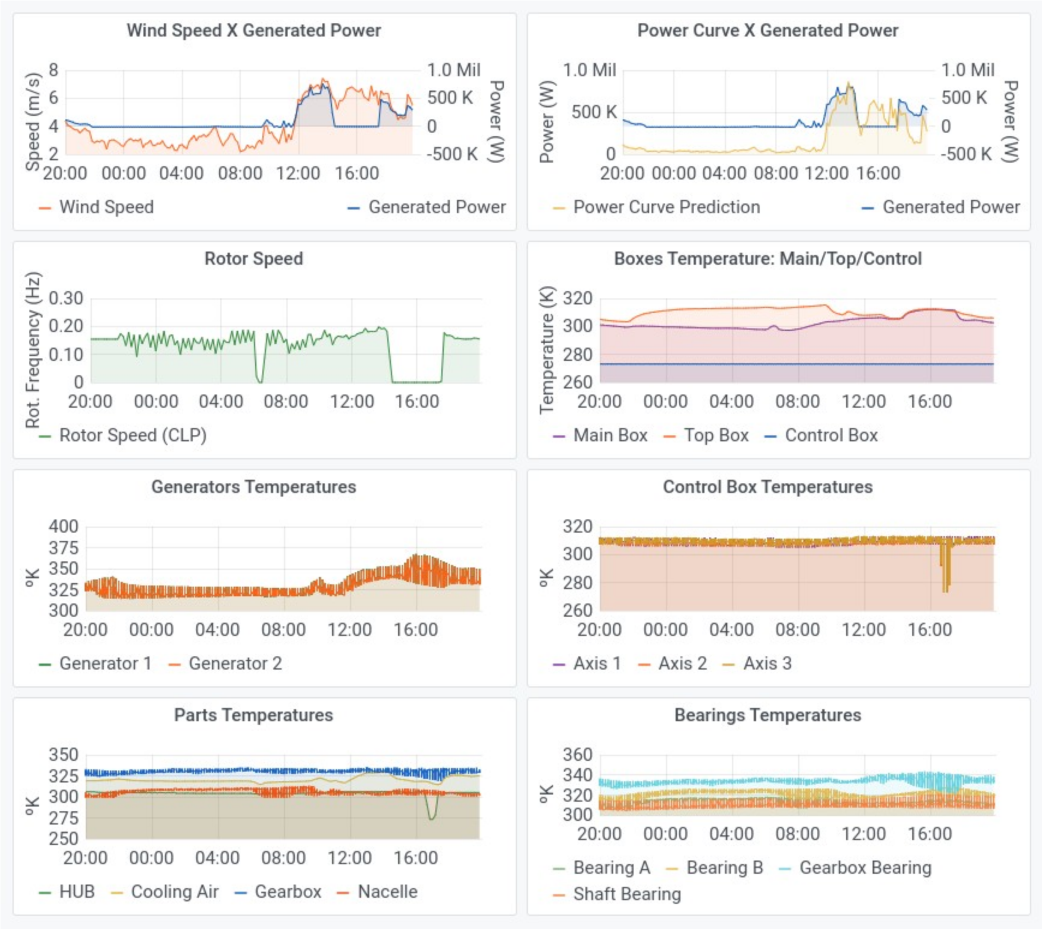
Predictors for Confidence Attribution

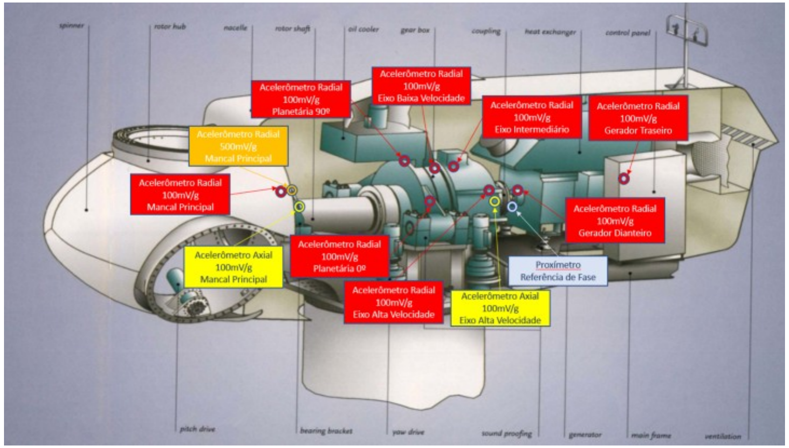




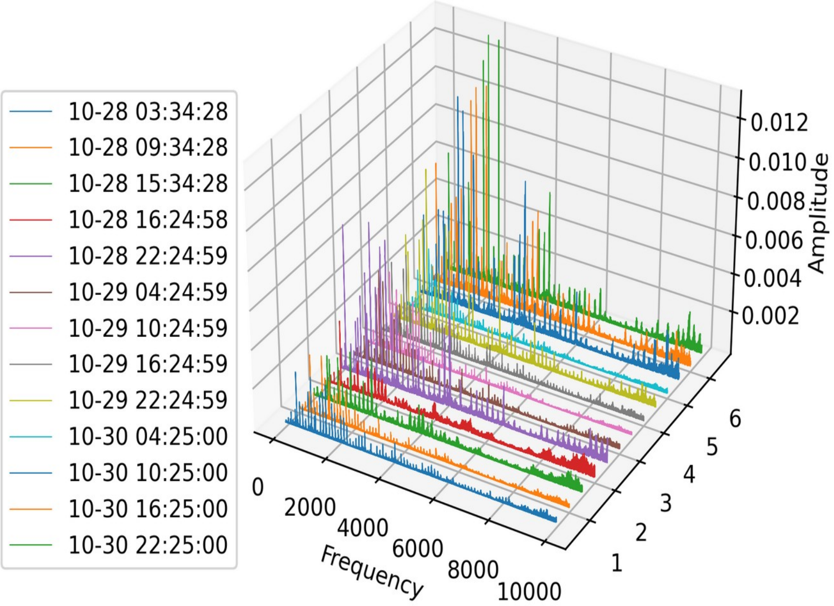
$$f(v,\hat{v}) = \begin{cases} 1, & if \quad |v-\hat{v}| \leq \beta \times MAE \\ 1 - \frac{|v-\hat{v}|-\beta\times MAE}{\alpha\times MAE}, & otherwise \end{cases}$$

Predictors for Anomalies in Wind Turbines

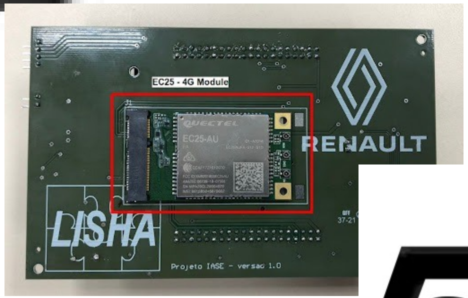


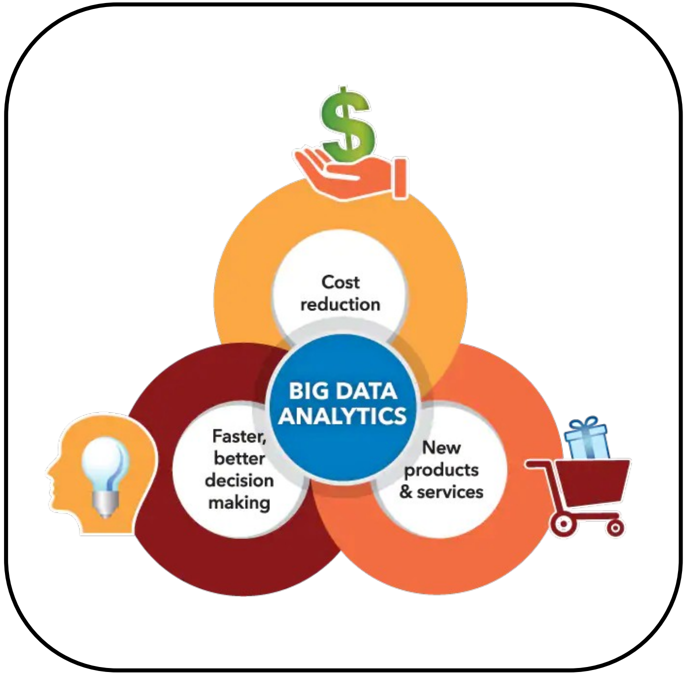


Predictors for Anomalies in Hydroelectric Plants

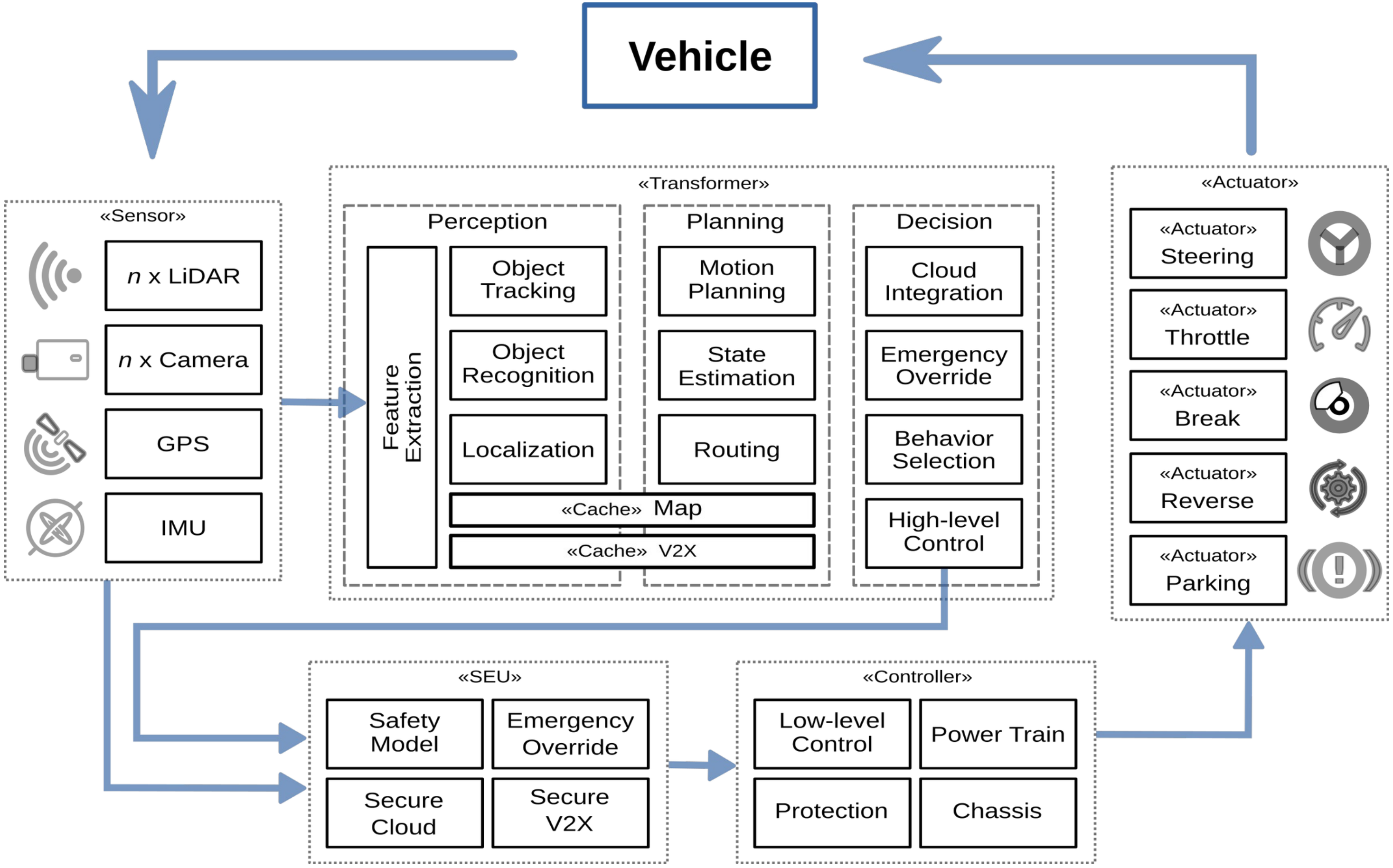


Predictors for Engine Calibration



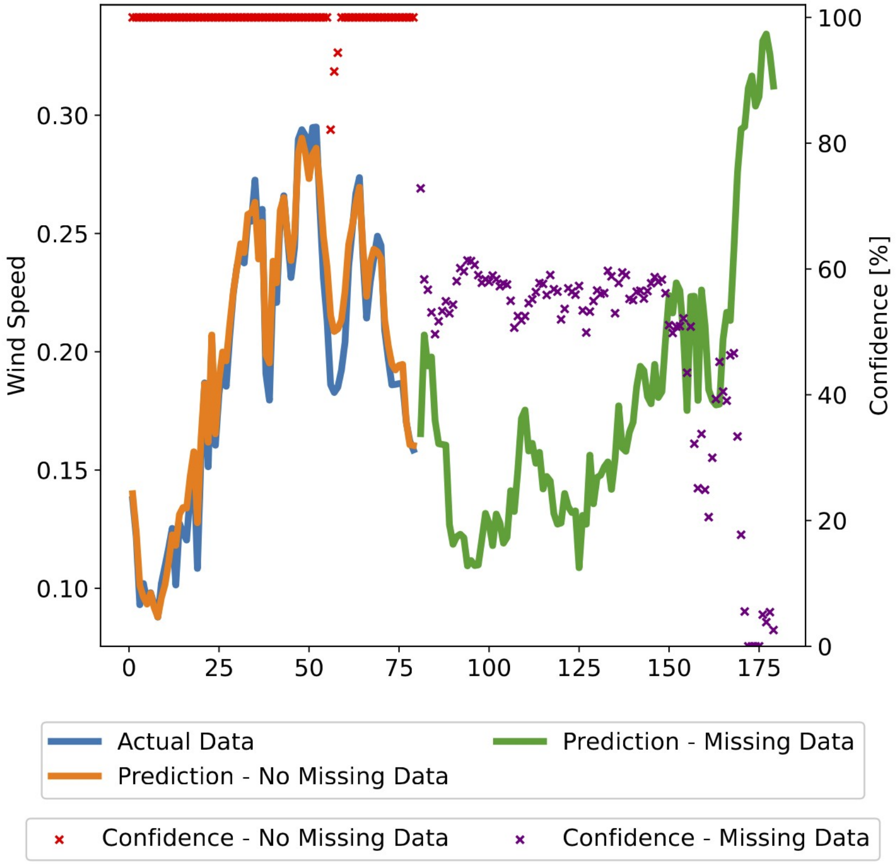


Predictors for AV Control



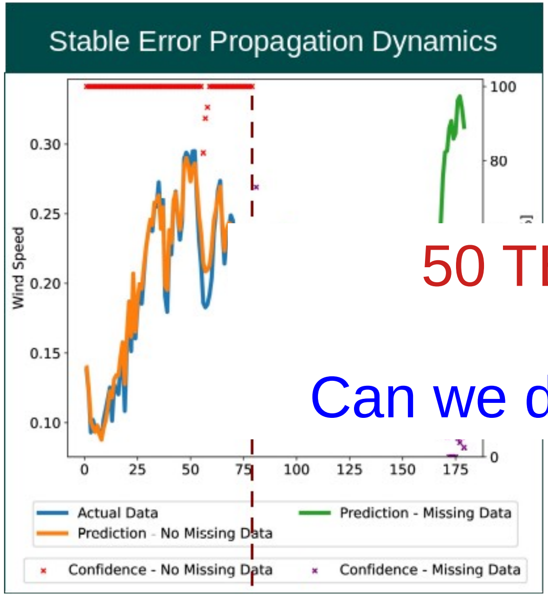
Predictors for AV Control

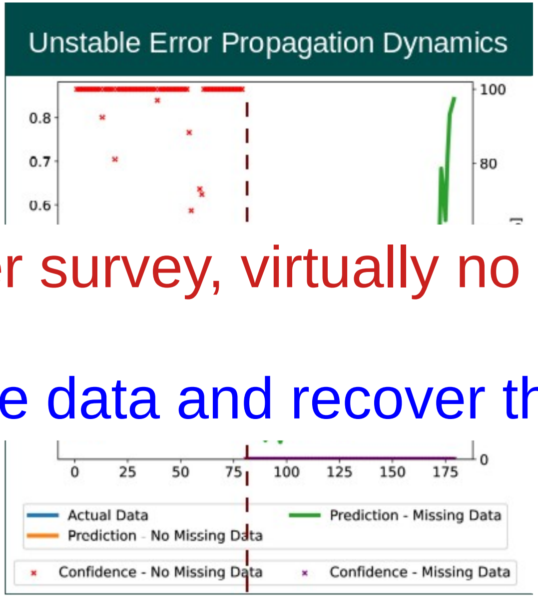
Predictors for Data Imputation



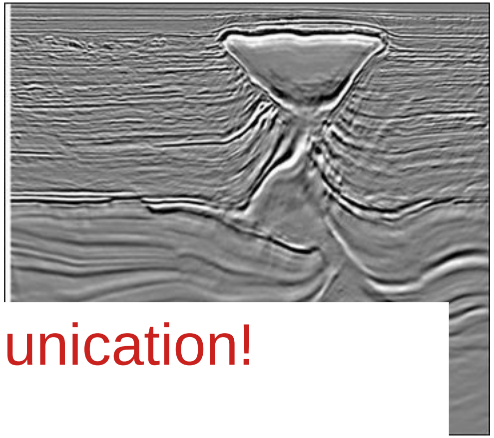
Replace missing data by high-confidence predicted values!

Predictors for Seismic Data Compressor





Inputs start being replaced by predictions



50 TB per survey, virtually no communication!

Can we delete data and recover them with predictors?

Problem Definition

- Typical mechanisms to evaluate Predictors
  - Accuracy (e.g., MSE, MAE, RMSE)
  - Computing power (e.g., cycles, committed instructions, cache misses)
- As pointed by Yang and others in 2020, such evaluations usually consider Independent and Identically Distributed Variables
- Sensing is subject to errors
  - Datasets often contain bad data
- How can we evaluate interdependent predictors accounting for the impacts of prediction error propagation?

Proposed Solution

- This work proposes a method to estimate the impact of using predicted values as input for a multivariate predictor based on the stability of a general dynamic system

- Predictor is a function $v_i = g_i(x_i)$
  - x_i vector of inputs
  - v_i scalar quantity prediction for i_{th} variable in a set

- g_i is assumed to be infinitely differentiable
  - Sigmoid, Hyperbolic Tangent, Softmax, Swish and CoLU (but not ReLU)

- g_i expanded into a Taylor series
  - Evaluate error propagation dynamics over the Taylor series to verify error boundedness

Procedure for Analysis

- The gradient of g_i is $\frac{\partial g_i(\vec{x}_i)}{\partial \vec{x}_i}$

$$\hat{v}_i = \hat{v}_i^* + \frac{\partial g_i(\vec{x}_i^*)}{\partial \vec{x}_i}(\vec{x}_i - \vec{x}_i^*) + \frac{1}{2}\frac{\partial^2 g_i(\vec{x}_i^*)}{\partial \vec{x}_i^2}(\vec{x}_i - \vec{x}_i^*)^2 + \ldots$$

- Considering the deviation of the predictor's input is small, or g_i resembles a linear function, we can truncate the Taylor series to the first order terms
  - Other terms would be negligible
  - The deviation of the prediction can be related to the deviation of the input

$$\hat{v}_i - \hat{v}_i^* = \frac{\partial g_i(\vec{x}_i^*)}{\partial \vec{x}_i}(\vec{x}_i - \vec{x}_i^*)$$

Procedure for Analysis

- Considering the *N* components of the input vector, the error can be summarized as

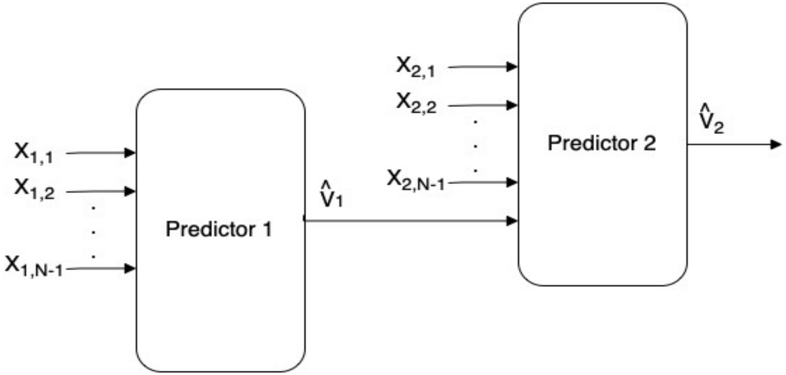
$$\hat{e}_i = \sum_{j=0}^{N-1} \frac{\partial g_i(\vec{x}_i^*)}{\partial x_{i,j}} e_j + MAE_i$$

- Using a linear approximation for linear time-invariant system
  - Predictor gradient changes
    - Bounded in absolute value (worst-case)
    - Error propagation Dynamics
    - Bounded-Input Bounded-Output (BIBO) stability (property of linear systems)

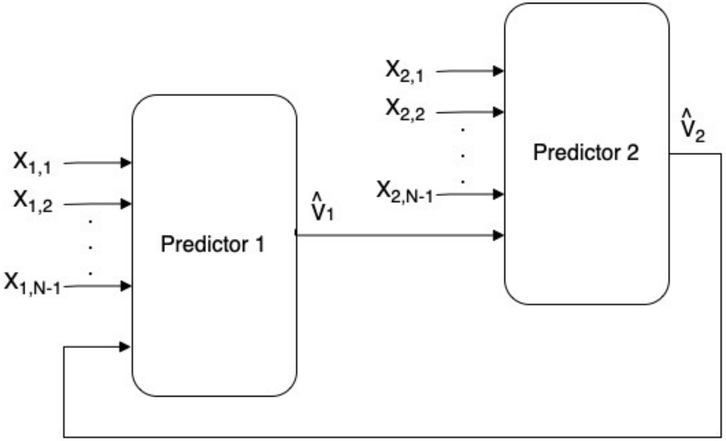
$$\|\hat{e}_i\| \leq \sum_{j=0}^{N-1} \left\| \frac{\partial g_i(\vec{x}_i^*)}{\partial x_{i,j}} \right\| \|e_j\| \leq \sum_{j=0}^{N-1} max \left\{ \left\| \frac{\partial g_i(\vec{x}_i^*)}{\partial x_{i,j}} \right\| \right\} \|e_j\|$$

Types of Predictor Interdependence

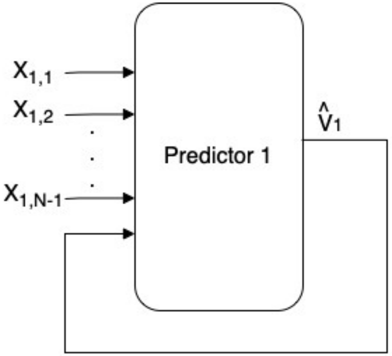
Cascade Prediction



Loop Prediction



Feedback Prediction

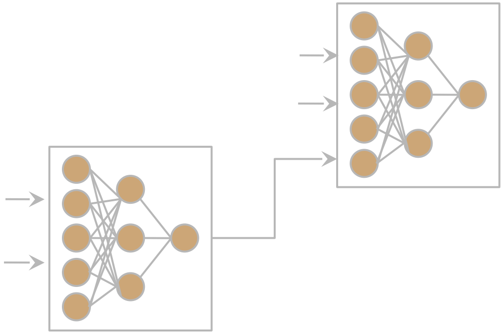


Estimation Error Stability Conditions

- The propagation of error has different impacts for each of the presented scenarios
- Considering stability as the boundedness of the error propagation
  - Cascade chains are stable (as long as there are a finite set of predictors)
  - Loop and Feedback scenarios are infinite due to recurrent predictions (cicle)
- Even in a stable propagation, the error can eventually exceed the tolerance defined by the application
  - We can track the estimated error and decide whether a new prediction is believed to exceed this margin or not following the equation for the prediction error

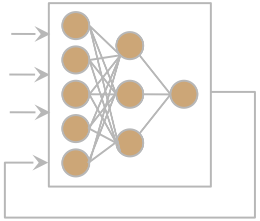
Estimation Error Stability Conditions

Cascade Prediction



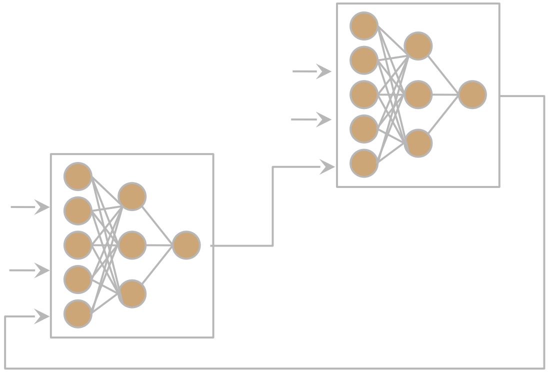
Always Stable

Feedback Prediction



$$\|z_1| = \lambda_i^r \leq 1$$

Loop Prediction



$$\|z_{1,2}\| = \sqrt{\sum_{j\in D_i} \lambda_j^i \lambda_i^j} \leq 1$$

$$\lambda_i^j = max\left\{\left\|\frac{\partial g_i(\vec{x}_i^*)}{\partial x_{i,j}}\right\|\right\}$$

Case Study

- Dataset
  - Hydraulic test rig (Helwig et al., 2015)
- Model Generation
  - Person Correlation
  - K features
  - Autoregressive and non-autoregressive

Sensor	Physical Quantity	Sampling Frequency
PS1	Pressure [bar]	100 Hz
PS2	Pressure [bar]	100 Hz
PS3	Pressure [bar]	100 Hz
PS4	Pressure [bar]	100 Hz
PS5	Pressure [bar]	100 Hz
PS6	Pressure [bar]	100 Hz
MPW	Motor Power [W]	100 Hz
FS1	Volume Flow [L/min]	10 Hz
FS2	Volume Flow [L/min]	10 Hz
TS1	Temperature [°C]	1 Hz
TS2	Temperature [°C]	1 Hz
TS3	Temperature [°C]	1 Hz
TS4	Temperature [°C]	1 Hz
VS1	Vibration [mm/s]	1 Hz
CE	Cooling Efficiency [%]	1 Hz
CP	Cooling Power [W]	1 Hz
SE	Efficiency Factor [%]	1 Hz

Target	Selected Inputs
PS1	PS1, MPW, SE, FS1
PS2	PS2, FS1, SE, PS3
PS3	PS3, FS1, PS2, SE
PS4	PS4, CE, TS2, TS4
PS5	PS5, PS6, TS3, TS4
PS6	PS6,PS5, TS3, TS4
MPW	MPW, PS1, SE, PS2
FS1	FS1, PS3, PS2, SE
FS2	FS2, TS4, TS3, TS2
TS1	TS1, TS2, TS4, TS3
TS2	TS2, TS4, TS1, TS3
TS3	TS3, TS4, TS2, TS1
TS4	TS4, TS3, TS2, TS1
VS1	VS1, FS2, CE, CP
CE	CE, TS4, CP, TS2
CP	CP, CE, TS4, TS2
SE	SE, PS2, FS1, PS1

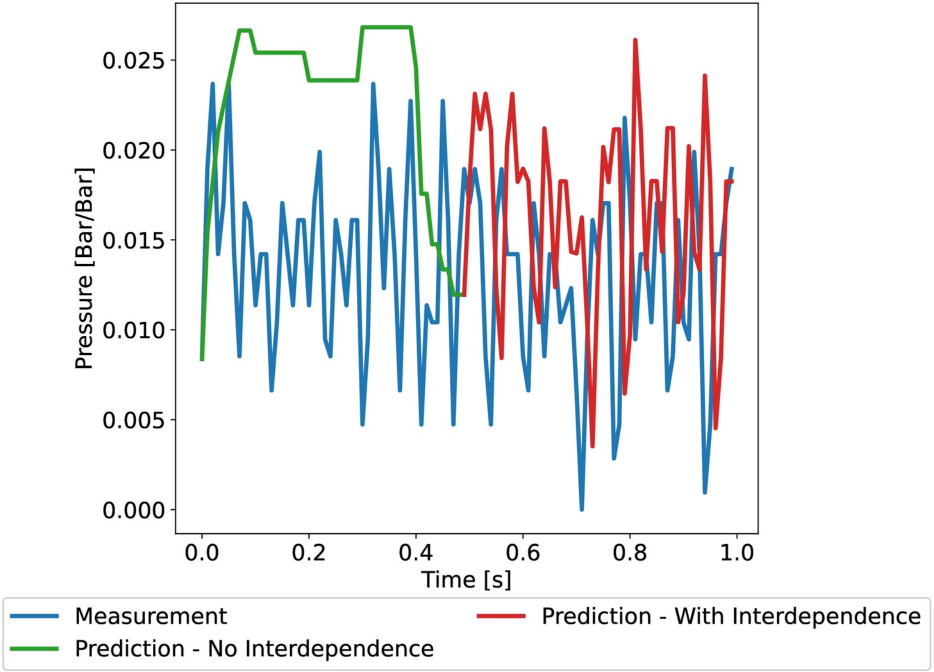
Autoregressive FS

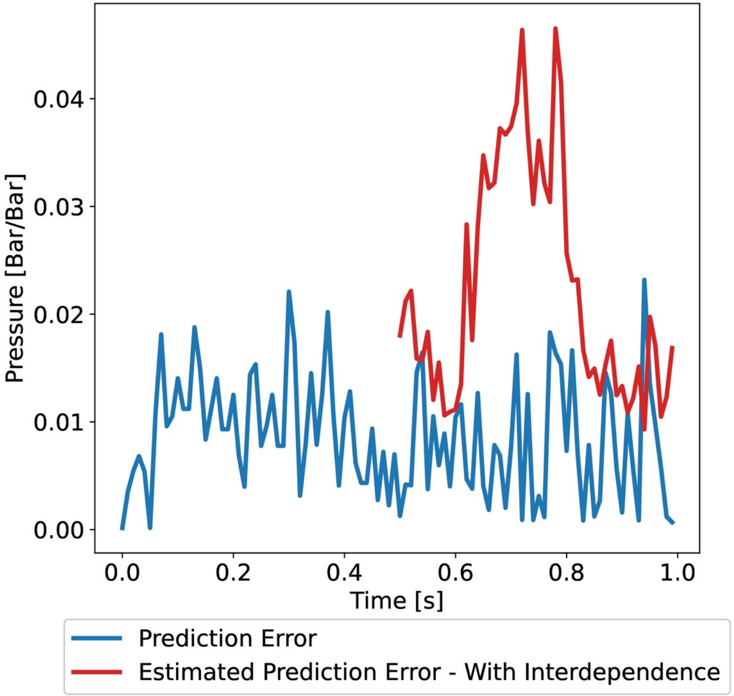
Target	Selected Inputs
PS1	MPW, SE, FS1
PS2	FS1, SE, PS3
PS3	FS1, PS2, SE
PS4	CE, TS2, TS4
PS5	PS6, TS3, TS4
PS6	PS5, TS3, TS4
MPW	PS1, SE, FS1
FS1	PS3, PS2, SE
FS2	TS4, TS3, TS2
TS1	TS2, TS4, TS3
TS2	TS4, TS1, TS3
TS3	TS4, TS2, TS1
TS4	TS3, TS2, TS1
VS1	FS2, CE, CP
CE	TS4, CP, TS2
CP	CE, TS4, TS2
SE	PS2, FS1, PS1

Non-autoregressive FS

Results – Cascade Configuration

- MPW to PS1
  - Input impact on predictor

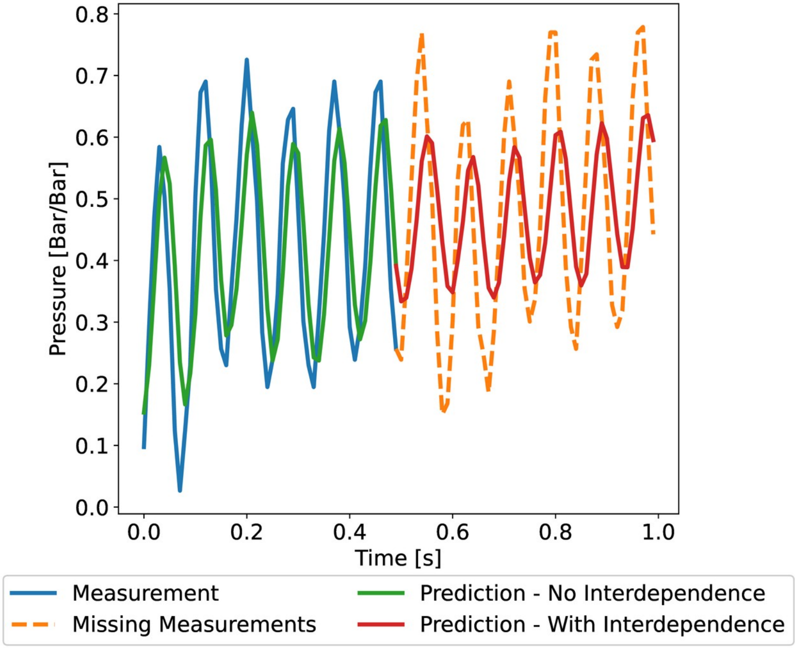


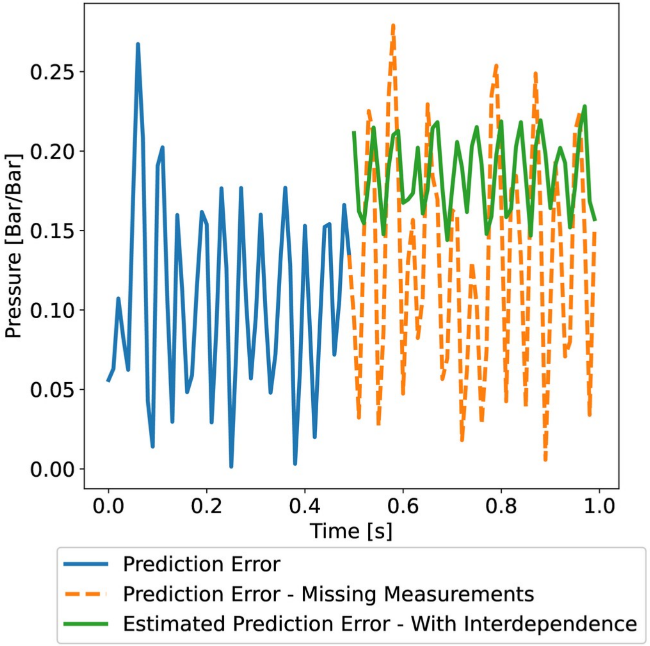


Results – Stable Feedback Configuration

- PS6
  - Calculate z following feedback stability condition $\|z_1| = \lambda_i^r \leq 1$
    - Z ≤ 1

$$\lambda^r_{PS6} = 0.36$$
$$z = 0.36$$



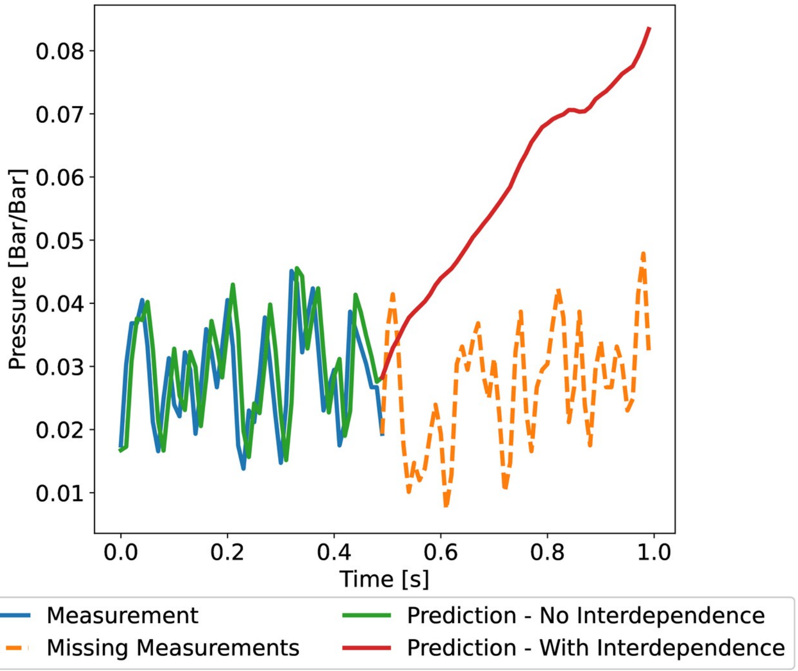


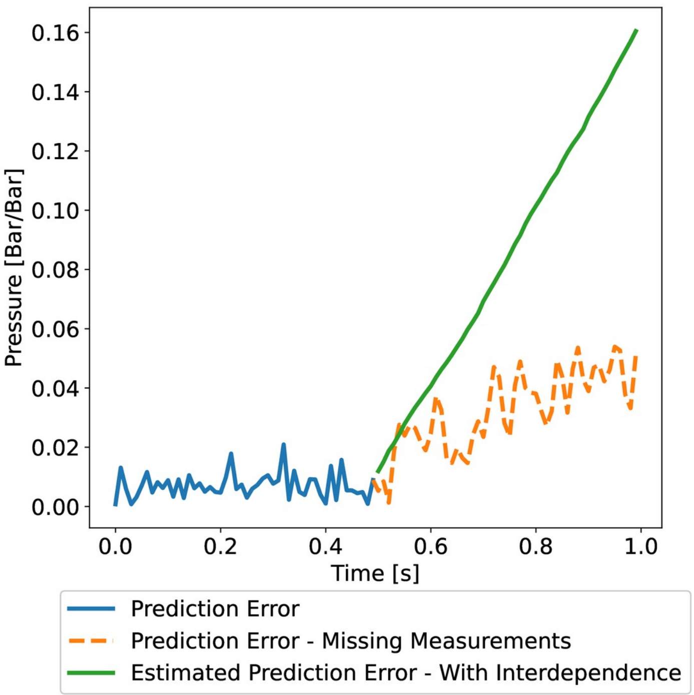
Results – Unstable Feedback Configuration

- PS2
  - Calculate z following feedback stability condition $\|z_1| = \lambda_i^r \leq 1$
    - Z ≥ 1

$$\lambda_{PS2}^r = 1.01$$

$$z = 1.01$$





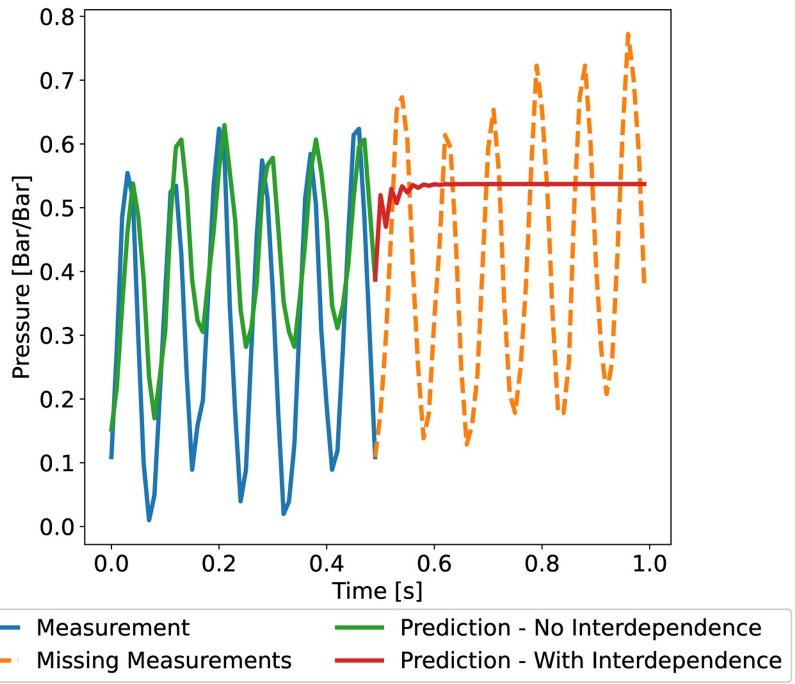
Results – Stable Loop Configuration

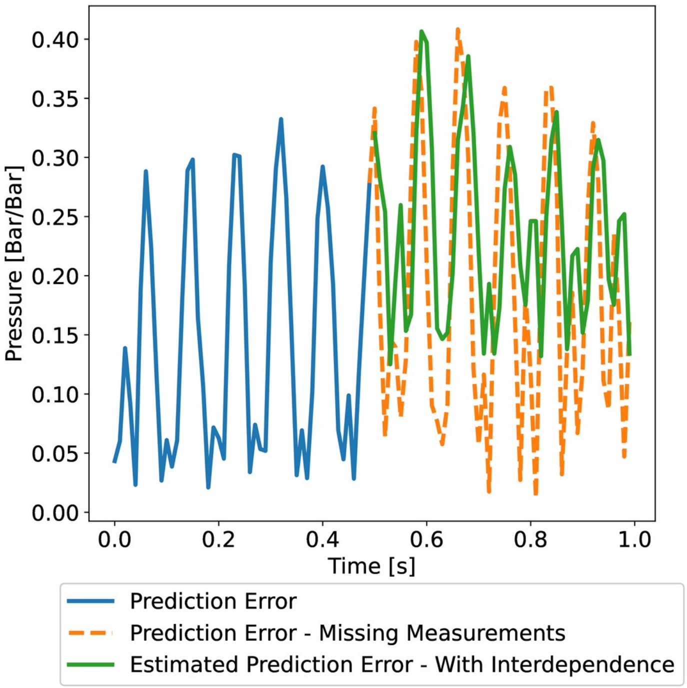
- PS5 and PS6 (ps5 → ps6, ps6 → ps5)
  - Calculate *z* following loop stability condition $\|z_{1,2}\| = \sqrt{\sum_{j \in D_i} \lambda_j^i \lambda_i^j} \leq 1$
    - *Z ≤ 1*

$$\lambda_{PS5}^{PS6} = 0.70$$

$$\lambda_{PS6}^{PS5} = 0.67$$

$$z = 0.68$$





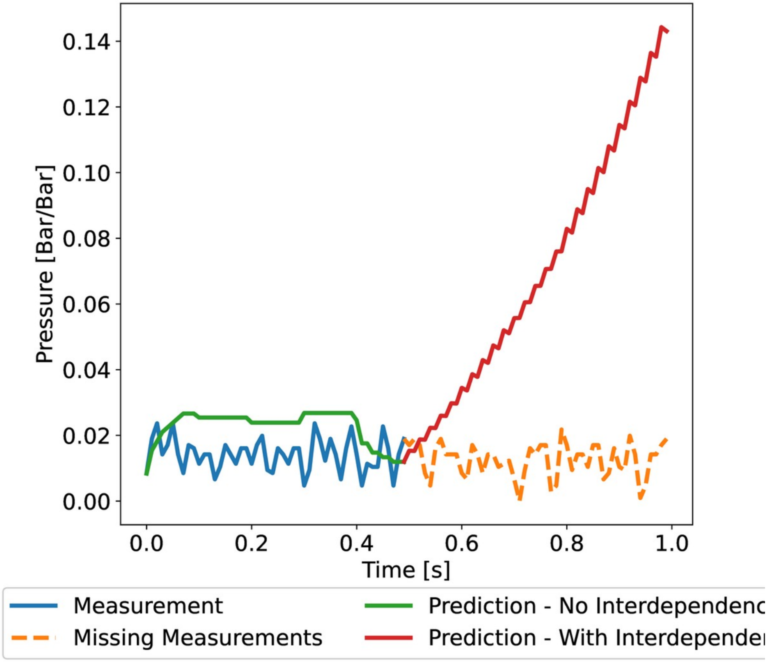
Results – Unstable Loop Configuration

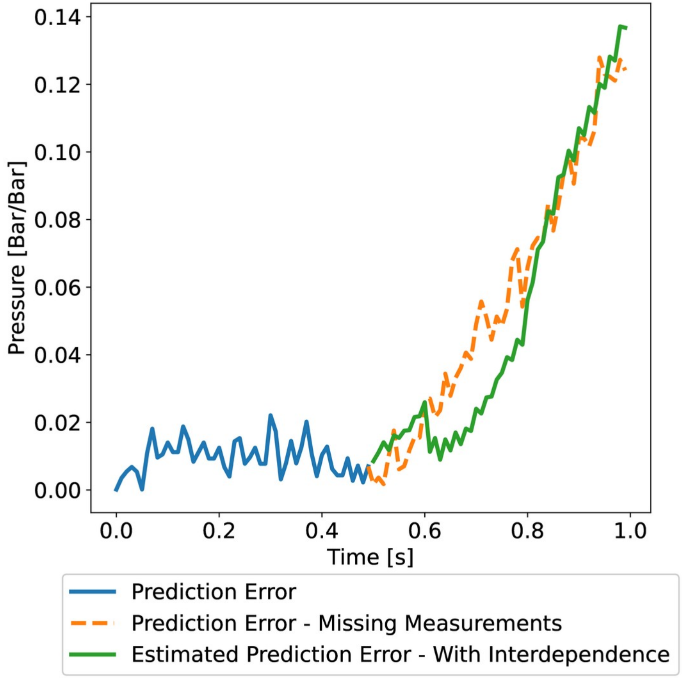
- PS1 and MPW
  - Calculate *z* following loop stability condition $\|z_{1,2}\| = \sqrt{\sum_{j \in D_i} \lambda_j^i \lambda_i^j} \leq 1$
    - *Z ≥ 1*

$$\lambda_{PS1}^{MPW} = 1.03$$

$$\lambda_{MPW}^{PS1} = 1.01$$

$$z = 1.02$$





Final Remarks

- This work presented an strategy to evaluate a predictor based on its ability to sustain accurate predictions when its inputs are replaced by predictions and face the impacts of prediction error
- Different datasets impact prediction accuracy
  - Mathematical analysis is valid as long as the activation function is infinitely differentiable
  - We do not evaluate the predictor’s accuracy but the fact it is able to maintain it when dealing with inputs that are predicted data
    - Boundedness
- Dataset variability / Input variability
  - Will affect model quality
    - Boundedness still follows the mathematical analysis