Advancements in Unsupervised Prognostics

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Contents

- Prognostics and Deep learning (supervised)

- Unsupervised Prognostics through Data Augmentation
  - Data Augmentation
  - Health Index Extraction
  - RUL Prediction

Prognostics

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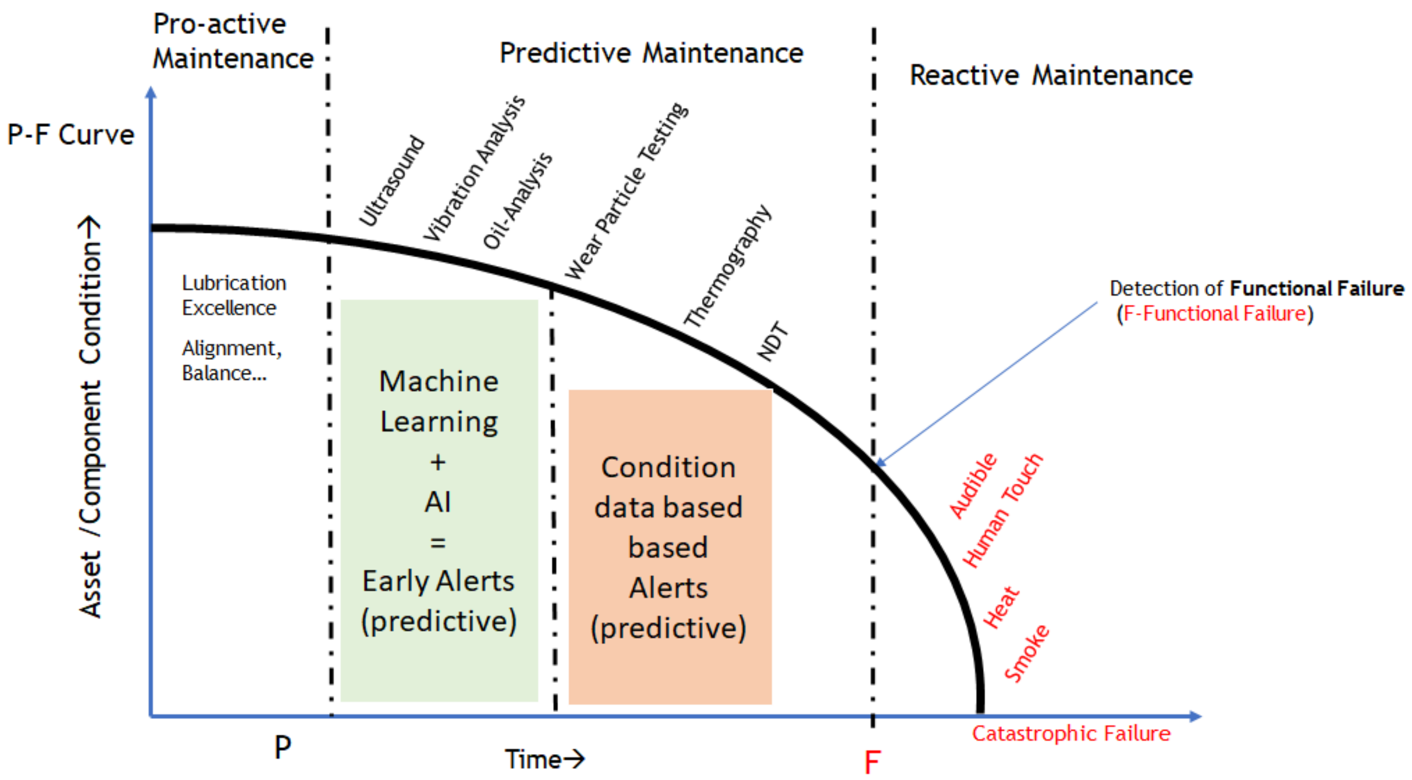
Prognostics

Prognostics:

- Estimate (state of health) → identification of degradation model.
- Prediction of future health + **Remaining Useful Life (RUL)**
- Evaluate: Decision "when failure occurs ???" "what maintenance strategy"



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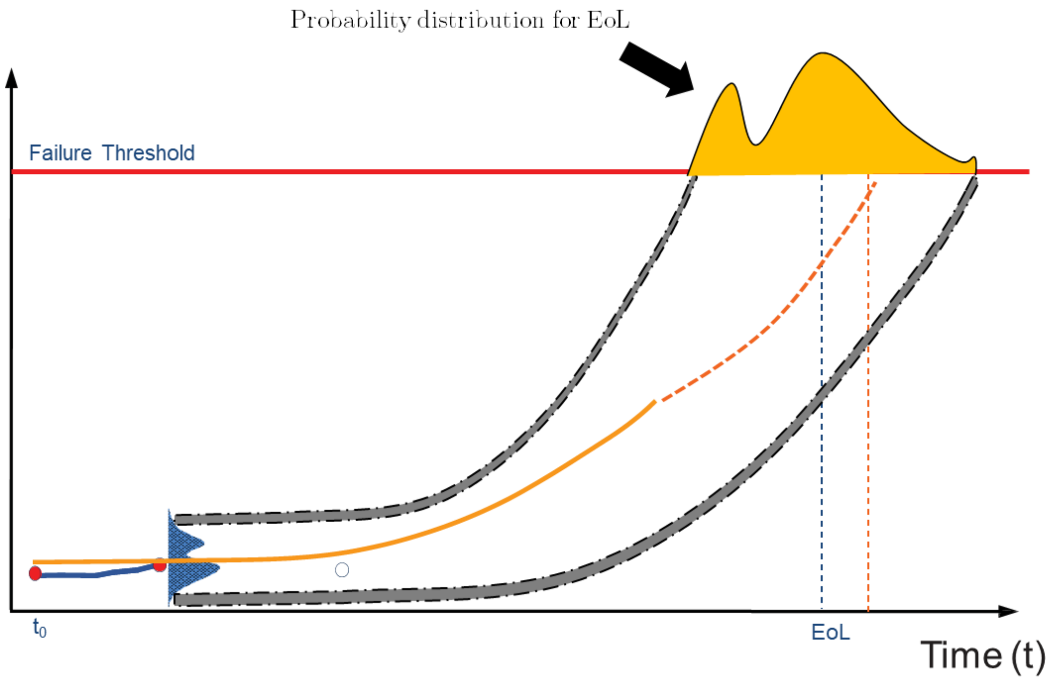

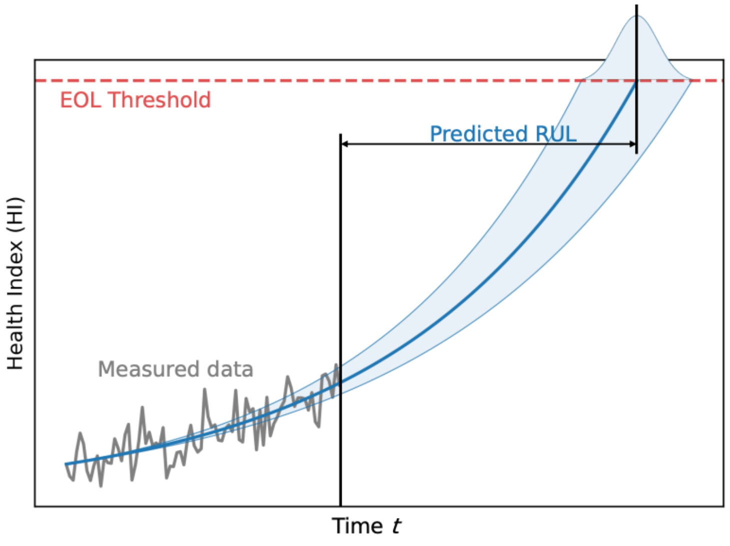

Figure: Traditional prognostics process.

Health Index (HI)

Indicator that estimates the true SOH of the system studied. Can be built by fusing multiple sensor signals [Lei et al., 2018].

Remaining Useful Life (RUL)

Time remaining between current instant t_k and EOL [Gouriveau et al., 2017].

$$RUL(t_k) = t_{EOL} - t_k \quad (1)$$

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Degradation Data

Degradation:

- unknown, non-linear varying dynamics
- sensor data: non-stationary → trend, seasonality, cyclic etc.
- depends on qualitative+ quantitative factors.

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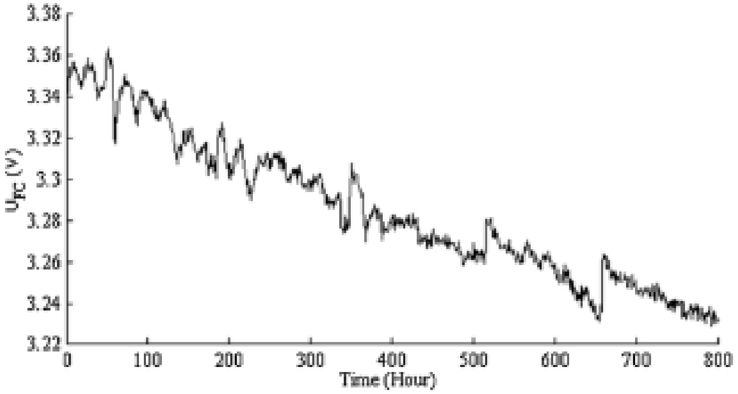

PEM Fuel Cell degradation (Jha et al. 2016)

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Degradation Data: Sequentially related Time Series data

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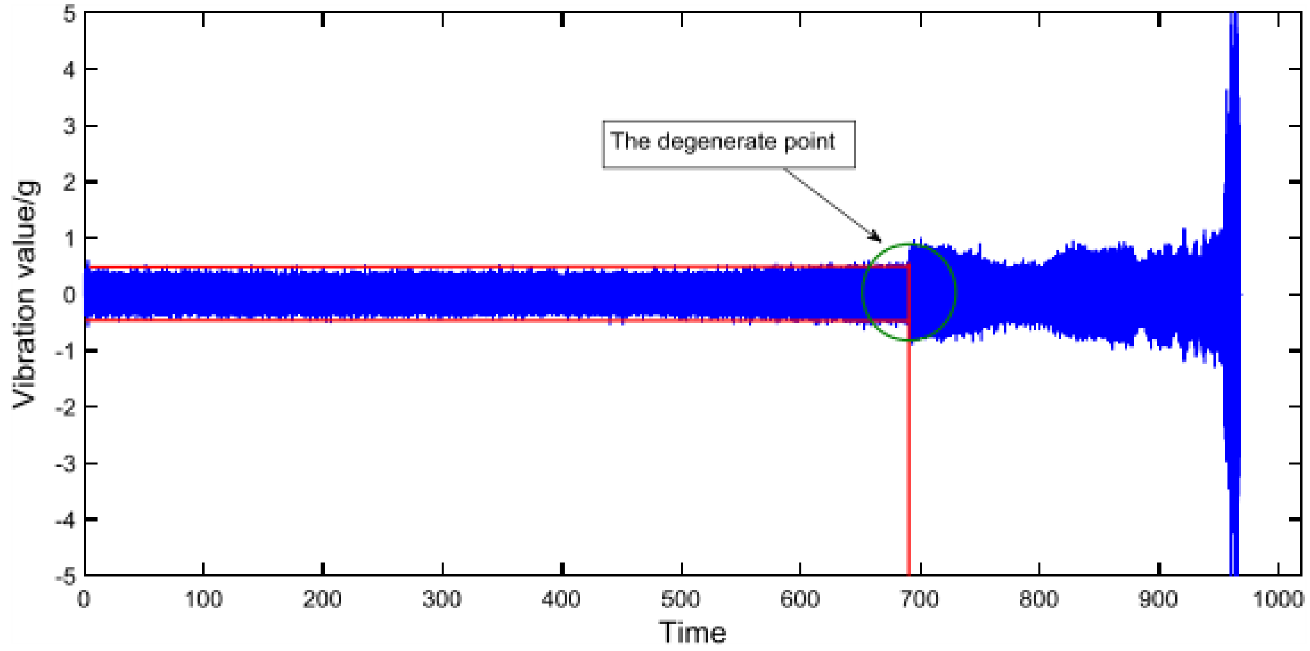

Roller bearing degradation (PRONOSTIA platform)

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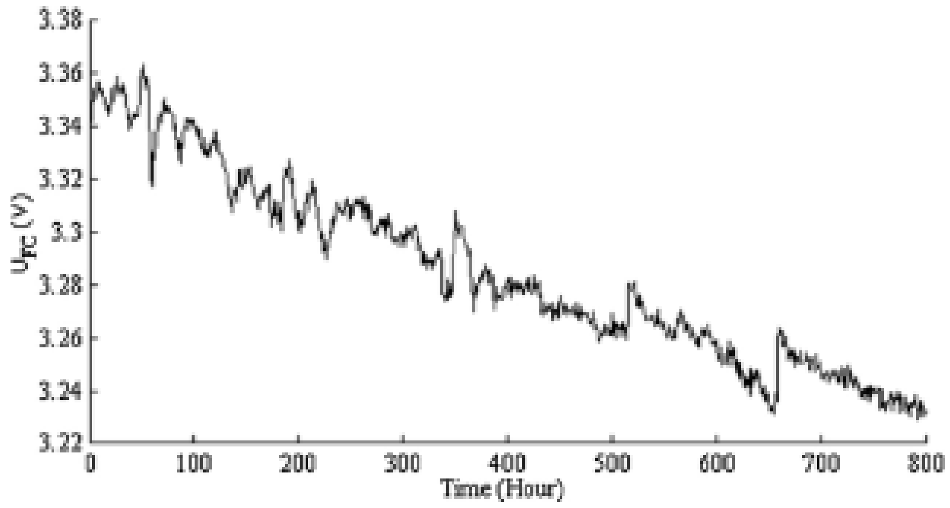

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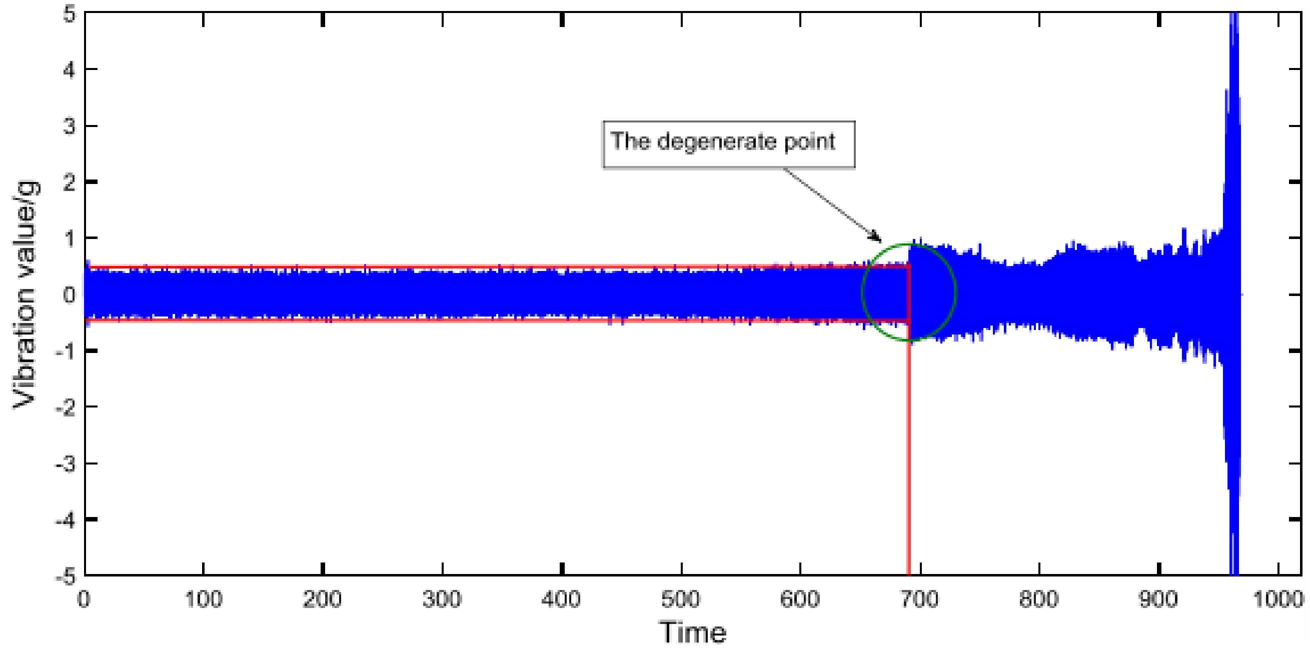

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Degradation Data

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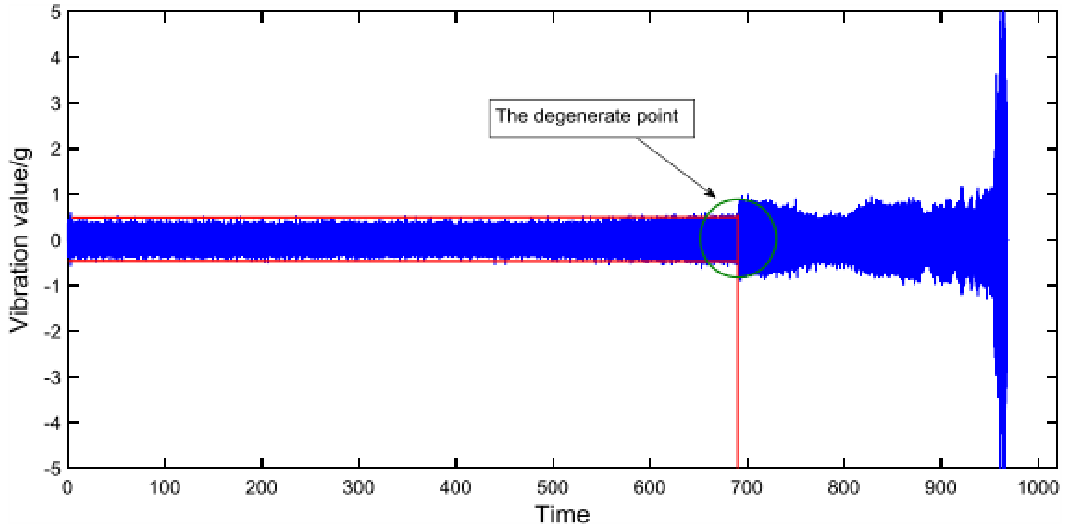
- Raw degradation data → Hidden features / representation:
  - Spatially varying
  - Temporally varying
  - Multimodal characteristics



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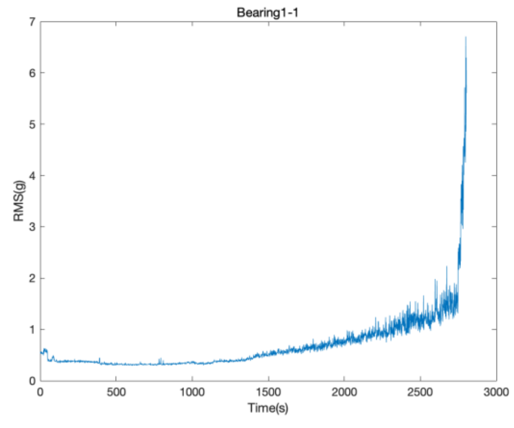

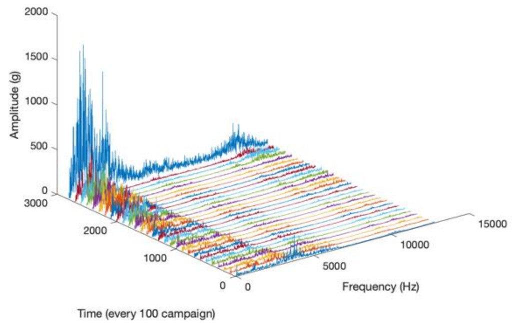

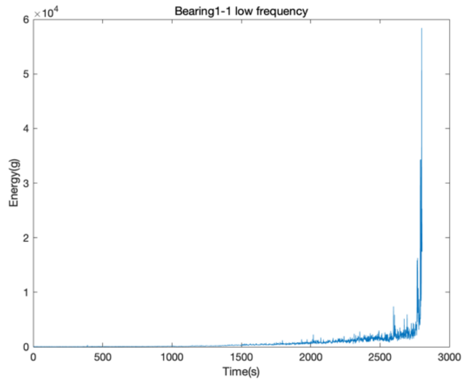

Photo: Report of Jha

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Prognostics and Deep Learning (Supervised Setting)

Convolutional Neural networks (CNNs)

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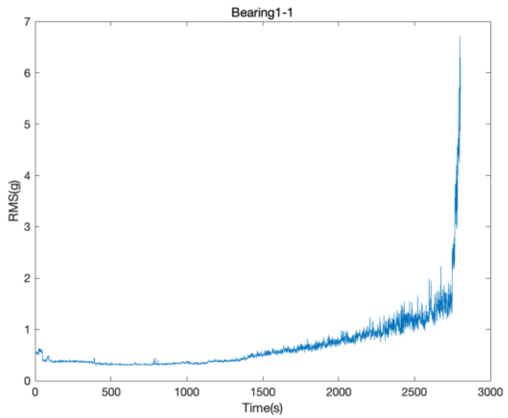
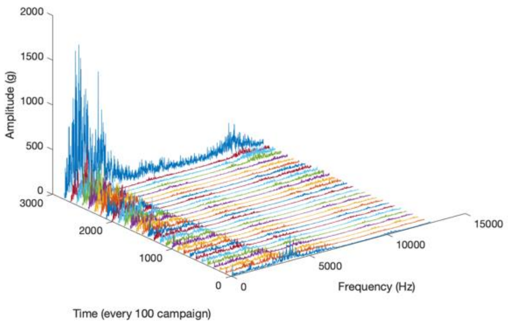
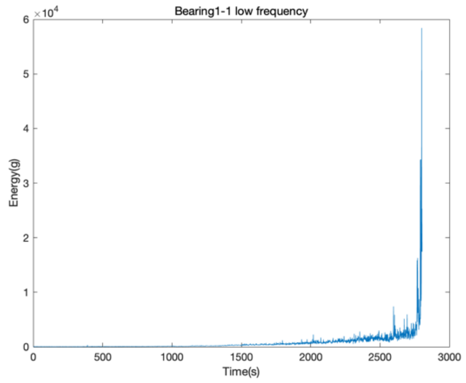
CNNs







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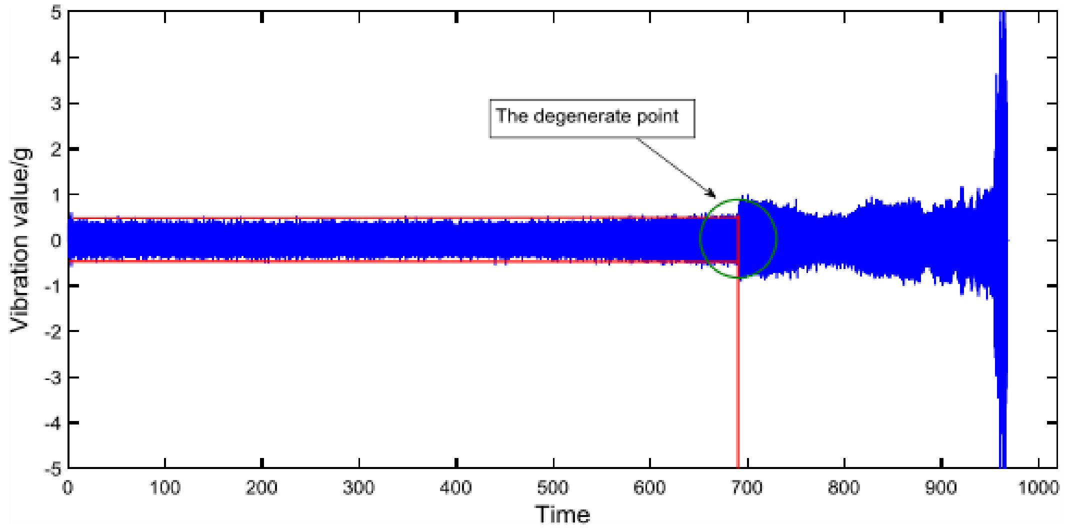
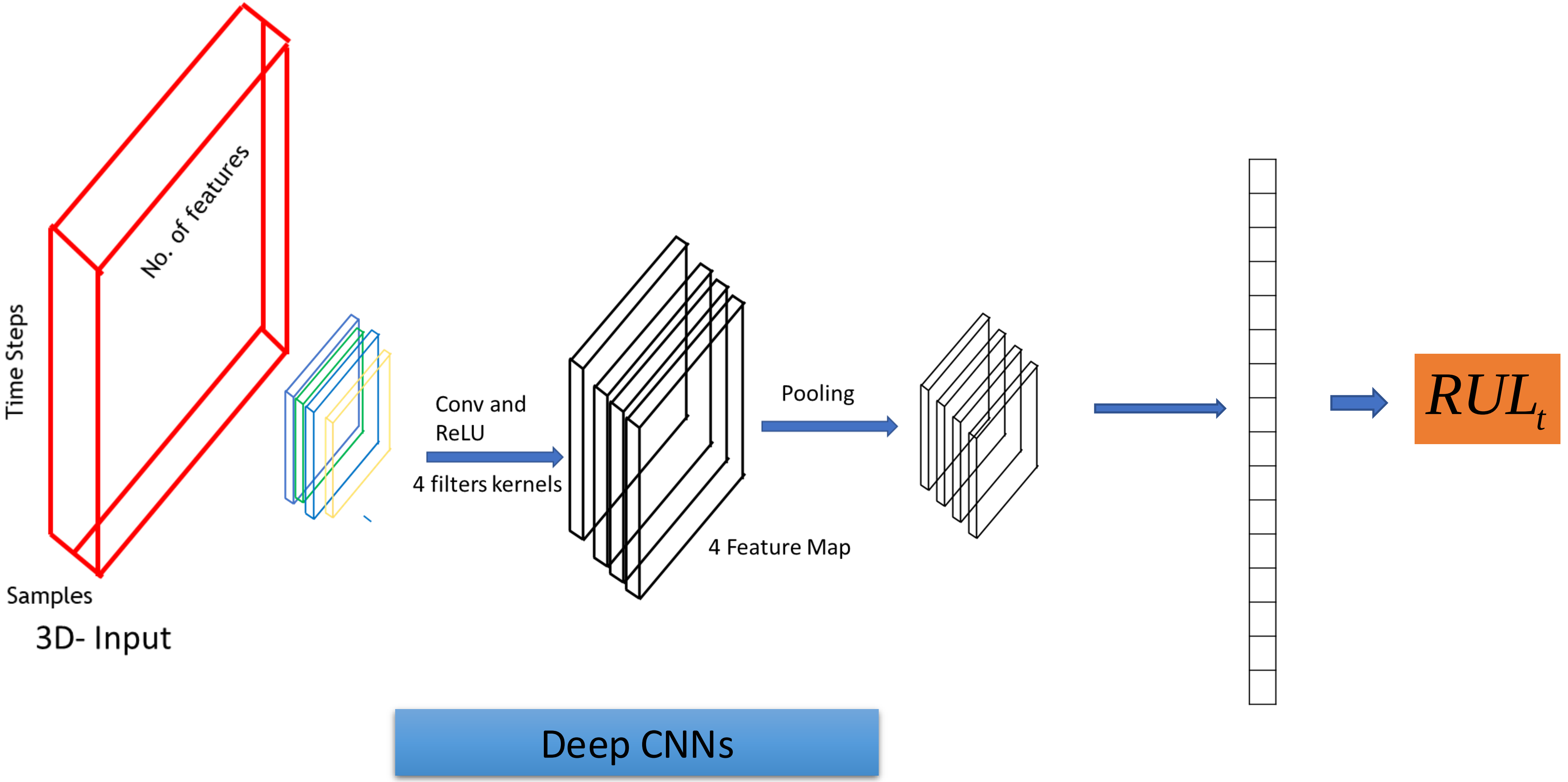


Roller bearing degradation (PRONOSTIA platform)

CNNs for Prognostics

- CNNs → Traditionally, 2D-3D structured data for face/object recognition
- Prognostics → 3D structured topology for sequence data



CNNs for Prognostics

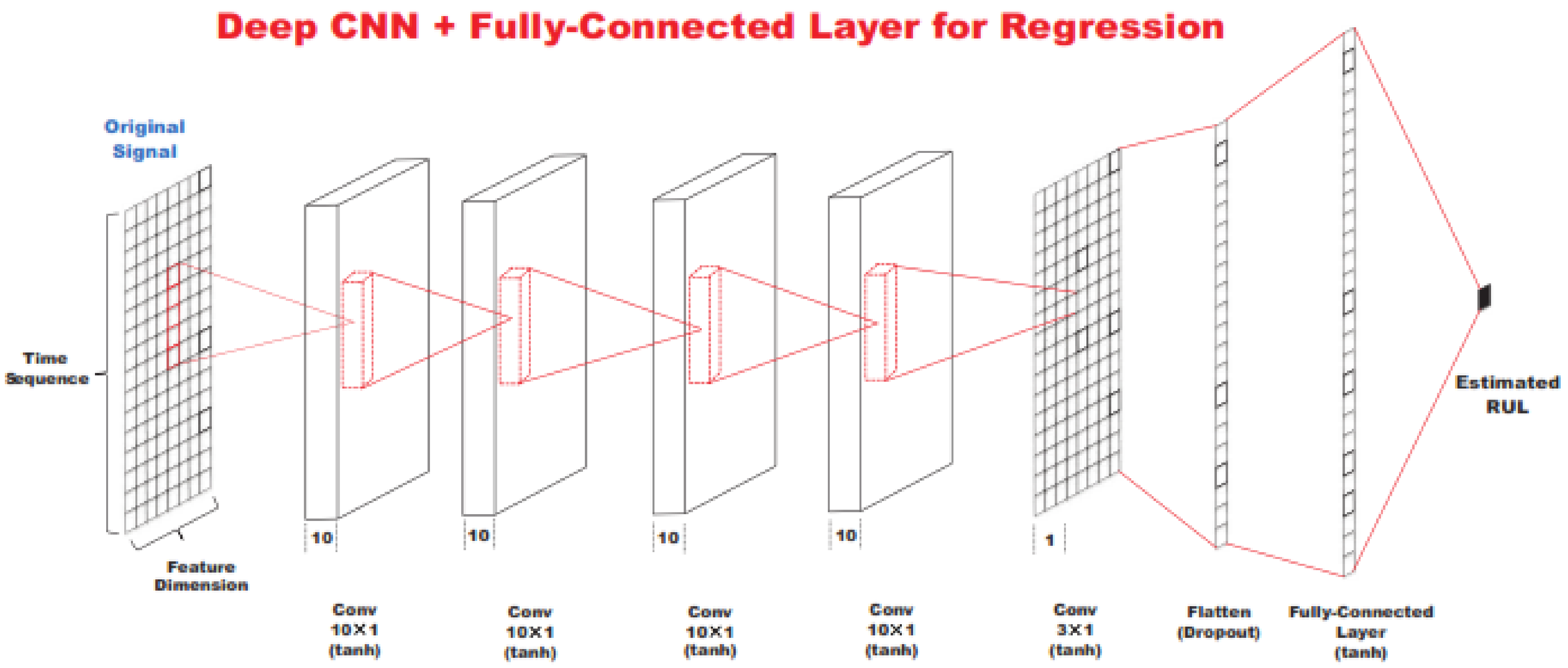
- Automatically learn feature representation, hidden multimodal distributions

[Liu et al., 2017] [Jing et al., 2017] [Li et al., 2018]

&

- Efficient learning with multi-variate sequential (time series) data.

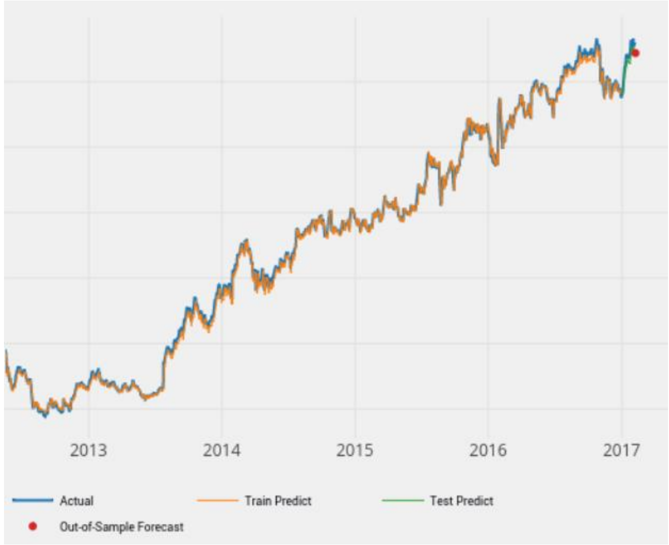
[Babu et al., 2016]



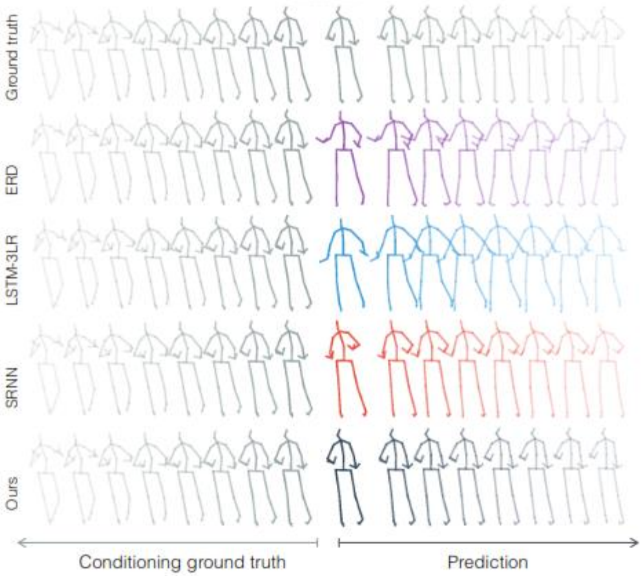
[Liu et al., 2017]

Sequence modelling : Motivations

- Sequential data:
  - time series forecasting,
  - motion prediction (human, self driving cars)
  - sensor data: machine health monitoring/prediction
  - text processing/prediction
  - machine translation



Financial market prediction (Dixon et al.)



Human Motion Prediction

Martinez et al., 2016

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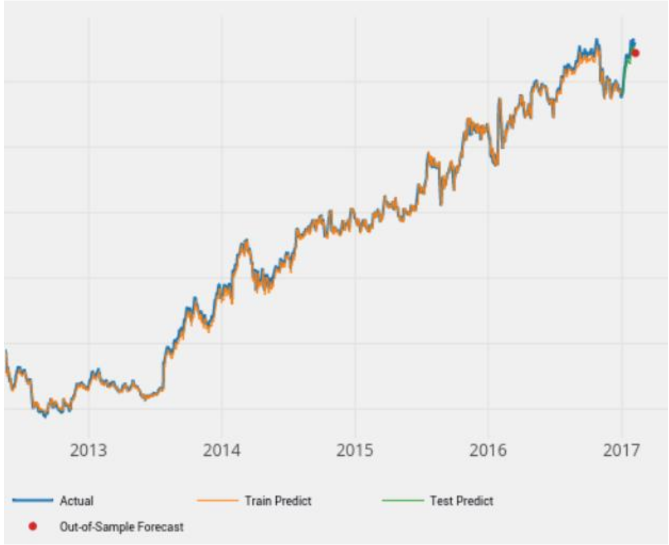
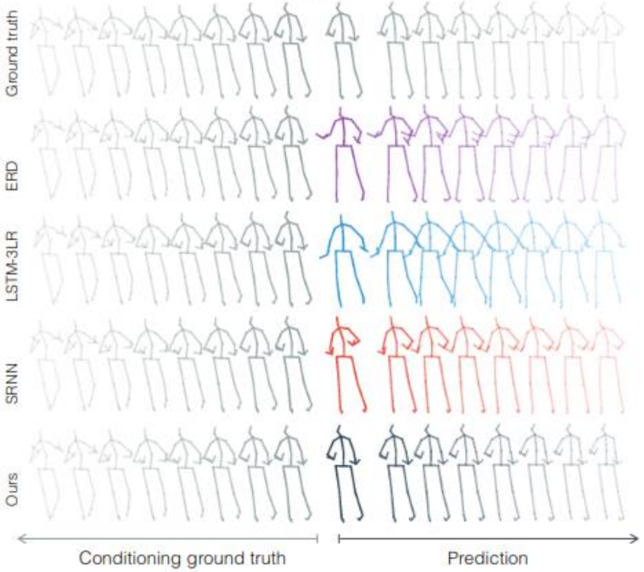


Financial market prediction (Dixon et al.)



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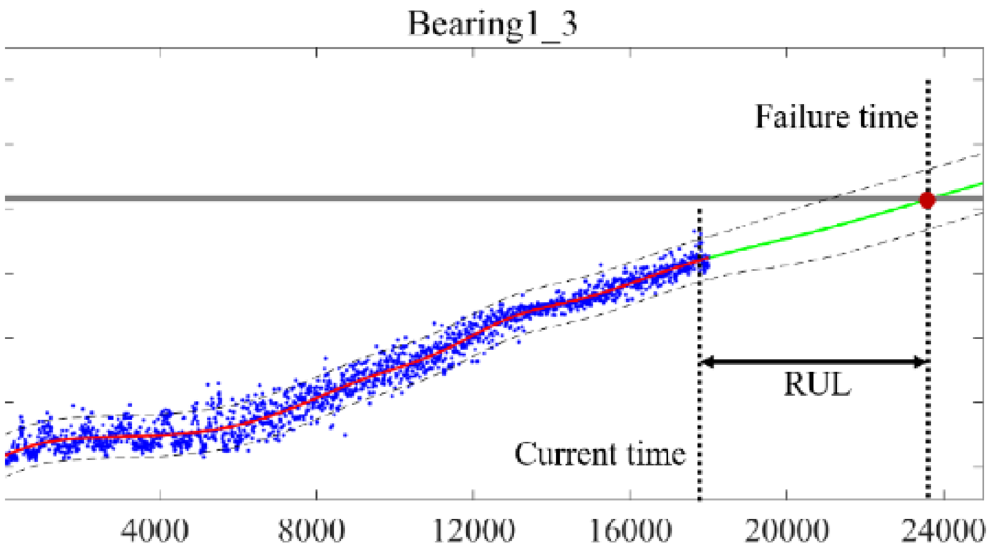
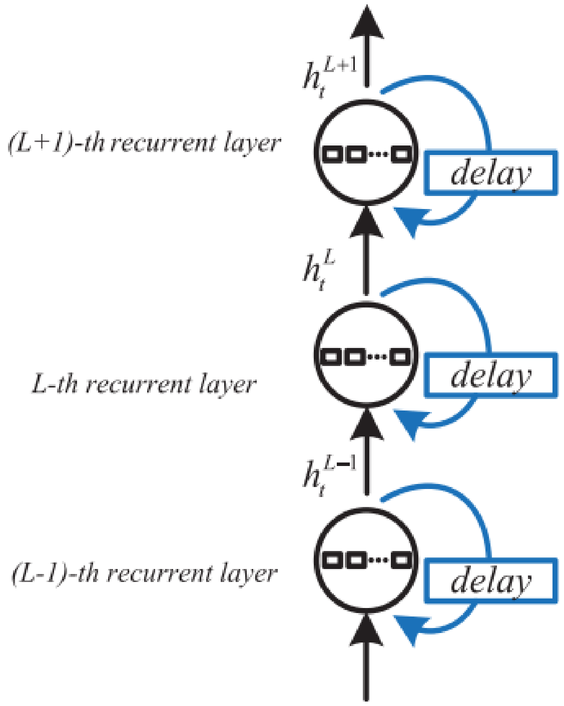


Component Failure Prediction
(Yoo et al., 2018)

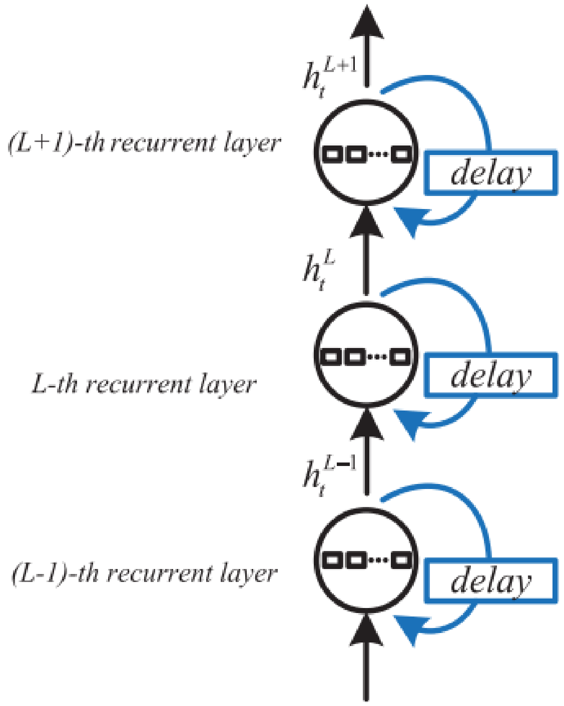
Deep (Stacked) LSTMs (Fernández, Graves, & Schmidhuber,2007):



Deep (Stacked) LSTMs (Fernández, Graves, & Schmidhuber,2007):

LSTM Variants:

- Peephole connections
- Gated Recurrent Units (GRUs) (Cho et al. 2014), Bi-LSTMs…..



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LSTM Variants:

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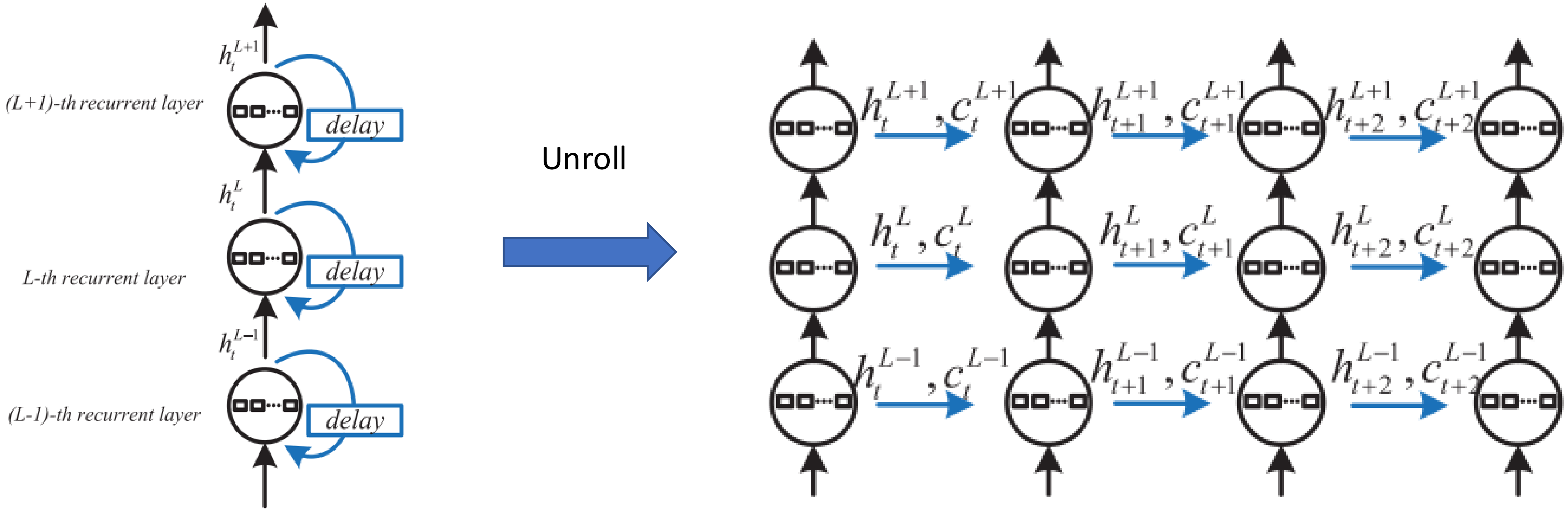

Image credits: Fernández, Graves, & Schmidhuber,2007

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Data Preparation for RUL prediction

- Degradation data➔ Time Series sequence ➔ segmented into sliding windows.
- Each sliding window is assigned a target RUL value [Zeng et al. 2017]

$X = [X_1, X_2, \ldots, X_t, \ldots X_{T-1}]$ to estimate RUL_{T-1}

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$[X_t, X_{t-1}, \ldots, X_{t-d+1}], \epsilon \mathbb{R}^d$

Many variants exist!

$[\mathrm{RUL}_{t+L}, \mathrm{RUL}_{t+L+1}, \ldots, \mathrm{RUL}_n]$

Training tuples:

$([X_t, X_{t-1}, \ldots, X_{t-d+1}], \mathrm{RUL}_{t+L})$

$\widehat{\mathrm{RUL}_{t+L}} = \phi(X_t, X_{t-1}, \ldots, X_{t-d+1})$

Loss Calculation : Error based cost function

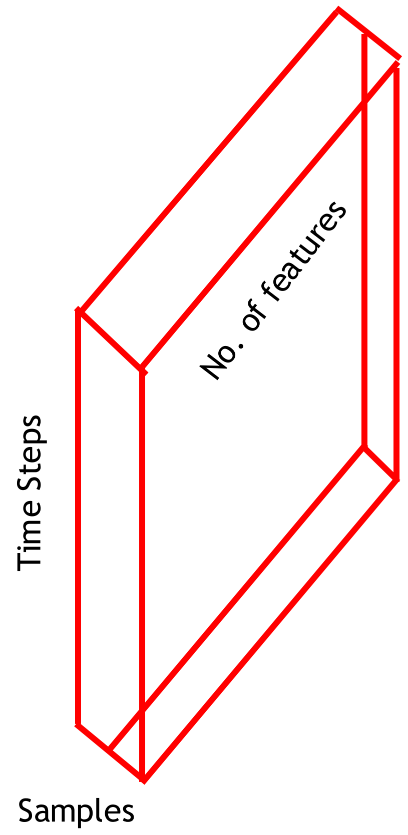
$$J = \sum_t \|(RUL_{est}^t - RUL_{calc}^t\|^2$$

Some issues:

- Independent Windows → to assure assumption of i.i.d
- Dependent windows → claim more realistic.

Deep LSTMs for Prognostics

Basic Architecture



3D- Input

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Deep LSTMs for RUL prediction

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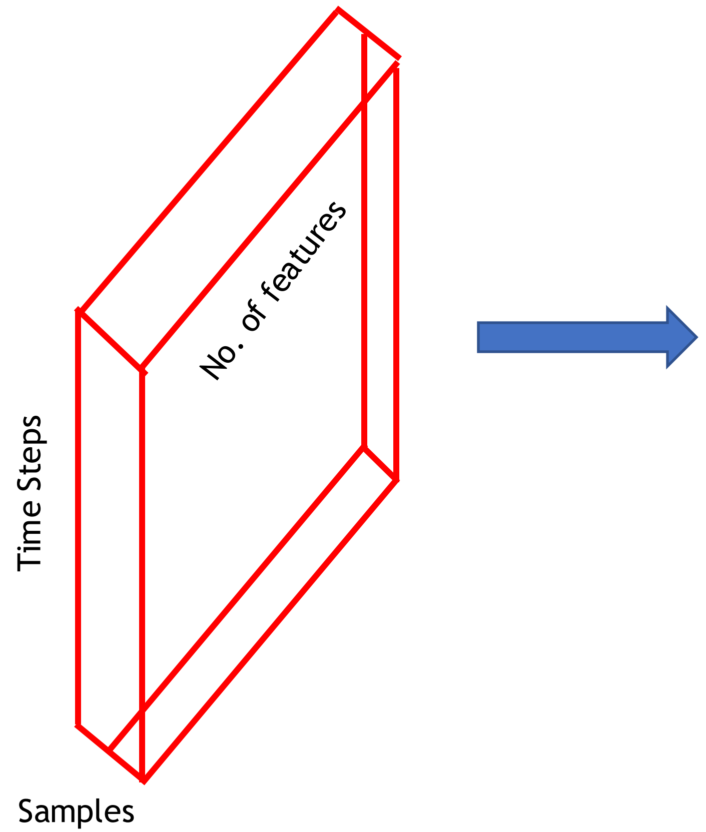

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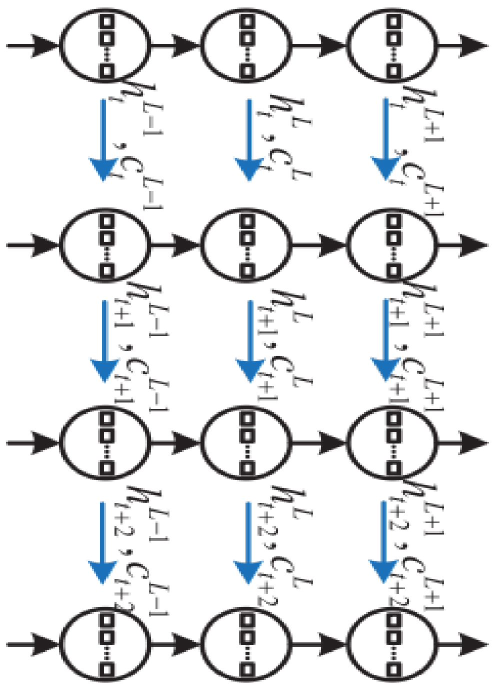

Image credits: Fernández, Graves, & Schmidhuber,2007

Deep LSTM
+ dropout schemes

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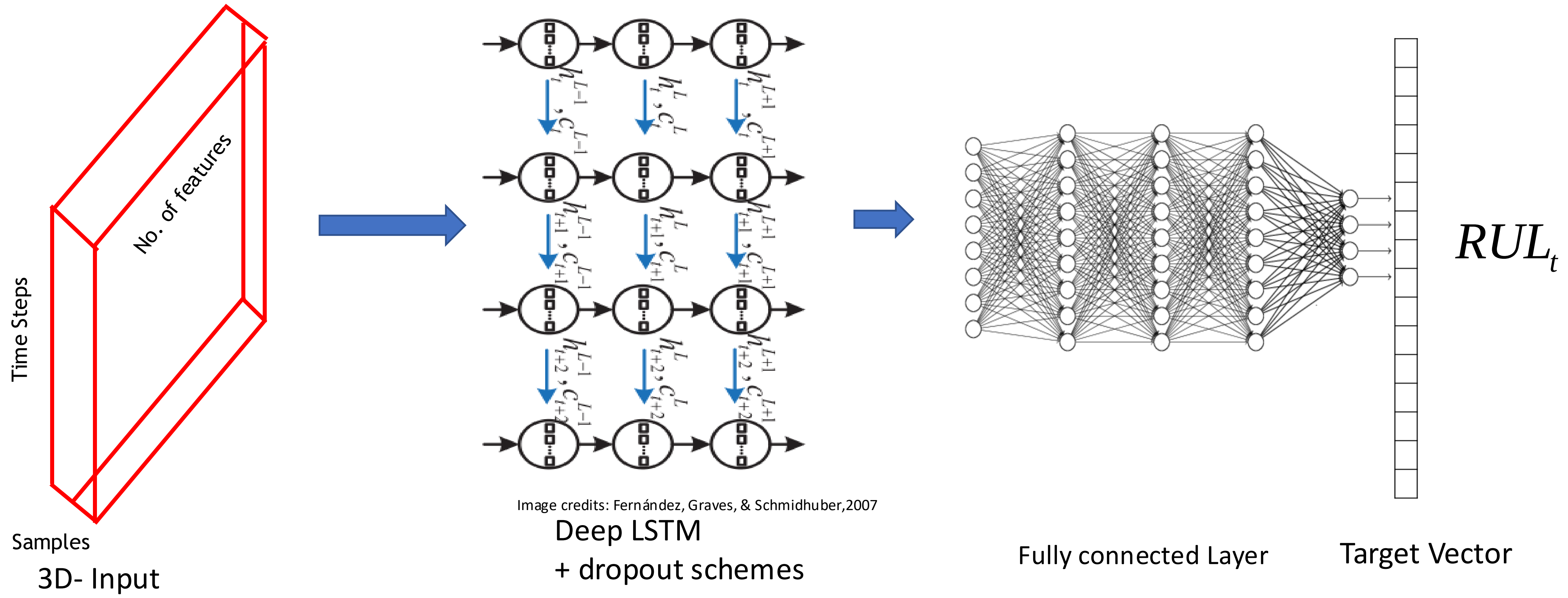
Deep LSTMs for RUL prediction

Basic Architecture: LSTMs: Temporal features + FNNs: Map features in RULs



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Deep LSTMs

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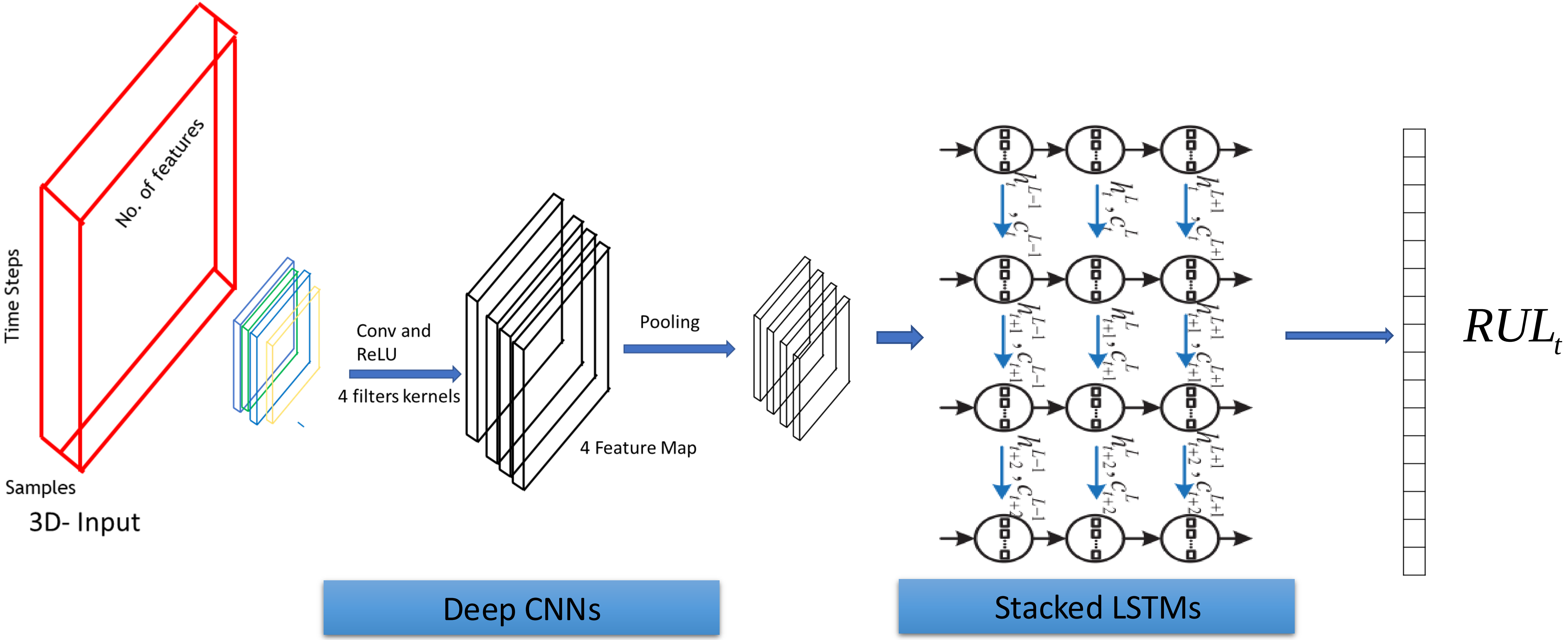

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CNNs+LSTMs for Prognostics

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& Efficient learning with multi-variate sequential (time series) data.

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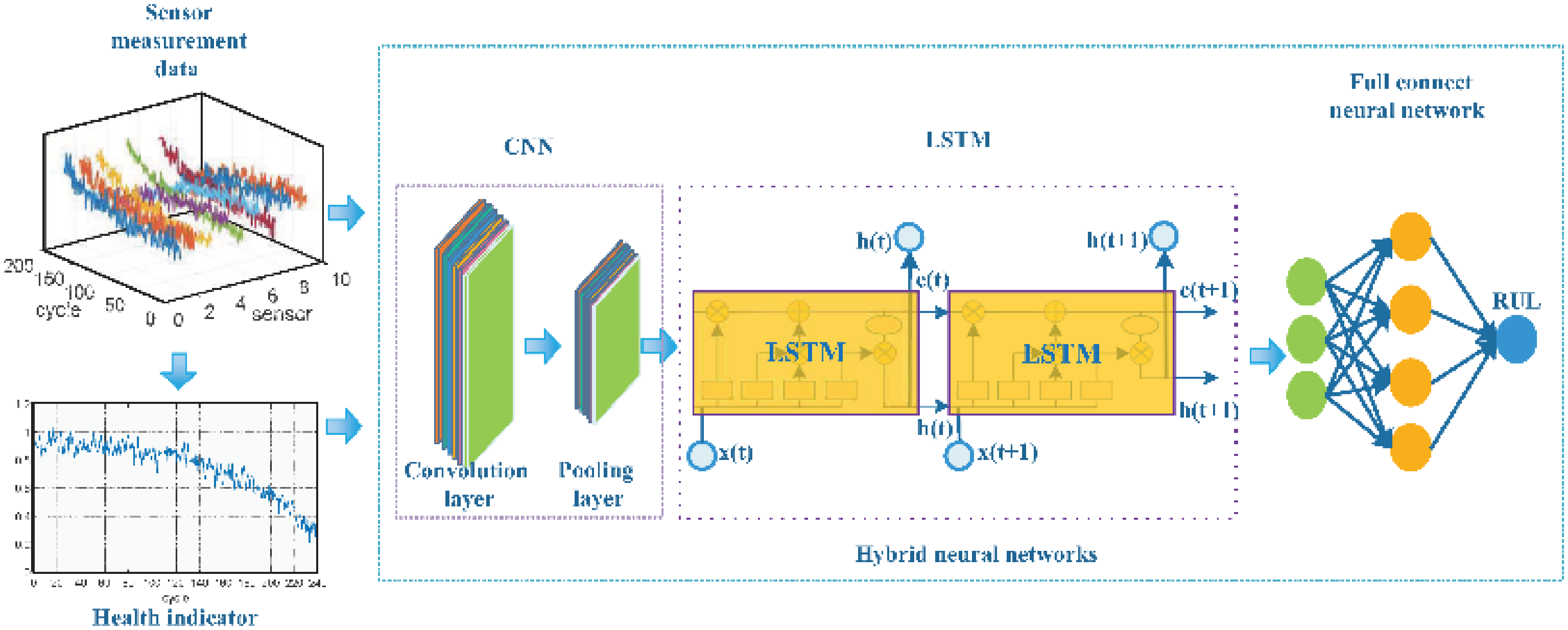
Hybrid structure

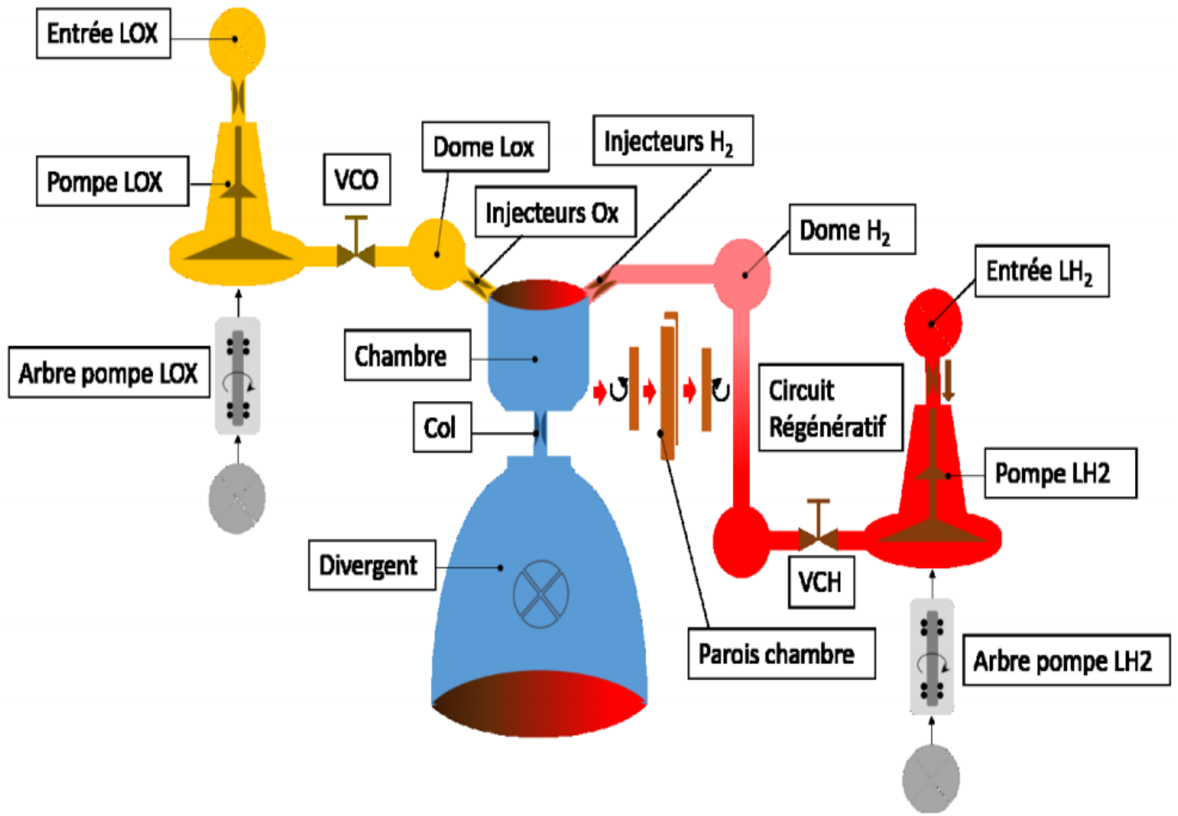


[Kong et al. 2019]

Deep Learning based Prognostics (supervised)

Dr. Mayank JHA, Prof. Didier Theilliol

System of Interest: Reusable Liquid Rocket Engine



Simulation Engine: CNES RT-NT-2510000-CNES

01 LOX LH2 engine with 10 kN thrust thrust with liquid propellant supply

02 Main components of a liquid ergol engine the fuel system and a combustion chamber

03 Typical engine life profiles :
a. flight engines

04 Variables controlled :
Chamber pressure
Mixing ratio

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Unsupervised Prognostics through Physics Informed Data Augumentation

Collaborators:

Dr. Martin Herve deBeaulieu (Phd @ CRAN/Dassault Av., **Most Slides Credit**)

Prof. Hugues Garnier (CRAN)

Dr. Farid Cerbah (Dassault Aviation)

Challenges:

First challenge: RUL-labeled data limitation

- RUL-labeled data hardly available in real-life applications [Chaoub et al., 2022]
- Limiting reliance on measured RUL-labeled data for model training.

Second challenge: *A priori* knowledge and physics integration

- Leverage existing system knowledge
- Use physics of degradation
- Strengthen the AI-based prognostics

Proposed approach:

Step 1: Data Augumentation

Step 2: Health Index Extraction

Step 3: Remaining Useful Life Prediction

- Dassault Aviation data from Falcon 6X [Hervé de Beaulieu et al., 2023]
  - New generation of aircraft with increased in-flight data collection capabilities (sensor time series from all embedded systems)
  - First test flight in 2021
  - Only historical nominal data available (i.e. no measured degradation)
  - Focus on the cockpit temperature control system

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Global Schema:

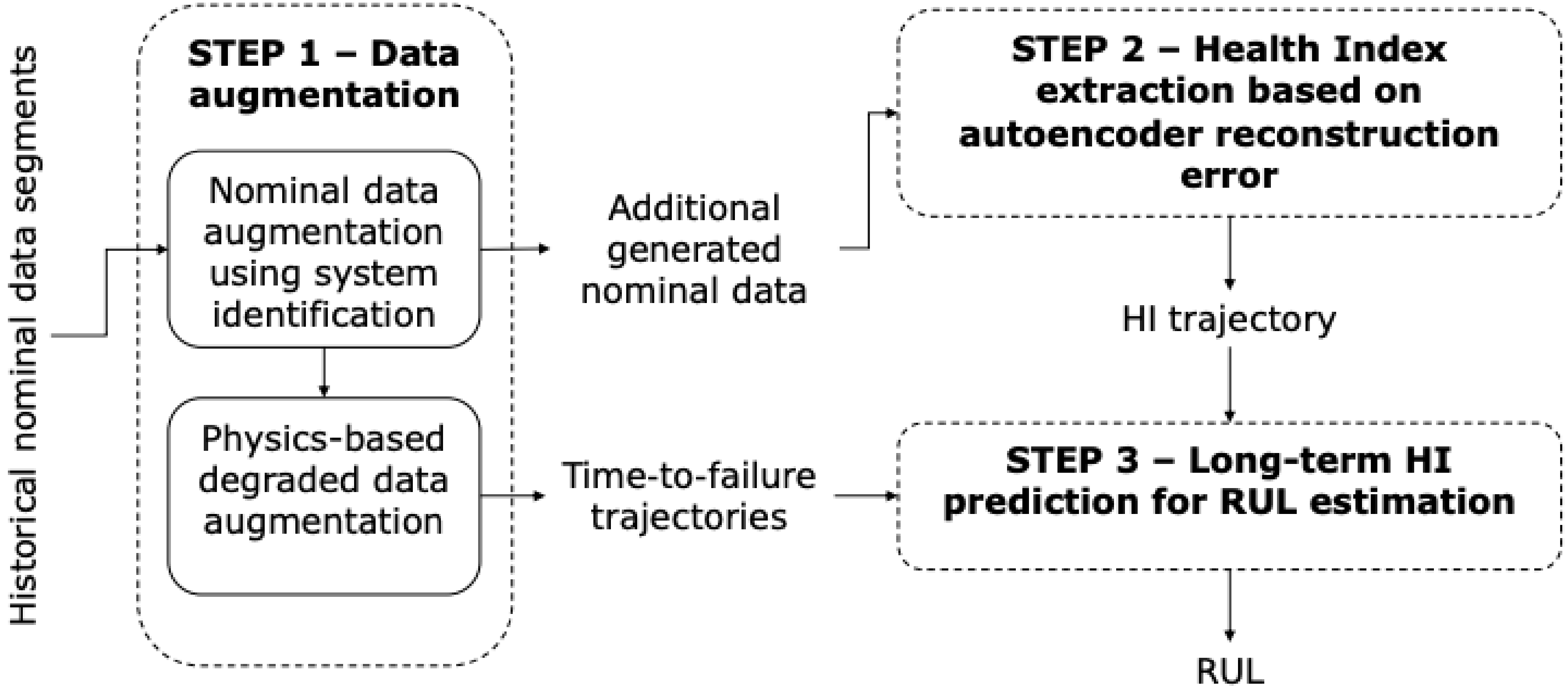


Figure: Overall proposed approach.

Step 1: Data Augumentation

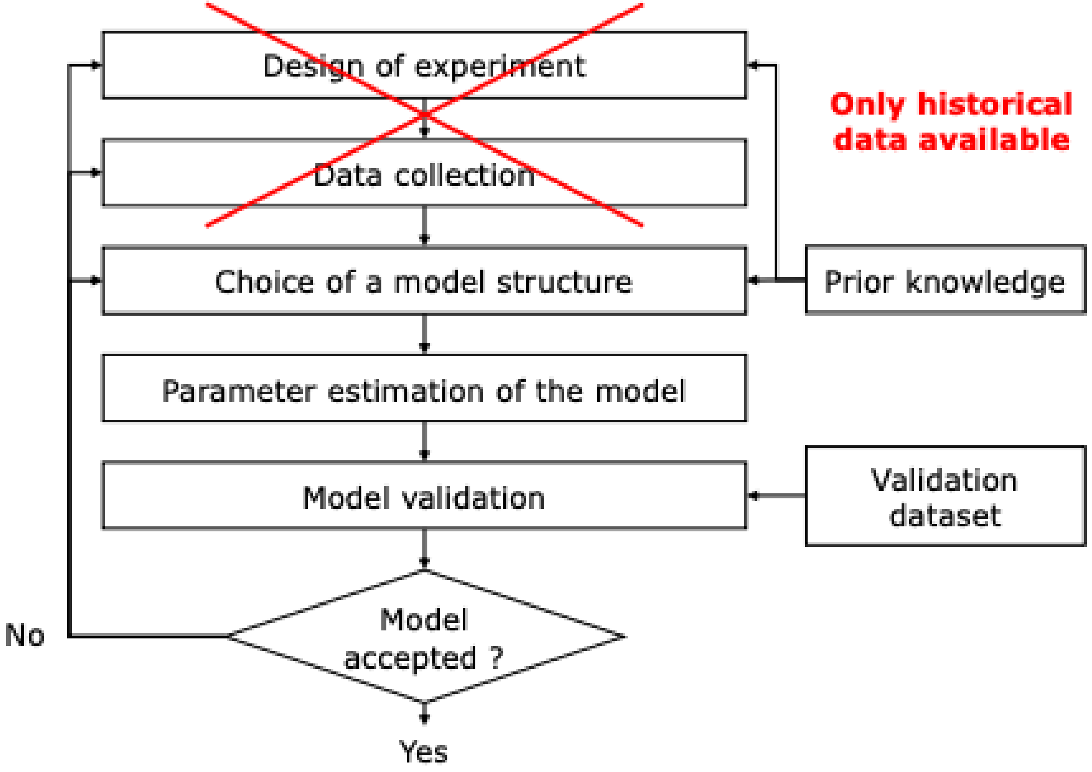
Step 1: Data Augmentation

Objective

- Compensate for the lack of data
- Both nominal and degraded data augmentation

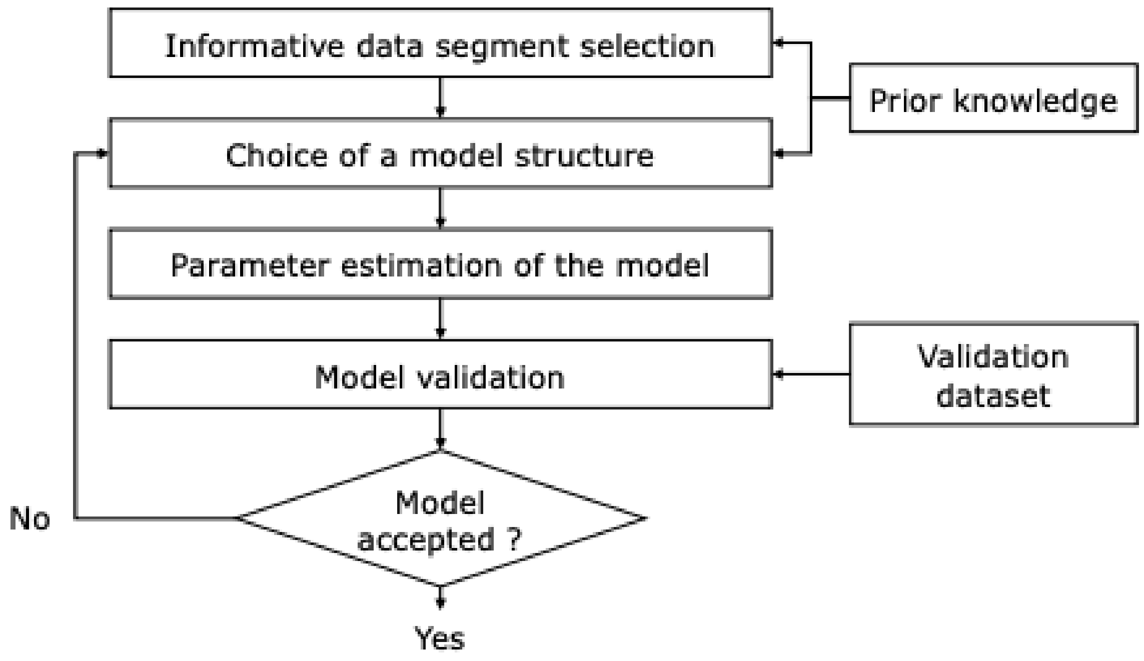
- Generate more training samples from existing ones in order to improve the performance of a prediction made by a neural network.

Historical Data available. NOT Design of Experiment!!



- Experiment design is not possible

Historical Data available. NOT Design of Experiment!!



- Experiment design is not possible
- Limited amount of data only from historical flights.
- Only a few and not sufficiently informative changes of the setpoint.

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Example: Historical Dataset

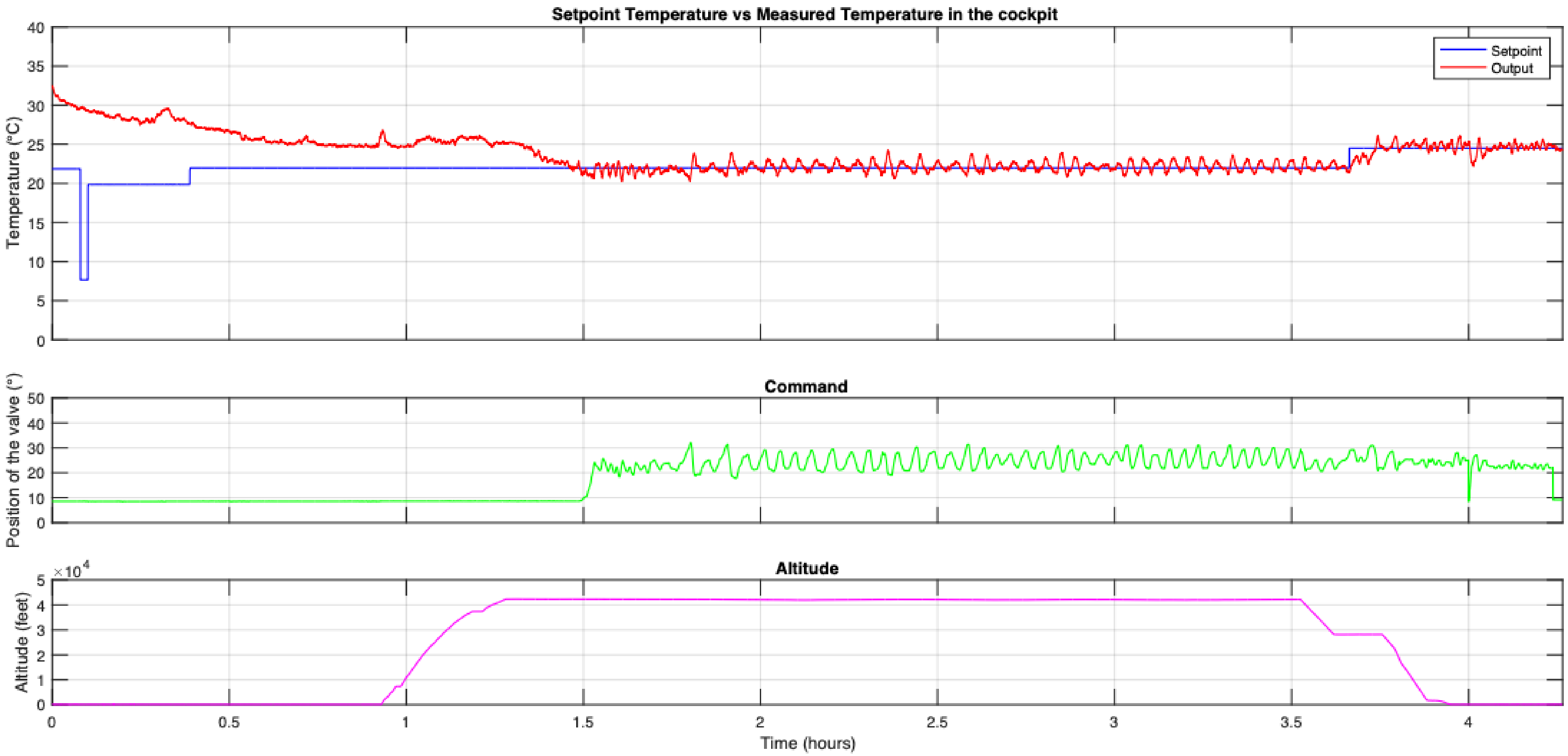


Figure: Recording of test flight of September 27, 2021.

System: Cockpit Temperature Control System

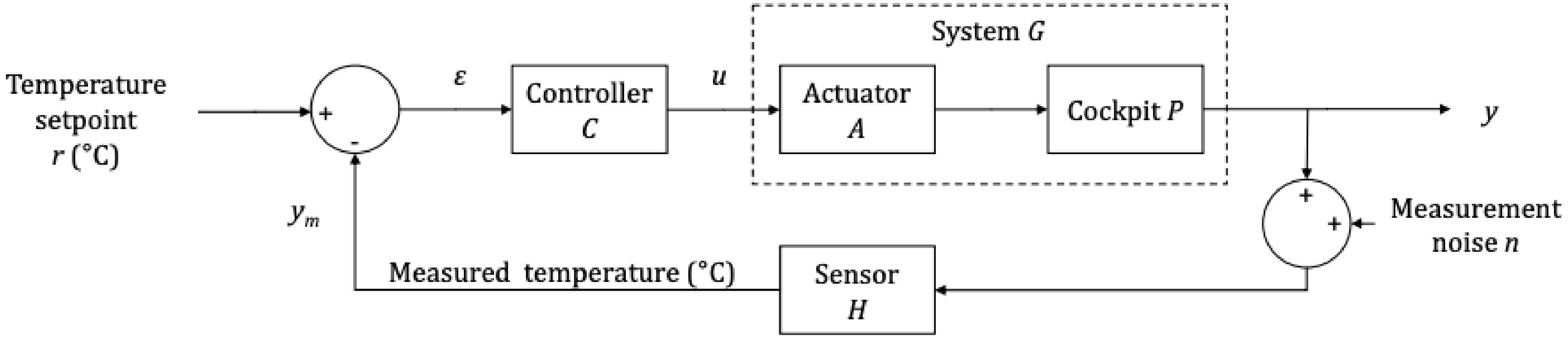
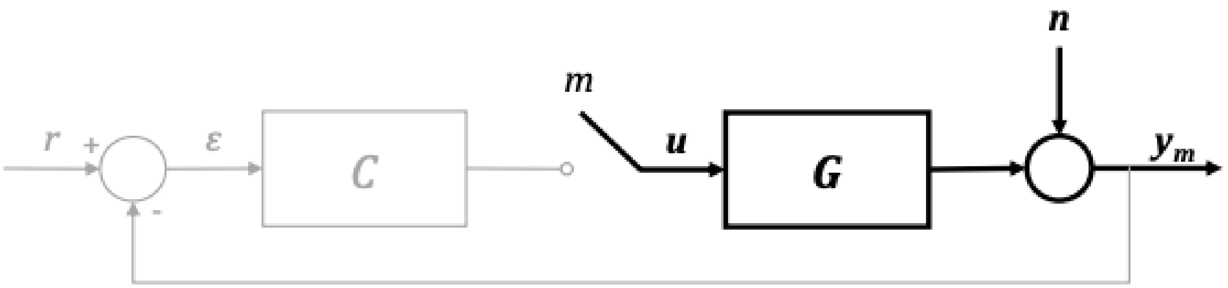


Figure: Block diagram of the cockpit temperature control system

- C and G must be identified
- Closed-loop system
- Setpoint r mostly around $22^\circ C$
- Continuous-time linear system identification

Step 1.1 : Identification of Plant model (G)



"Manual mode"

- Open-loop behavior
- Variation on command u
- Identification of G

$$y_m = Gu + n \tag{2}$$

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Step 1.1 : Identification of Plant model G

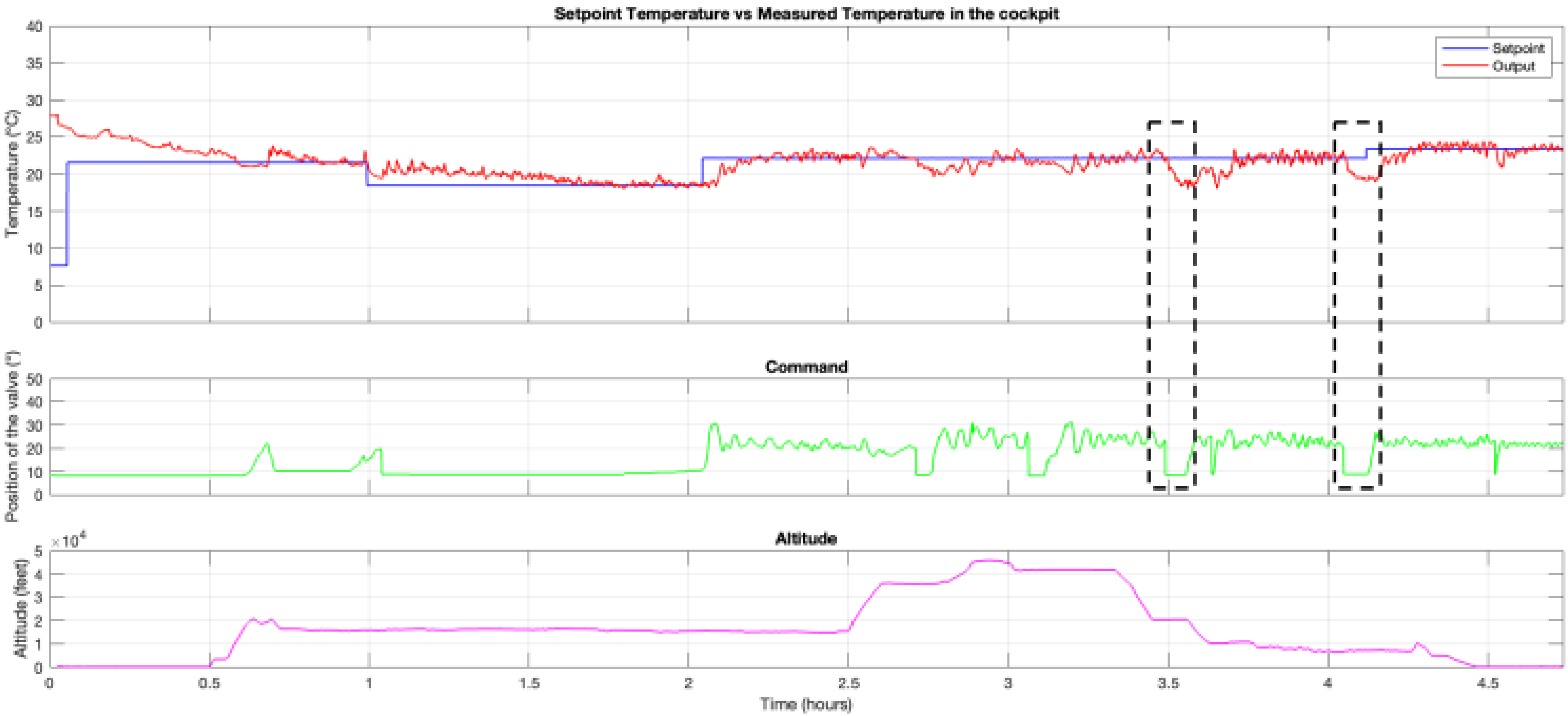
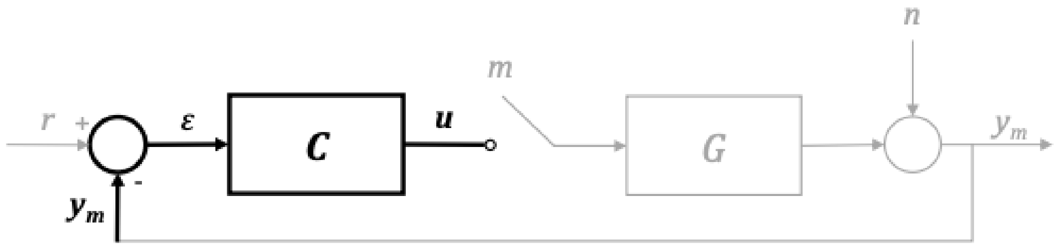


Figure: Flight of October 5, 2021, Aircraft 3.

Step 1.2: Identification of the controller C



"Auto mode"

- Closed-loop behavior
- Setpoint r remains constant
- Identification of the inverse of the controller [MacGregor and Fogal, 1995, Huang and Kadali, 2008]

$$y_m = -\frac{1}{C}u \tag{3}$$

Step 1.2: Identification of the controller C

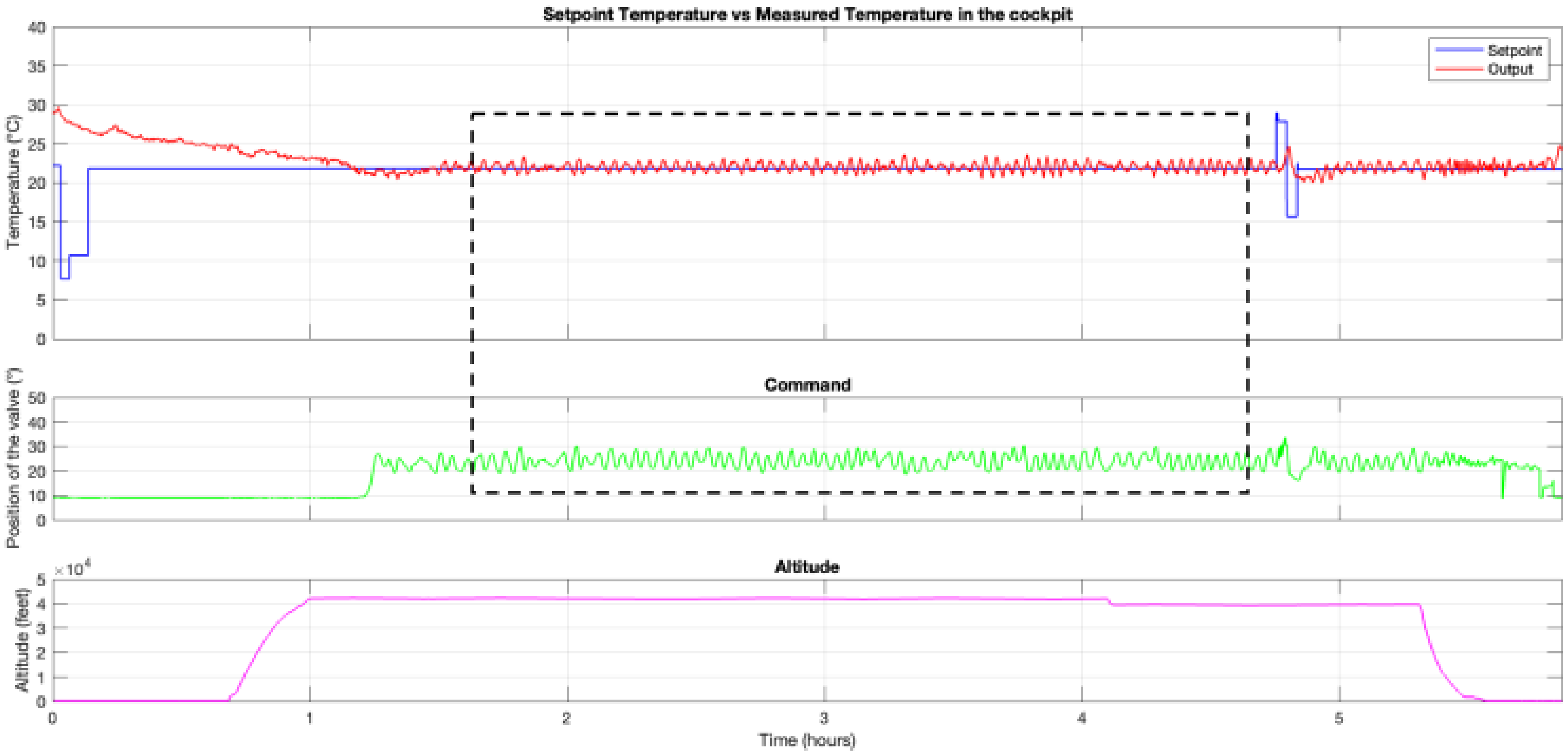
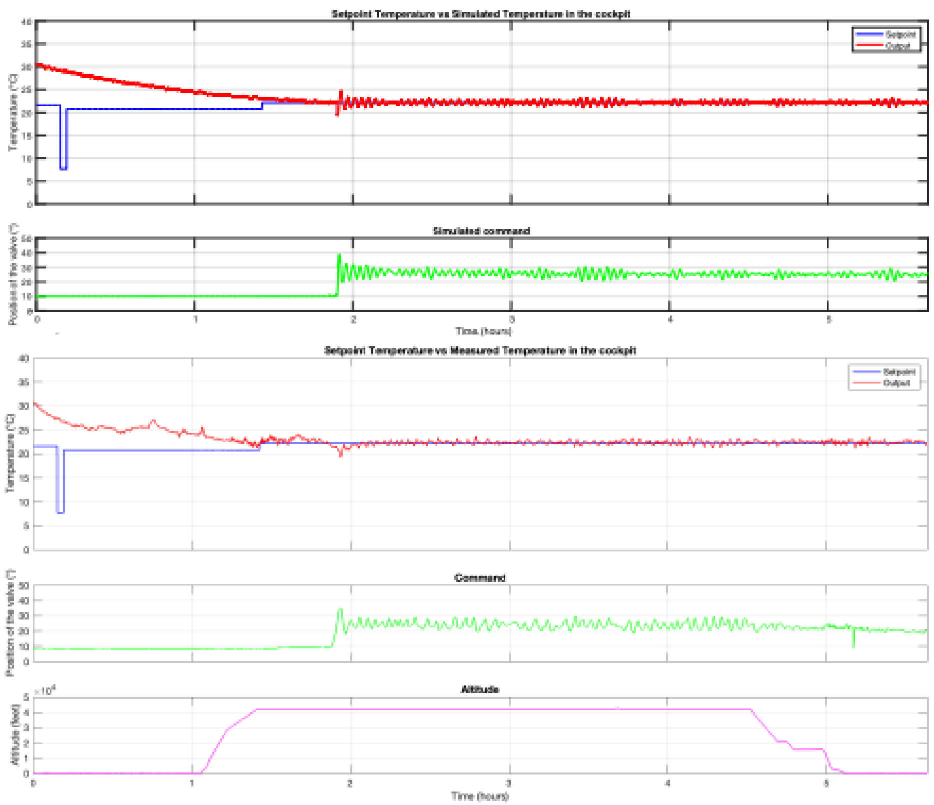


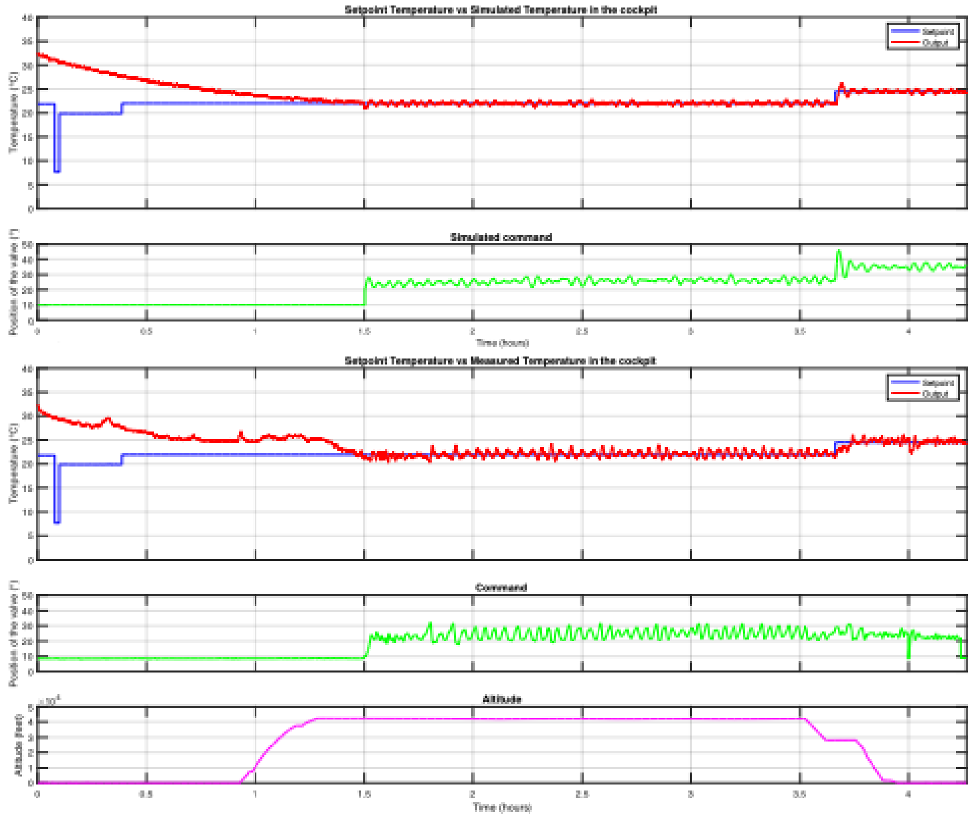
Figure: Flight of September 29, 2021, Aircraft 3.

1.3 Validation: Replicate different - existing flights!



Replication

Ground truth



Replication

Ground truth

Step 1.5: Nominal Data Augumentation

- **Nominal data augmentation**

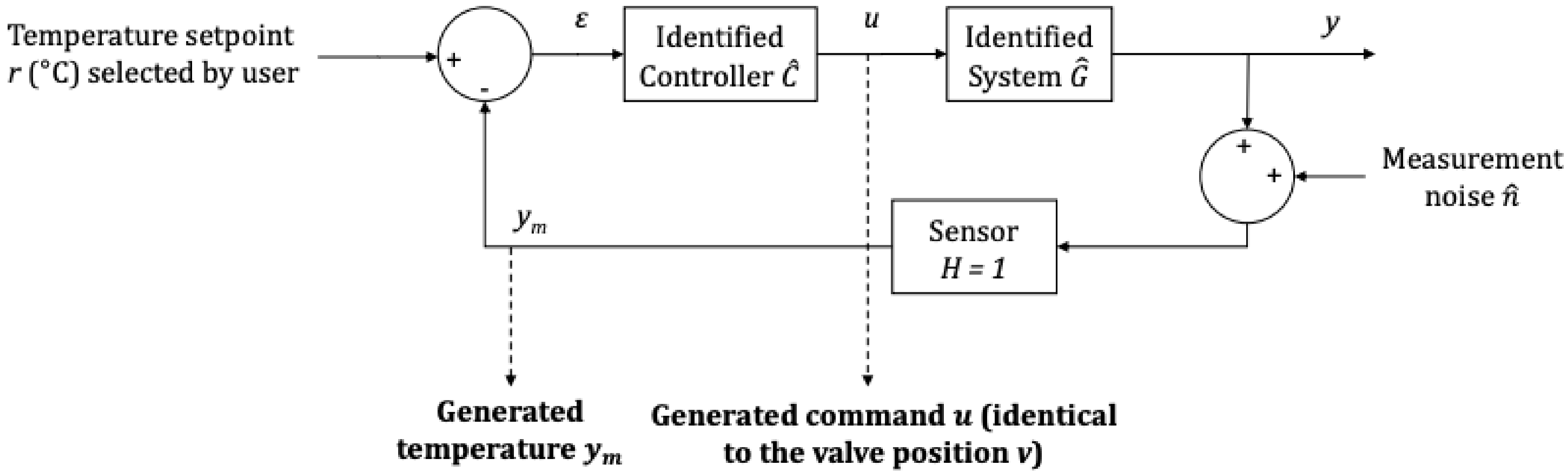


Figure: Global air distribution system model used to generate additional nominal data.

Step 1.6 Physics Based Degraded Data augumentation

Hybrid process: data-driven models supplemented by a physics-based degradation model.

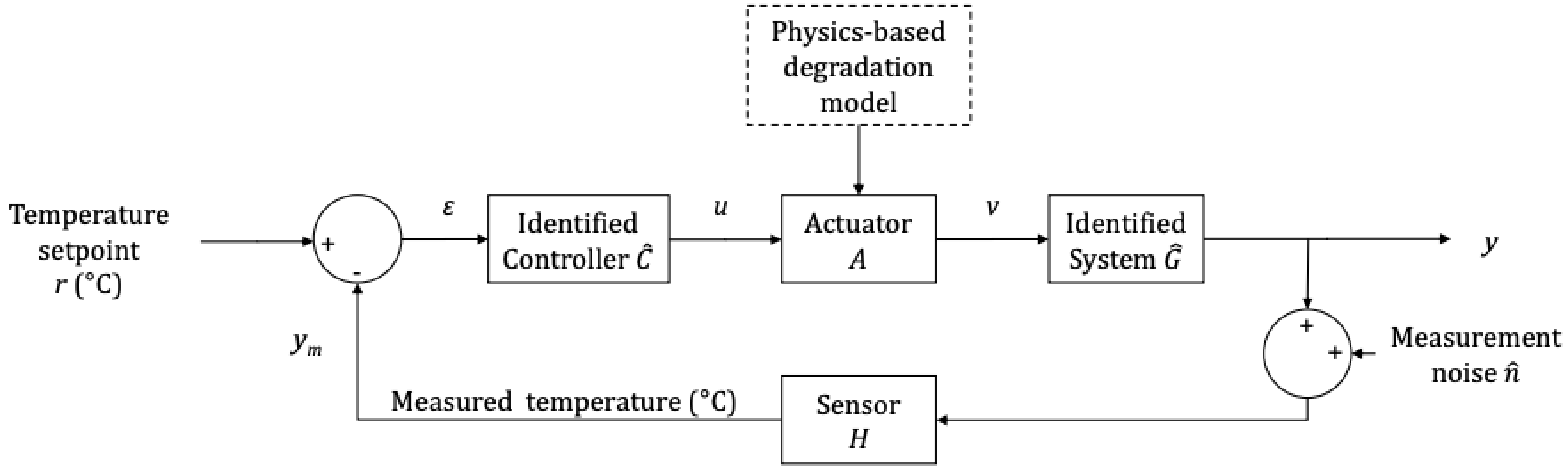


Figure: Injection of non-linear effects of degradation in the actuator.

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Step 1.6 Physics Based Degraded Data augumentation: Valve Stiction

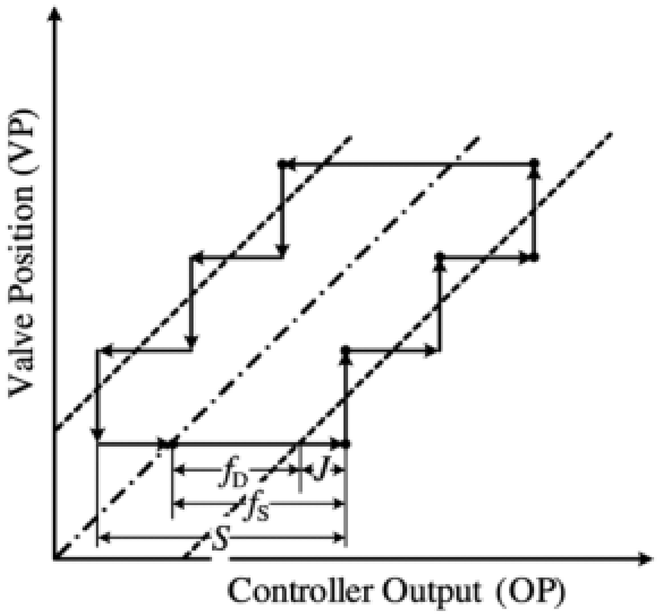


Figure: Valve stiction modeling [He and Wang, 2010].

Stiction model [Siraskar, 2021, Choudhury et al., 2004]:

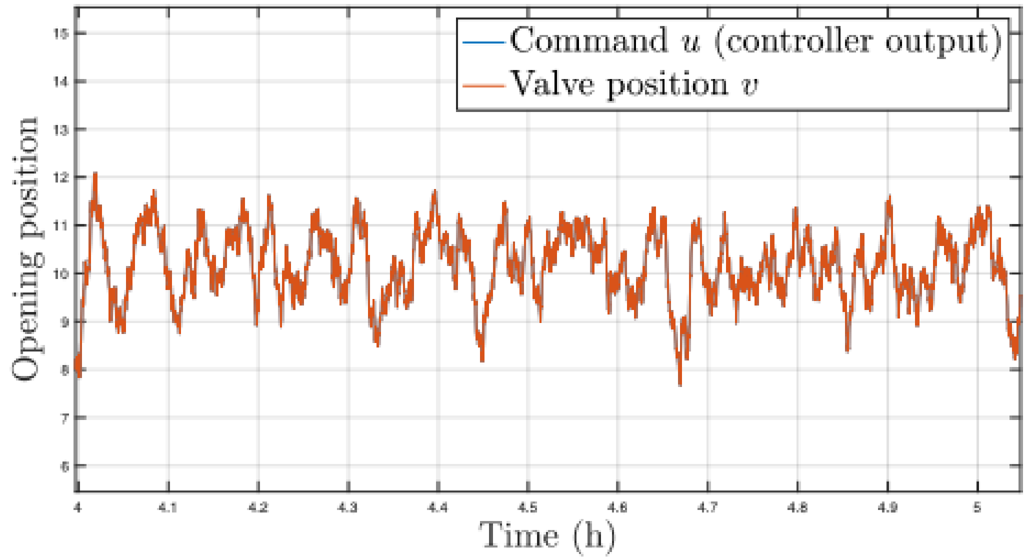
$$x_k = \begin{cases} x_{k-1} + (e_k - sign(e_k) f_D), & \text{if } |e_k| > f_S \\ x_{k-1}, & \text{if } |e_k| \leq f_S \end{cases} \tag{4}$$

with $e_k = u_k - x_{k-1}$, f_S and f_D the static and dynamic stiction parameters.

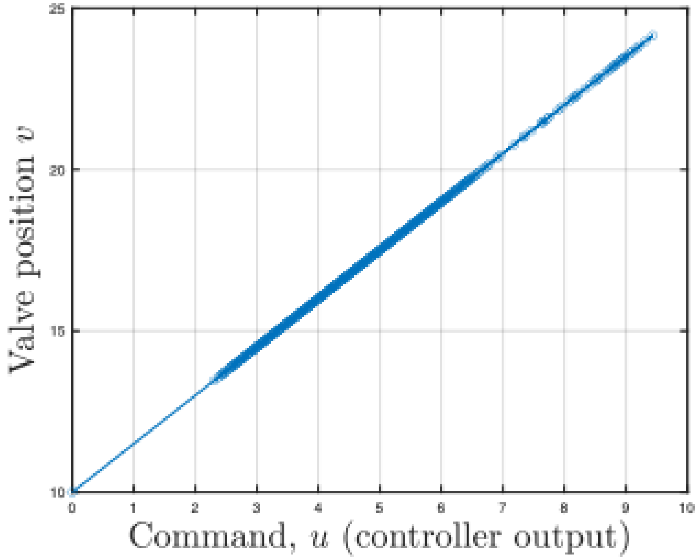
Step 1.6 Physics Based Degraded Data augumentation: Degradation Modelling

Simple failure mode: increasing the value of the parameter f_S alone, following a time t-dependent exponential degradation model.

$$f_S = \beta e^{\alpha t} \tag{5}$$



(a) Command (from the controller) and valve position when $f_S = 0$.



(b) Valve characteristic when $f_S = 0$.

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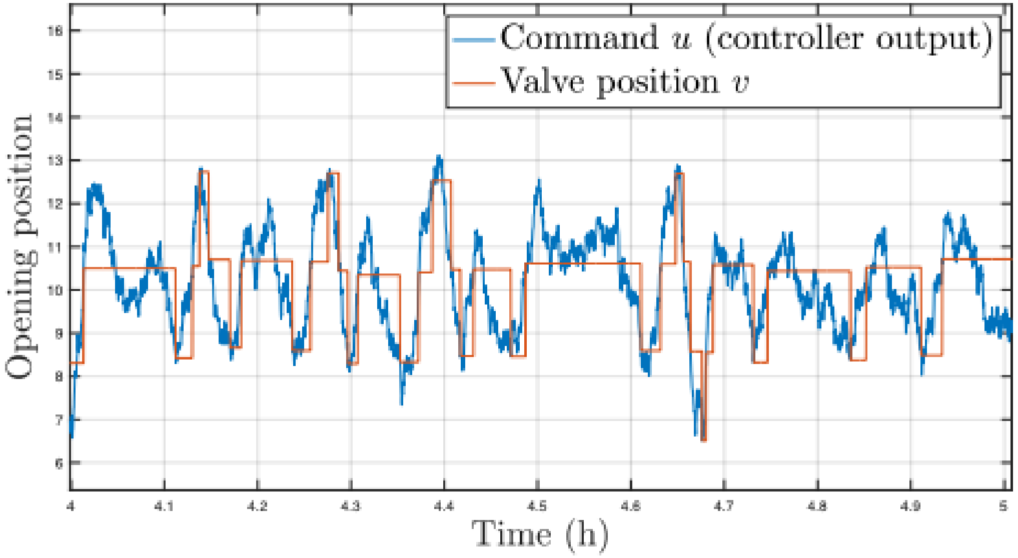
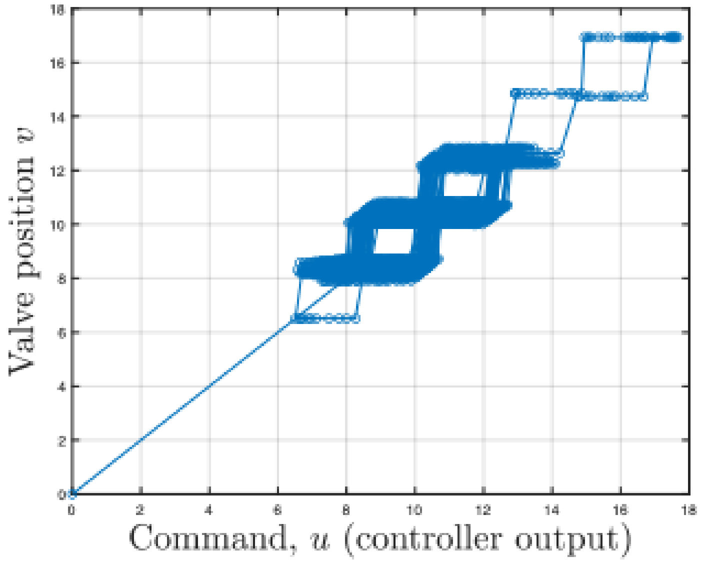
Step 1.6 Physics Based Degraded Data augumentation: Degradation Modelling

Simple failure mode: increasing the value of the parameter f_S alone, following a time t-dependent exponential degradation model.

$$f_S = \beta e^{\alpha t} \quad (5)$$



(c) Command (from the controller) and valve position when $f_S = 15$.



(d) Valve characteristic when $f_S = 15$.

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Step 1.6 Physics Based Degraded Data augumentation: Time to Failure Trajectory generation

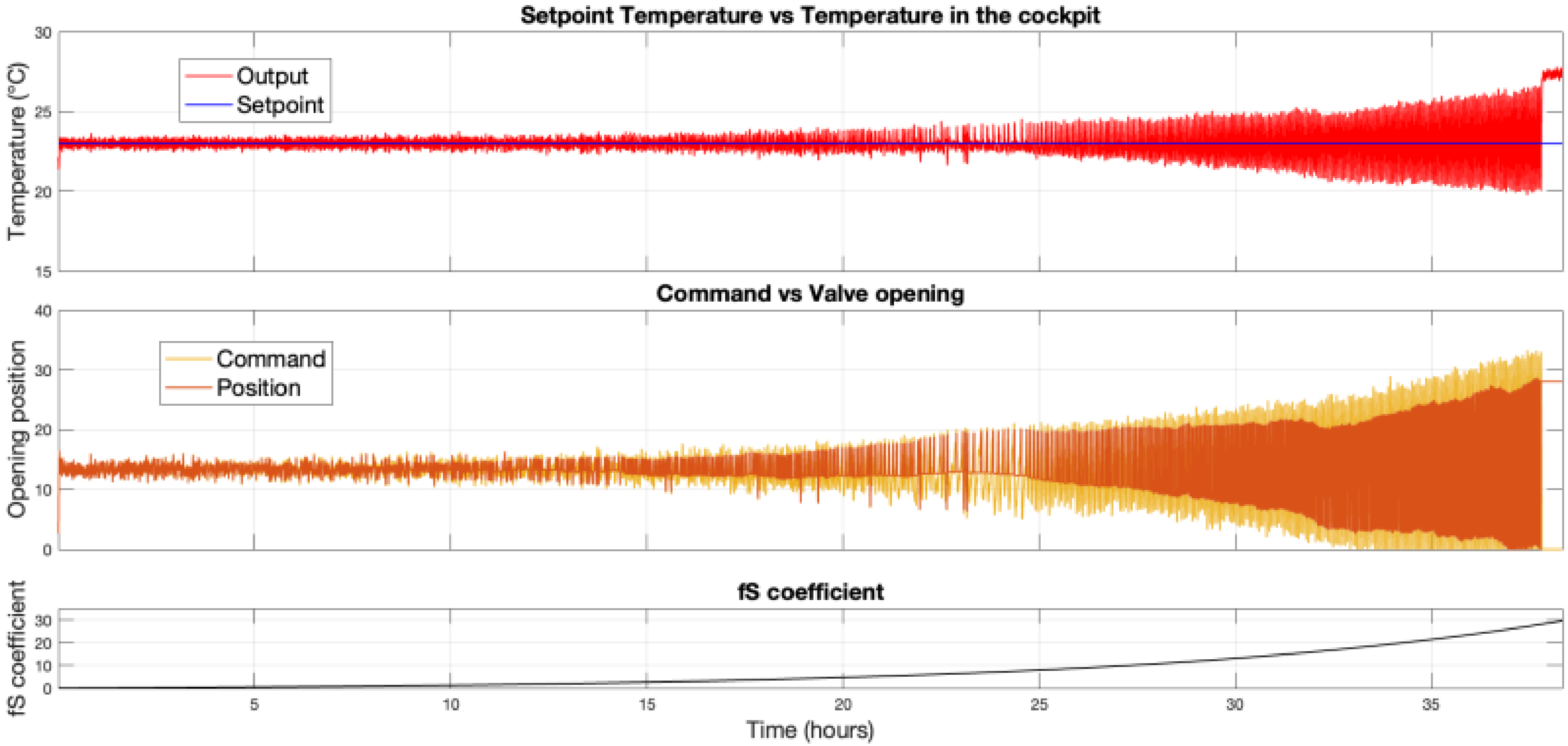

Figure: Time to Failure (TTF) trajectory generation.

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Step 2: Health Index Extraction

Step 2: Health Index Extraction

Objective

- Extract Health Index (HI) from raw sensor data
- Using nominal data only (i.e. without degradation)

- Unsupervised method
- Fusing multiple sensor signals into one variable
- Autoencoders
  - Unsupervised
  - Very efficient at extracting features from raw sensor data [Gensler et al., 2016, Hu et al., 2016]
  - Data-related : Able to extract relevant features only from data within similar distribution to training set

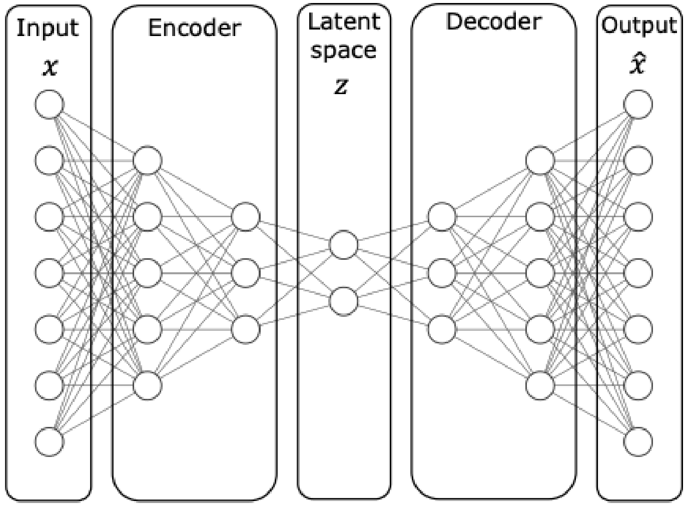

Figure: Autoencoder structure.

$$z = f_{\theta_e}(x) \tag{6}$$

$$\hat{x} = g_{\theta_d}(z) \tag{7}$$

$$\hat{x} = g_{\theta_d}(f_{\theta_e}(x)) \tag{8}$$

$$J_{AE}(\theta_e, \theta_d) = \sum L(x, g_{\theta_d}(f_{\theta_e}(x))) \tag{9}$$

Step 2: Health Index Extraction: Reconstruction Error

Consider a nominal training domain:

$$D_N = \{\mathbf{X}_N^i\}_{i=1}^{N_N} \tag{10}$$

where each sample $\mathbf{X}_N^i$ belongs to a *nominal feature space* $\mathcal{X}_N$.
Training on nominal data samples

$$E(t_w) = \left\|\mathbf{X}_N^i(t_w) - g_{\theta_d}(f_{\theta_e}(\mathbf{X}_N^i(t_w)))\right\| \tag{11}$$

where

$$\mathbf{X}_N^i(t_w) = \{X_{t_k}^i\}_{k=w}^{w+\Delta} \tag{12}$$

with t_w as the start time step of the window and Δ as its total duration.
Leading to optimal parameters $\theta_e^\star$ and $\theta_d^\star$

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Step 2: Health Index Extraction: Reconstruction Error

Consider now a system under degradation: $\mathbf{X}_D^i$ belongs to a *degraded feature space* $\mathcal{X}_D$

Degraded feature space

The distribution of data samples in $\mathcal{X}_D$ drifts increasingly from the distribution of nominal samples as the system approaches its EOL.

$$P(\mathbf{X}_N^i) \neq P(\mathbf{X}_D^i). \tag{13}$$

With parameters derived from nominal data:

$$E_{total}(t_w) = \sum_{k=w}^{w+\Delta} \left\| \mathbf{X}_D^i(t_k) - g_{\theta_d^*}(f_{\theta_e^*}(\mathbf{X}_D^i(t_k))) \right\| \tag{14}$$

Health Index

Due to the distribution shift in $P(\mathbf{X}_D^i)$, E_{total} continues to grow until the system fails completely. This time varying, certainly increasing reconstruction error is used as HI.

Step 2: Health Index Extraction: Autoencoder Structure

Autoencoder made of Fully Connected Layer (FCL)

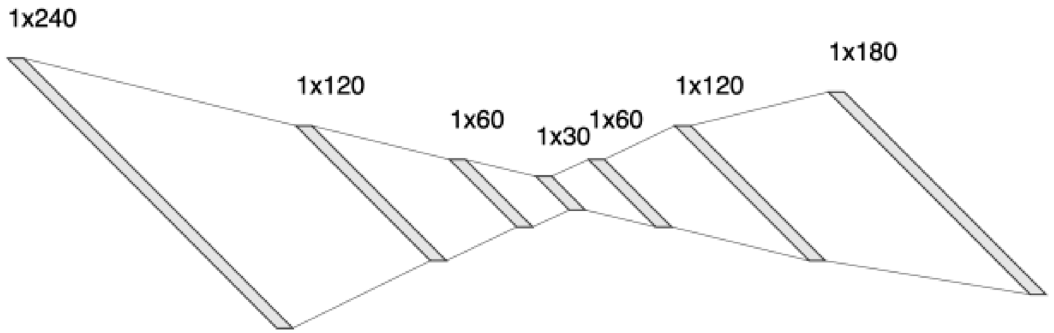

Figure: Autoencoder structure for signals reconstruction.

Training:

$$\widehat{vec(\mathbf{X}_N^i(t_w))} = g_{\theta_d}(f_{\theta_e}(vec(\mathbf{X}_N^i(t_w))))$$

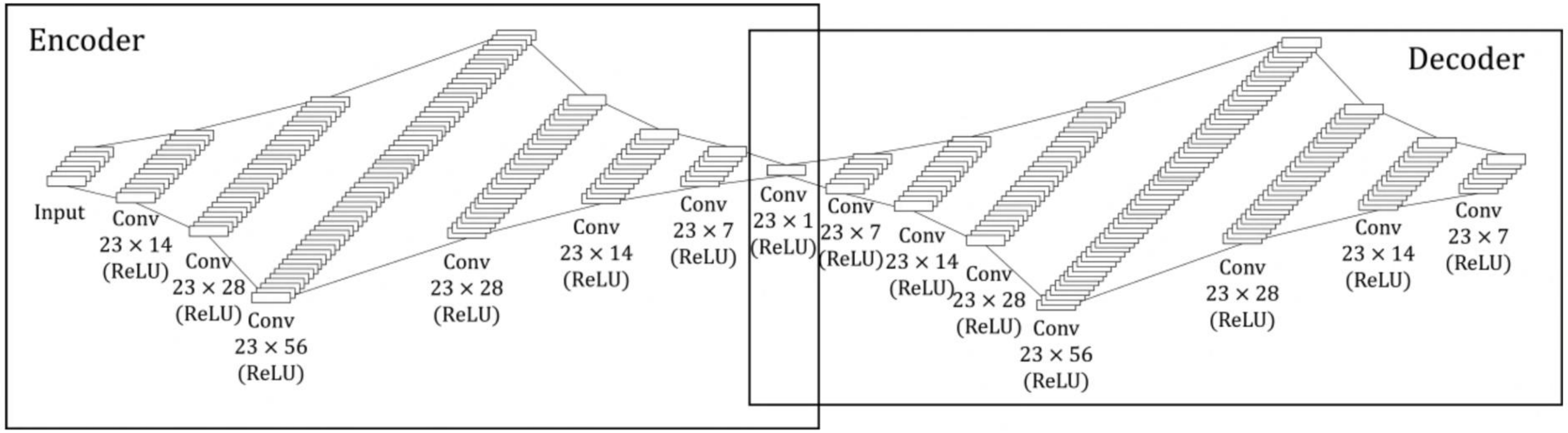

Figure 2. Proposed deep CNN autoencoder structure for VHI extraction.

Step 2: Health Index Extraction

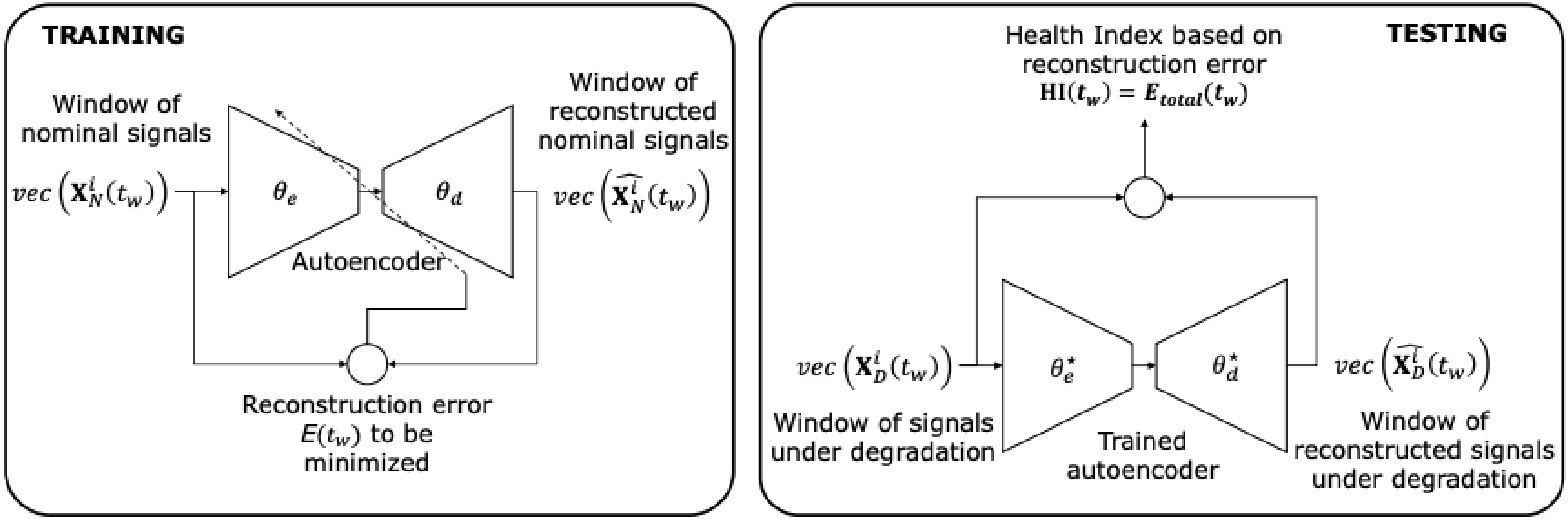

Figure: Extracting HI from sensor data using the reconstruction error of an autoencoder.

Step 2: Health Index Extraction:

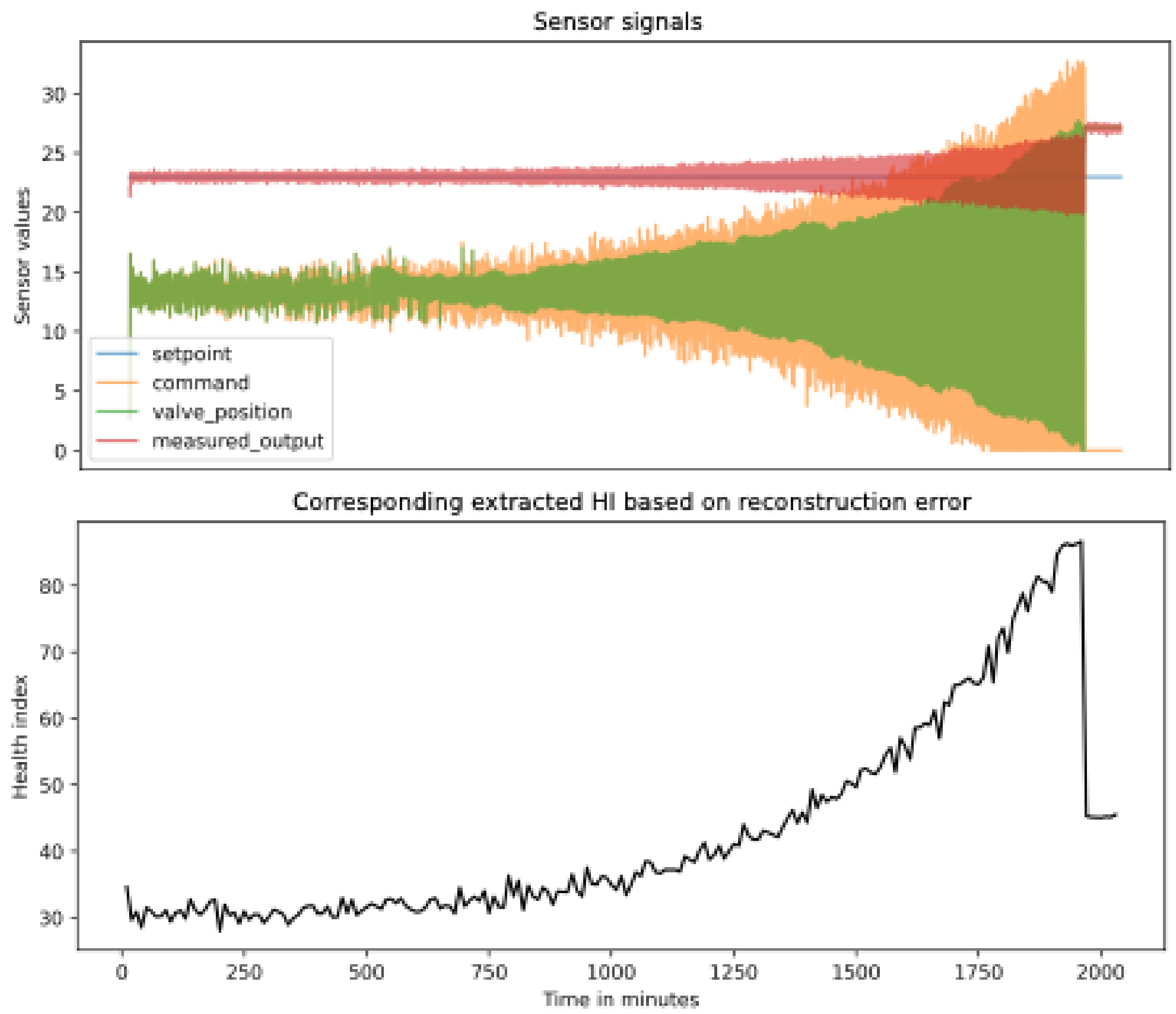

Figure: Example of HI extraction based on reconstruction for one TTF trajectory.

Step 2: Health Index Extraction: Consclusions

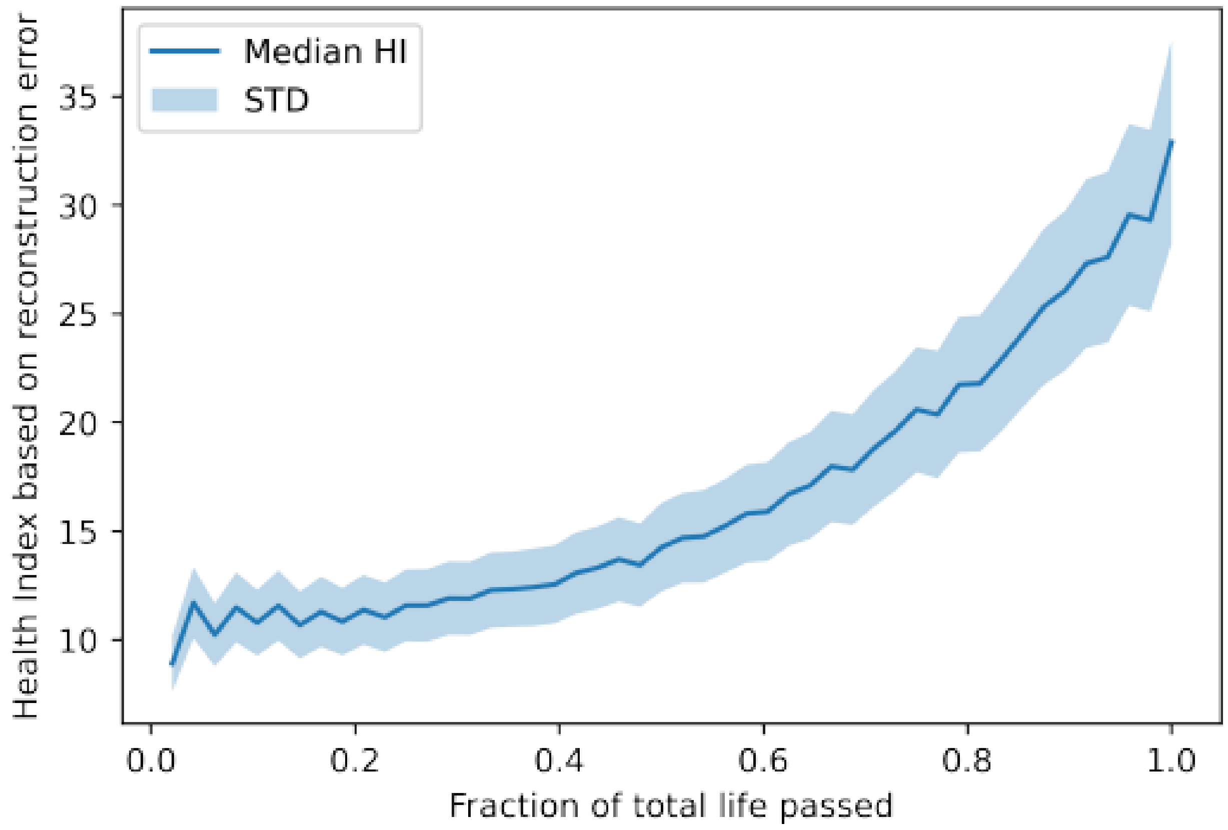

Figure: Median HI trajectory based on reconstruction error, w.r.t. fraction of total life passed.

Contribution to research challenges

- Training based exclusively on nominal data
- Fully unsupervised
- Excellent generalization capabilities as it only relies on the nominal system behavior (potential to detect any degradation)

Step 3:RUL Prediction

Step 3: RUL Prediction

Objective

Predicting Remaining Useful Life (RUL) without using RUL-labeled data

- Using degraded augmented data (Step 1)
- Long-term HI prediction
- Extrapolation - Cumulative prediction error
- Until End of Life (EOL) detection
- Leading to RUL deduction

Step 3: RUL Prediction: A Sequence to Sequence Prediction Problem

- Sequence prediction [Sun and Giles, 2001]:

$$\left[X_{t_{k=1}}, \dots, X_{t_{k=\Delta_{input}}}\right] \mapsto \widehat{X}_{t_{k=\Delta_{input}+1}} \tag{17}$$

- Sequence-to-sequence prediction [Brownlee, 2017]:

$$\left[X_{t_{k=1}}, \dots, X_{t_{k=\Delta_{input}}}\right] \mapsto \left[\widehat{X}_{t_{k=\Delta_{input}+1}}, \dots, \widehat{X}_{t_{k=\Delta_{input}+\Delta_{pred}}}\right] \tag{18}$$

- Chained sequence-to-sequence prediction:

$$\begin{gathered}\left[X_{t_{k=1}}, \dots, X_{t_{k=\Delta_{input}}}\right] \mapsto \left[\widehat{X}_{t_{k=\Delta_{input}+1}}, \dots, \widehat{X}_{t_{k=\Delta_{input}+\Delta_{pred}}}\right] \\ \left[\widehat{X}_{t_{k=\Delta_{input}+1}}, \dots, \widehat{X}_{t_{k=\Delta_{input}+\Delta_{pred}}}\right] \mapsto \left[\widehat{X}_{t_{k=\Delta_{input}+\Delta_{pred}+1}}, \dots, \widehat{X}_{t_{k=\Delta_{input}+2\Delta_{pred}}}\right] \\ \text{etc.}\end{gathered} \tag{19}$$

with Δ_{input}, Δ_{pred} the lengths of input and output sequences and $\mapsto$ the mapping model (which can typically be an RNN or its variants).

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Step 3: RUL Prediction: A Sequence to Sequence Prediction Problem

- Reusing previous predicted output sequences as input for future predictions
- Cumulative prediction error
- Overlapping concept proposed to improve continuity between windows
- Careful selection of hyperparameters Δ_{input}, Δ_{pred} and δ.

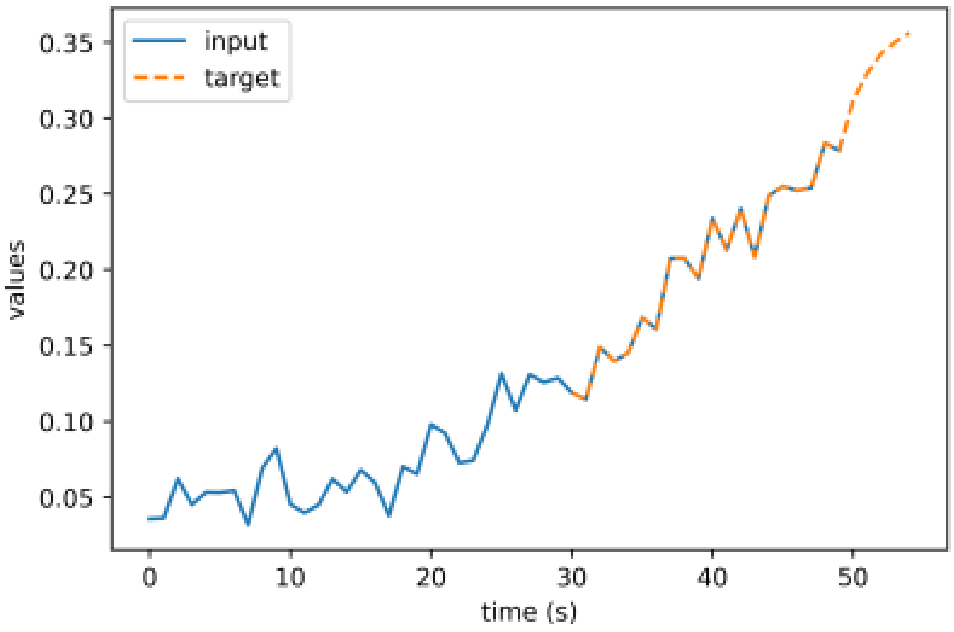

Figure: Overlapping sequences.

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Step 3: RUL Prediction: A Sequence to Sequence Prediction Problem

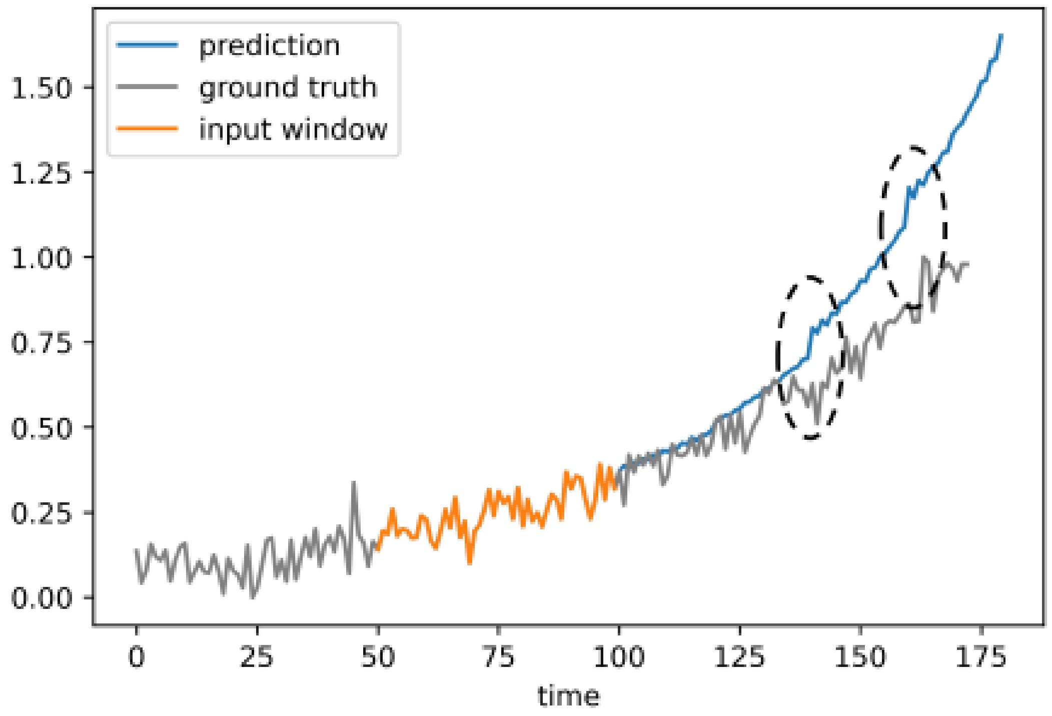

Figure: Without overlapping.

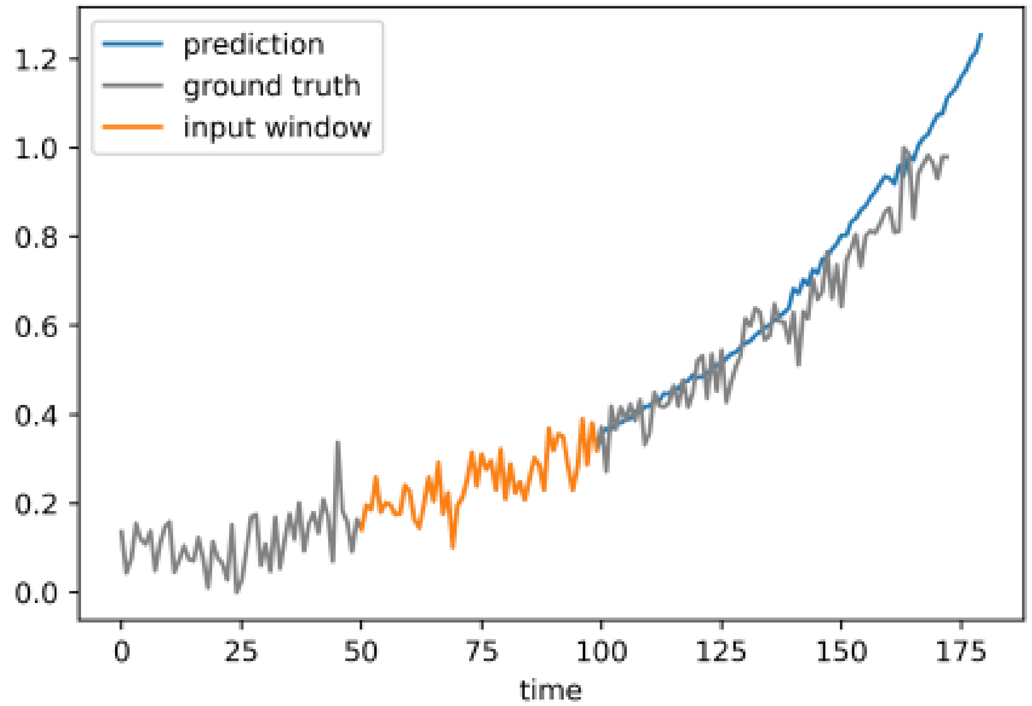

Figure: With overlapping δ.

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Step 3: RUL Prediction: Deep LSTM Structure

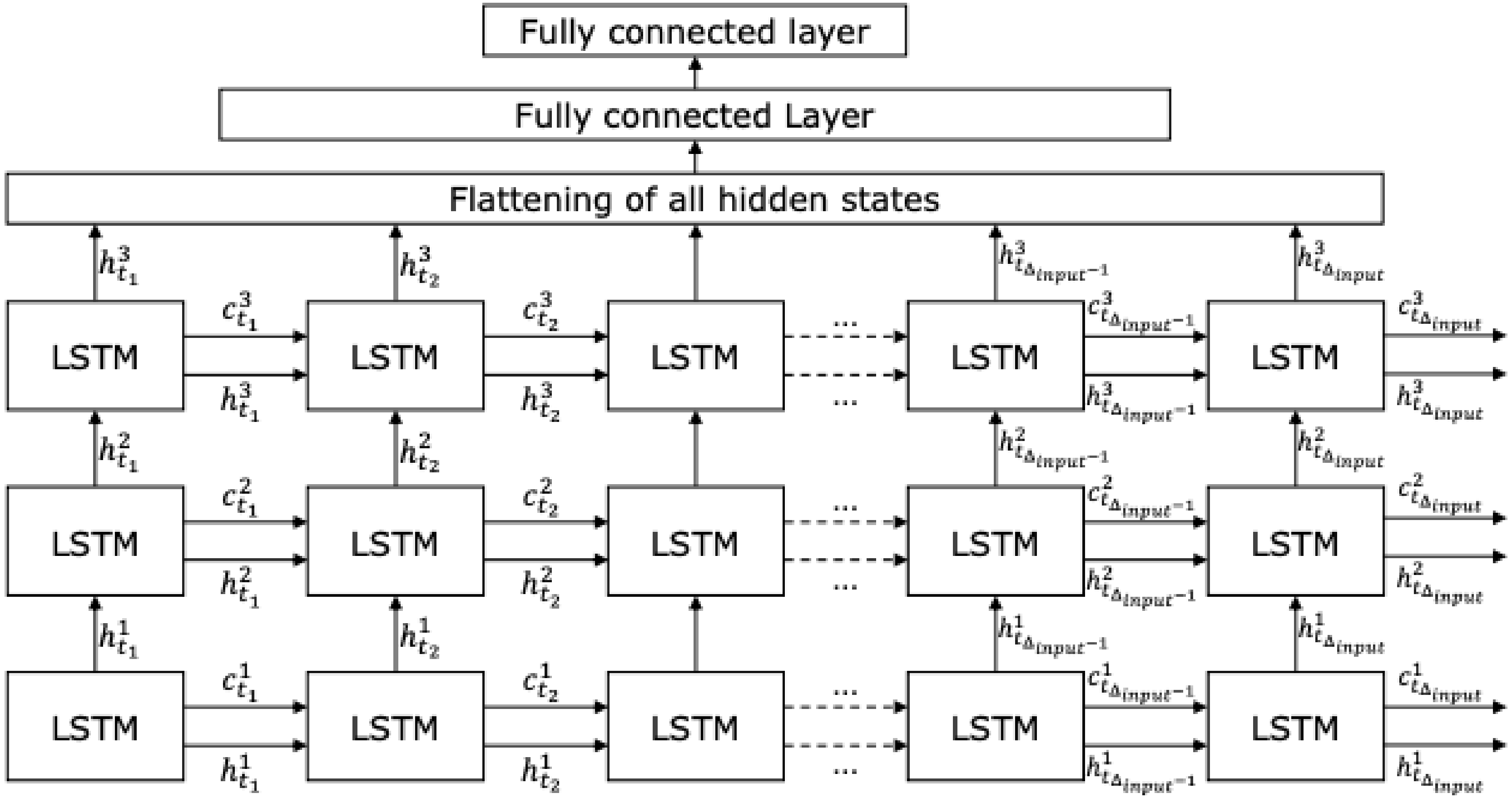

Figure: 3-layered stacked-LSTM network.

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Step 3: RUL Prediction: EOL Detection

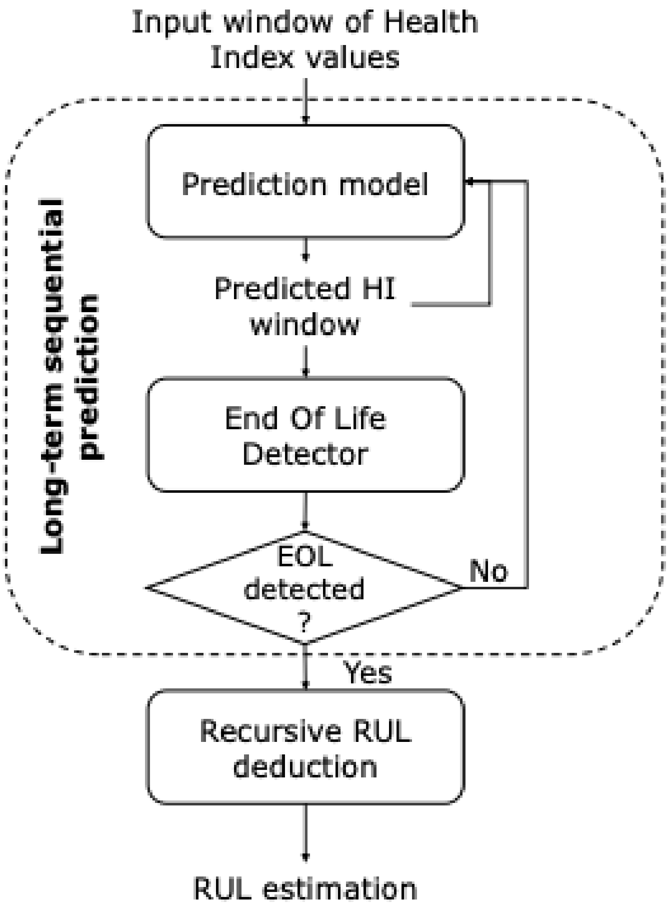

Figure: Overview of step 3 - prediction.

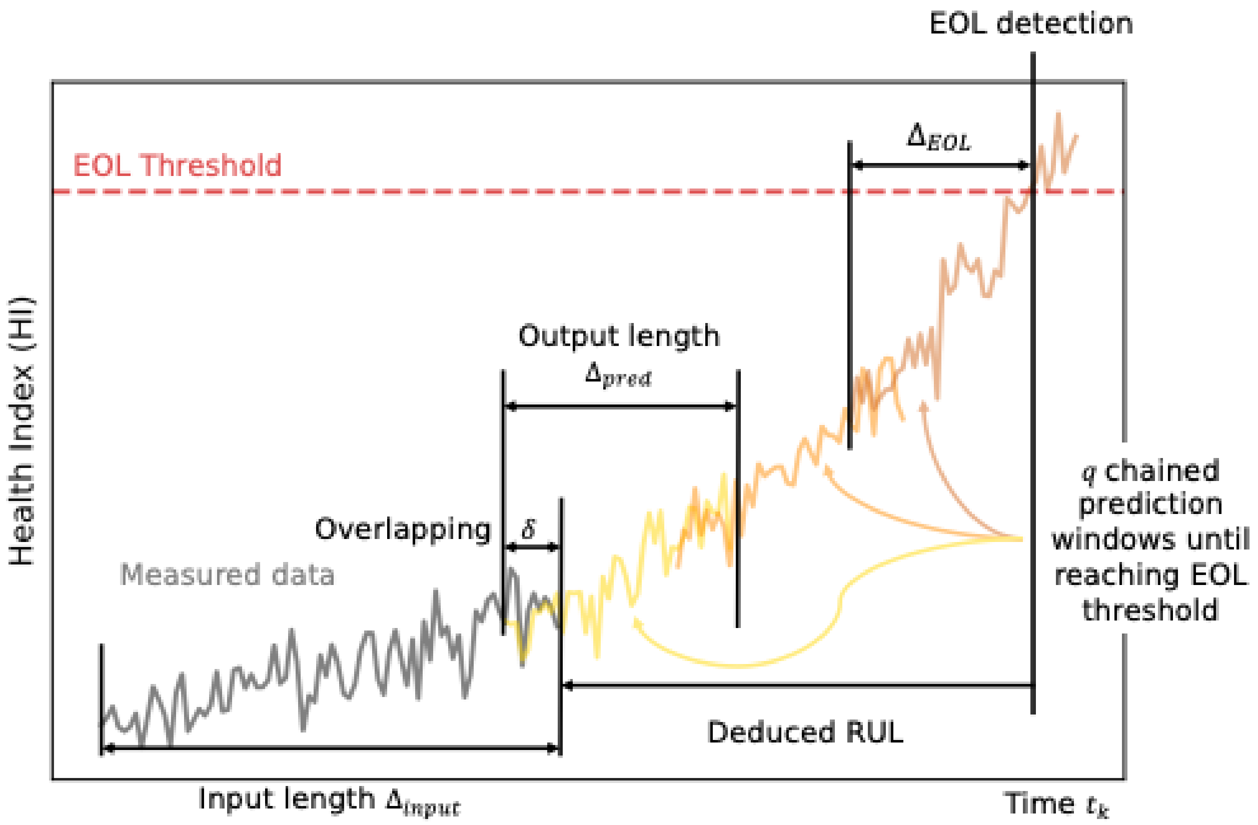

Figure: EOL detection by threshold overshooting strategy.

Step 3: RUL Prediction: HI Prediction

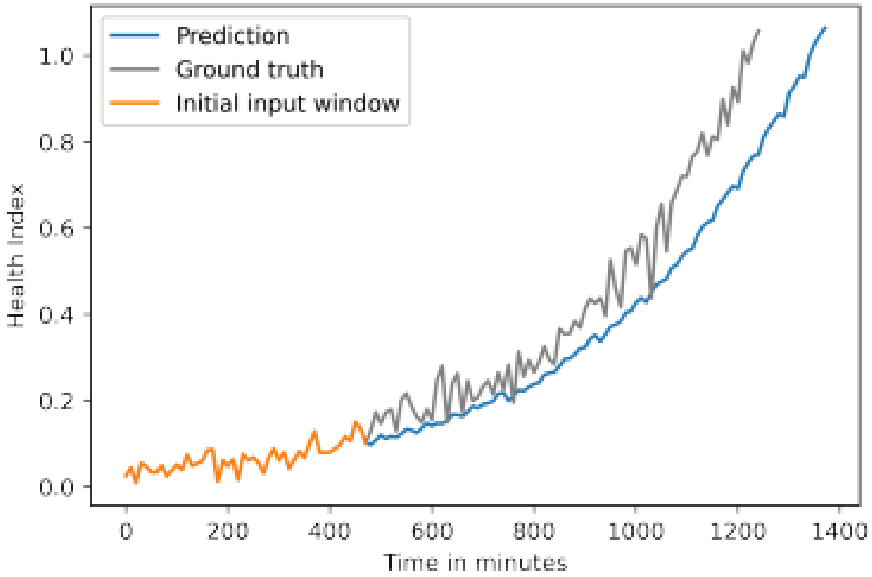

Figure: HI prediction for one TTF test trajectory, starting from $t_{k=480}$ minutes.

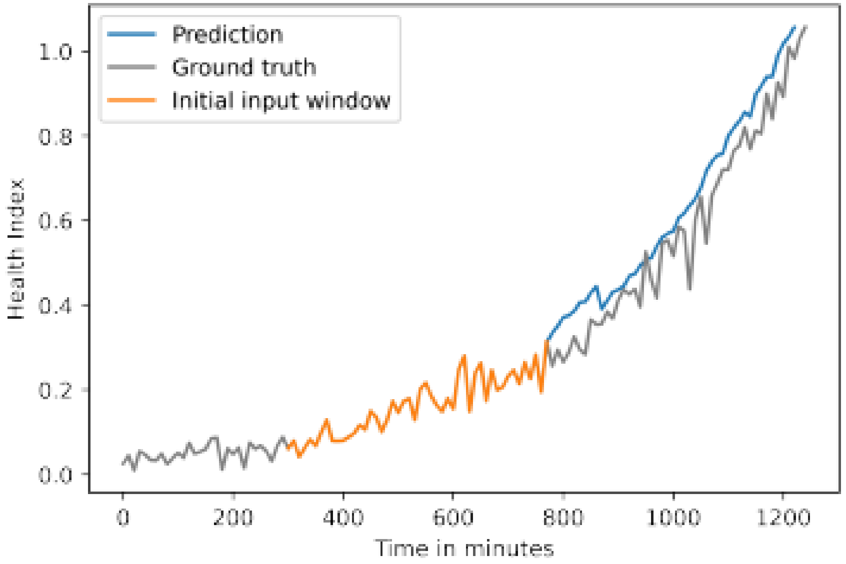

Figure: HI prediction for one TTF test trajectory, starting from $t_{k=800}$ minutes

Accumulation of prediction error leading to lower accuracy for early predictions.

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Step 3: RUL Prediction: RUL Prediction

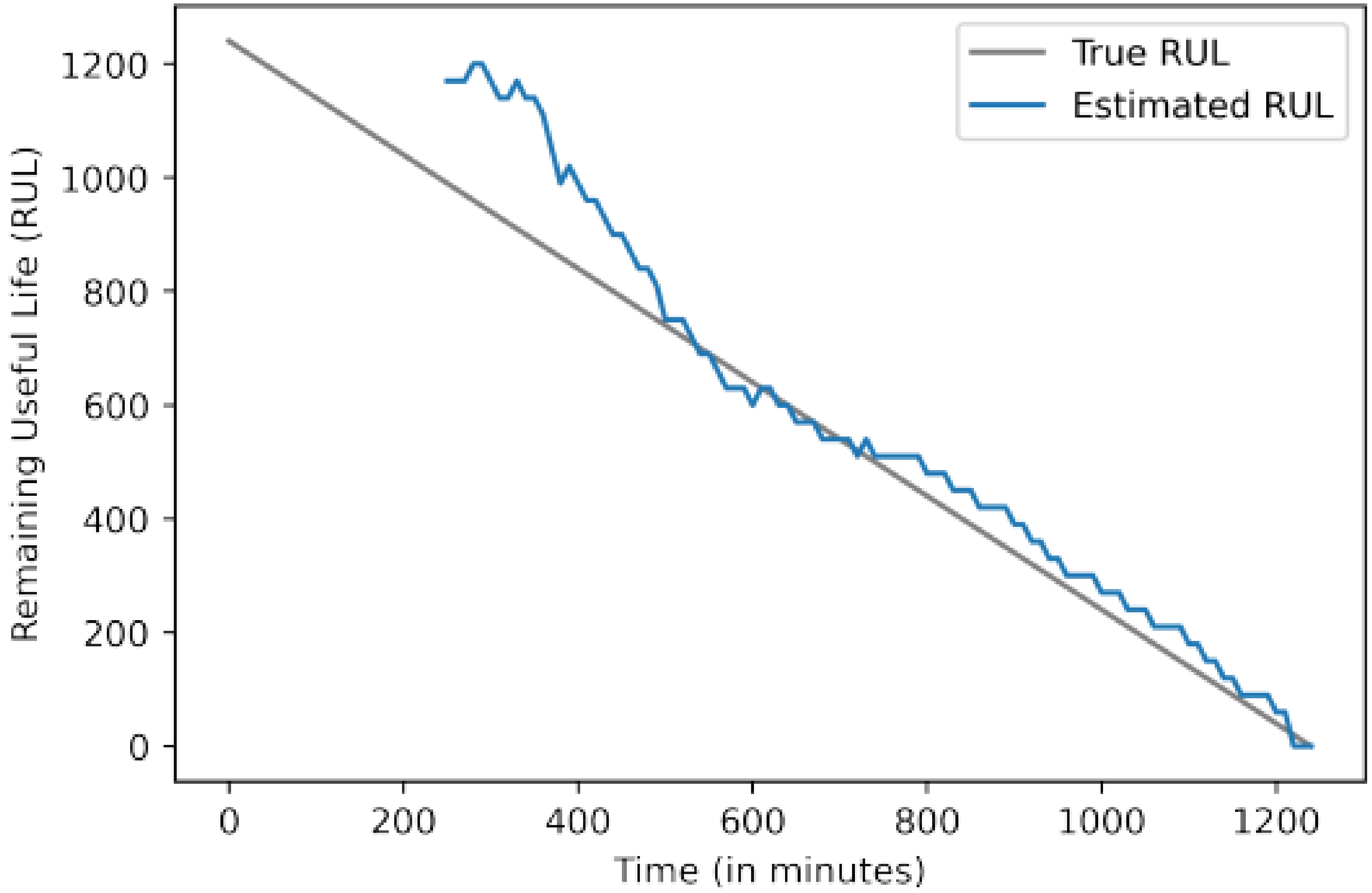

Figure: One complete predicted RUL trajectory for one TTF test trajectory.

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Step 3: RUL Prediction

Sequence-to-sequence prediction:

- Key parameters: Δ_{input}, Δ_{pred} and δ
- Overlapping always improves the performance of RUL prediction (all other hyperparameters being equal)
- $\Delta_{input} > \Delta_{pred}$
- Avoid excessive extrapolation

Stacked-LSTM model:

- Key parameters: Number of layers L size of the hidden state $|h_{t_k}|$
- Model complexity

Contribution to research challenges

- No use of RUL-labeled data
- Increase in prediction performance as EOL approaches

Conclusions

- Deep NNs based Prognostics
  - Powerful approach under supervised condtions
  - Excellent generalisation capability under diverse, rich conditons.
  - Good capacity in presence of qualitative, quantitative data (non stationanry, nonlinear dynamics etc.)
- Availibility of True Labelled target (output) a problem in real Industrial contexts
- Unsuperivised Prognostics ➔ still in nascent stage
- First contributions in this direction using system identification + deep autoencoders + LSTMS.

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