Machine Learning Applications

Winter semester 2019/2020

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Lecture IX

Prognosis Framework

Structure and content of the lecture

VW	Date	Content	Lead
1	18th Oct 2019	Introduction, Motivation and Organizational Information	FSR
2	25th Oct 2019	Introduction to Machine Learning I	CS
3	1st Nov 2019	Introduction to Machine Learning II	CS
4	8th Nov 2019	Introduction to Machine Learning III	CS
5	15th Nov 2019	Introduction to and Application of Machine Learning	CS
6	22nd Nov 2019	Presentation of Industrial Partner and Introduction of Practical Exam (Hackathon)	FSR/EXT
7	29th Nov 2019	**Data Understanding:** Data Acquisition, Preprocessing and Feature Engineering	FSR
8	6th Dec 2019	**Diagnostics:** Feature Engineering, Regression, Health Assessment	FSR
9	13th Dec 2019	**Prognostics:** Prediction, Remaining Useful Life, Uncertainty	FSR
10	20th Dec 2019	**System of Systems:** System Level, Systemwide Predictions, Decision Support, IoT	FSR
11	17th Jan 2020	**Predictive Maintenance:** Band Saw Application, Neural Networks for Condition Monitoring and Prediction	PTW
12	24th Jan 2020	**Predictive Quality:** Prediction of Product Quality during Machining Process	PTW
13	31st Jan 2020	**Energy Forecasting:** Electric Load Forecasting by the Example of a Machine Tool	PTW
14	7th Feb 2020	**Operational Control:** Optimized Control of Cross-Linked Energy Systems by Means of Reinforcement Learning	PTW
15	14th Feb 2020	**Recap on Lecture for Written Exam**	FSR

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What should you be able to take out of the lecture today?

- What is prognosis and when does it make sense?
- Determine health of a component and transfer curve into prognosis
- What is remaining useful life (RUL)?
- How to do a prognosis with Gaussian Process Regression?
- Can I trust in my prognosis?
- How to evaluate the prognosis performance?
- What are the challenges in real world application?

The prognosis is one of the last steps in OSA-CBM

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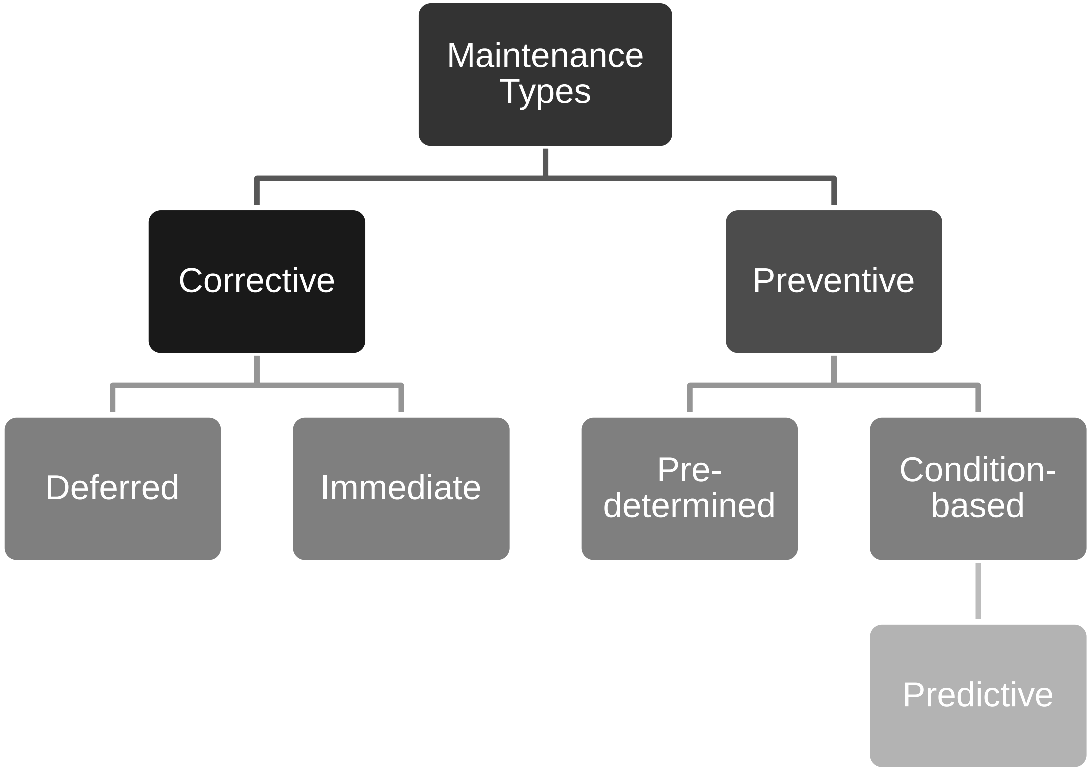
1.1	Data Acquisition (DA)
2.1	Data Manipulation (DM)
2.2	State Detection (SD)
2.3	Health Assessment (HA)
3.1	Prognostics Assessment (PA)
3.2	Advisory Generation (AG)
4.1	Presentation

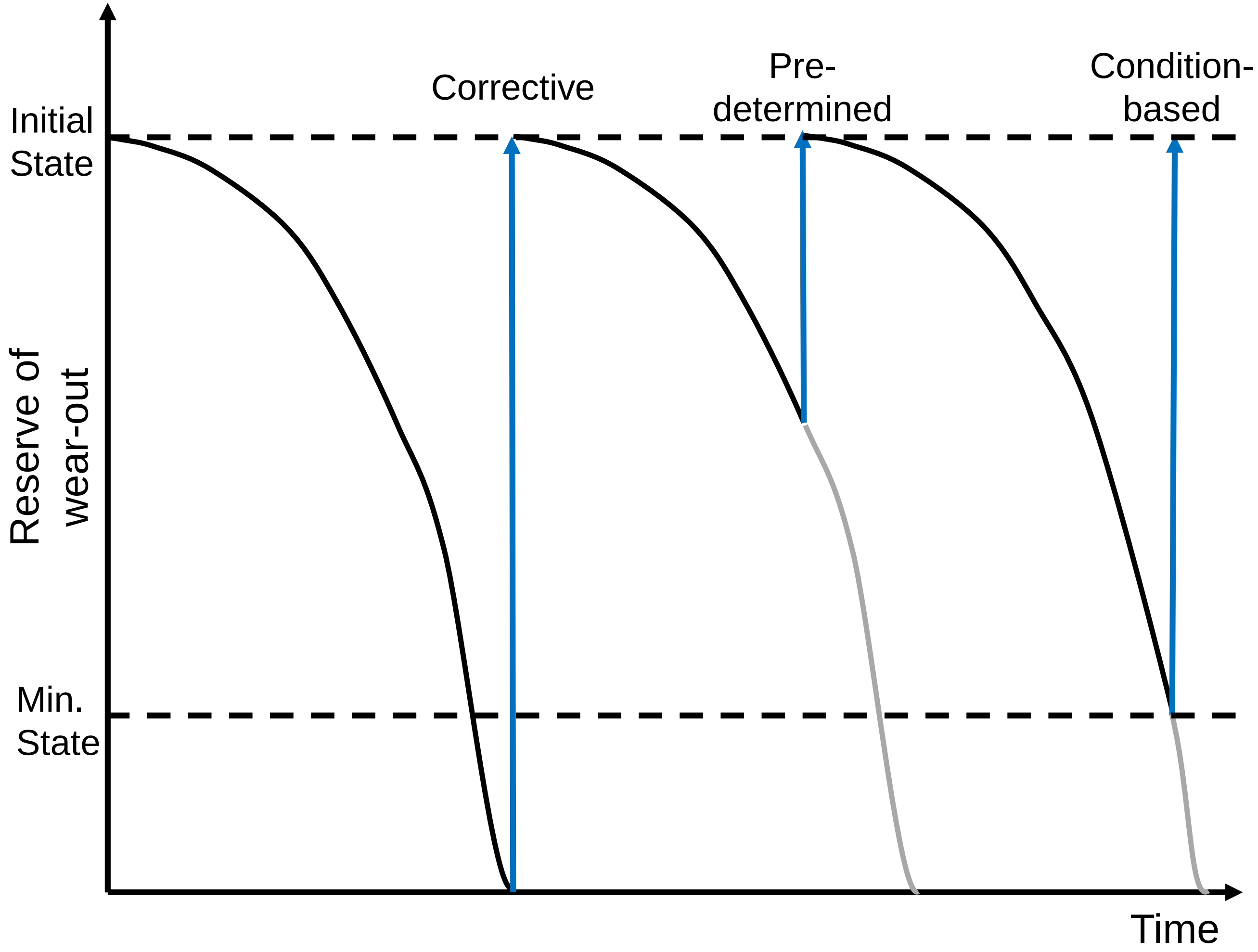
Increasing Level of Aggregation

- PA (typically) completely relies on previous steps 1.1 till 2.3
- PA aims to predict future behavior of investigated component
  How will the health of my component develop in the future?
- HA describes the health of a component (e.g. Health Index)
  What is the health status of my component?
- AG combines result of PA with system/expert knowledge
  Which actions and when should I take for the component?

THE GOAL OF PROGNOSIS

Maintenance can benefit from component‘s health prognosis

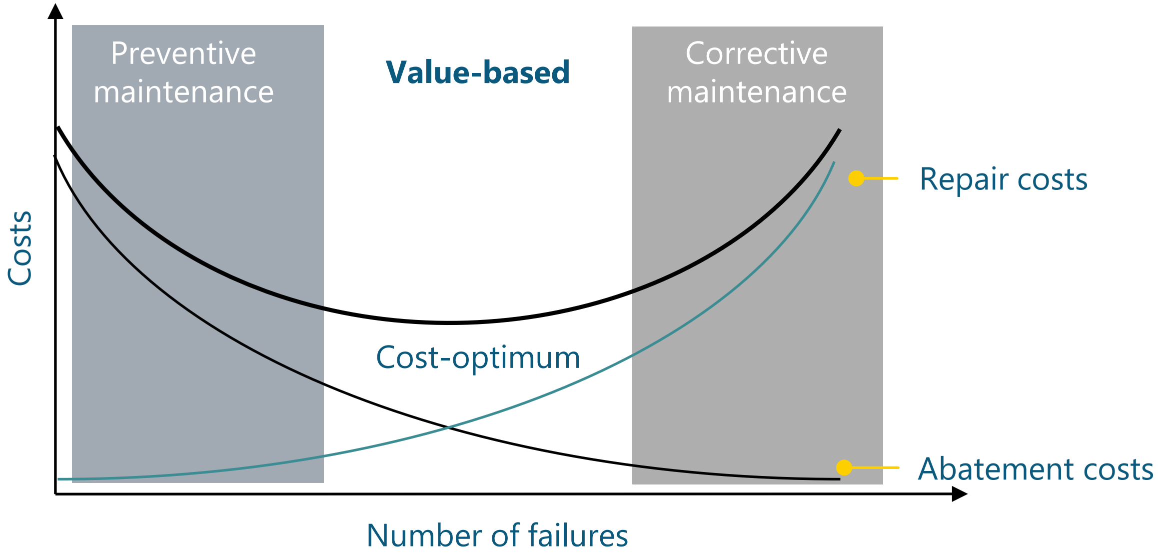




Condition-based maintenance can optimize the maintenance costs

- Model solely considers maintenance costs
- Development costs of value-based maintenance not covered
- Resulting costs from breakdown not covered → Revenue loss

➔ Each component needs to be analyzed individually



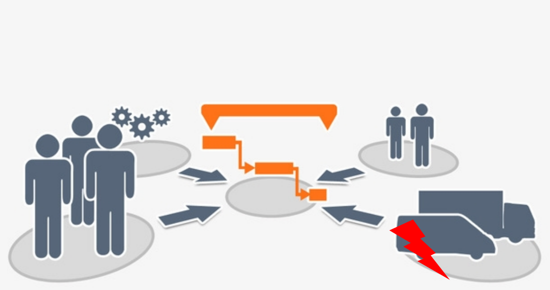
- Repair costs increases with higher number of failures
- Abatement costs increase for lower number of failures

➔ Optimum in the addition of both costs

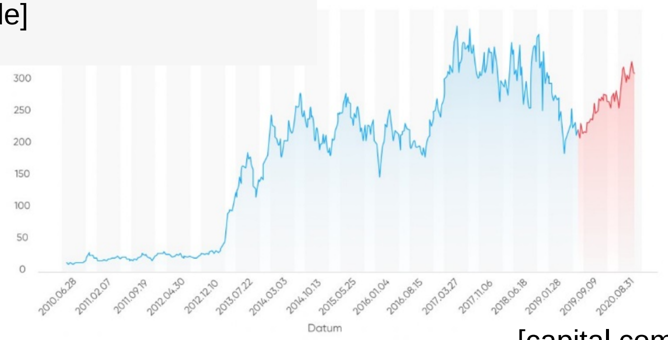
Maintenance is not the only reason for prognosis approaches

- Safety related components
  - Demand for high reliability
  - Alternative to conventional redundancy concepts
- Optimized resource planning
  - Know in advance when assets are not available
  - Know future demand for resources
- Prediction of process output
- Load prognosis
- Stock market
- …

[sfl-gmbh.de]



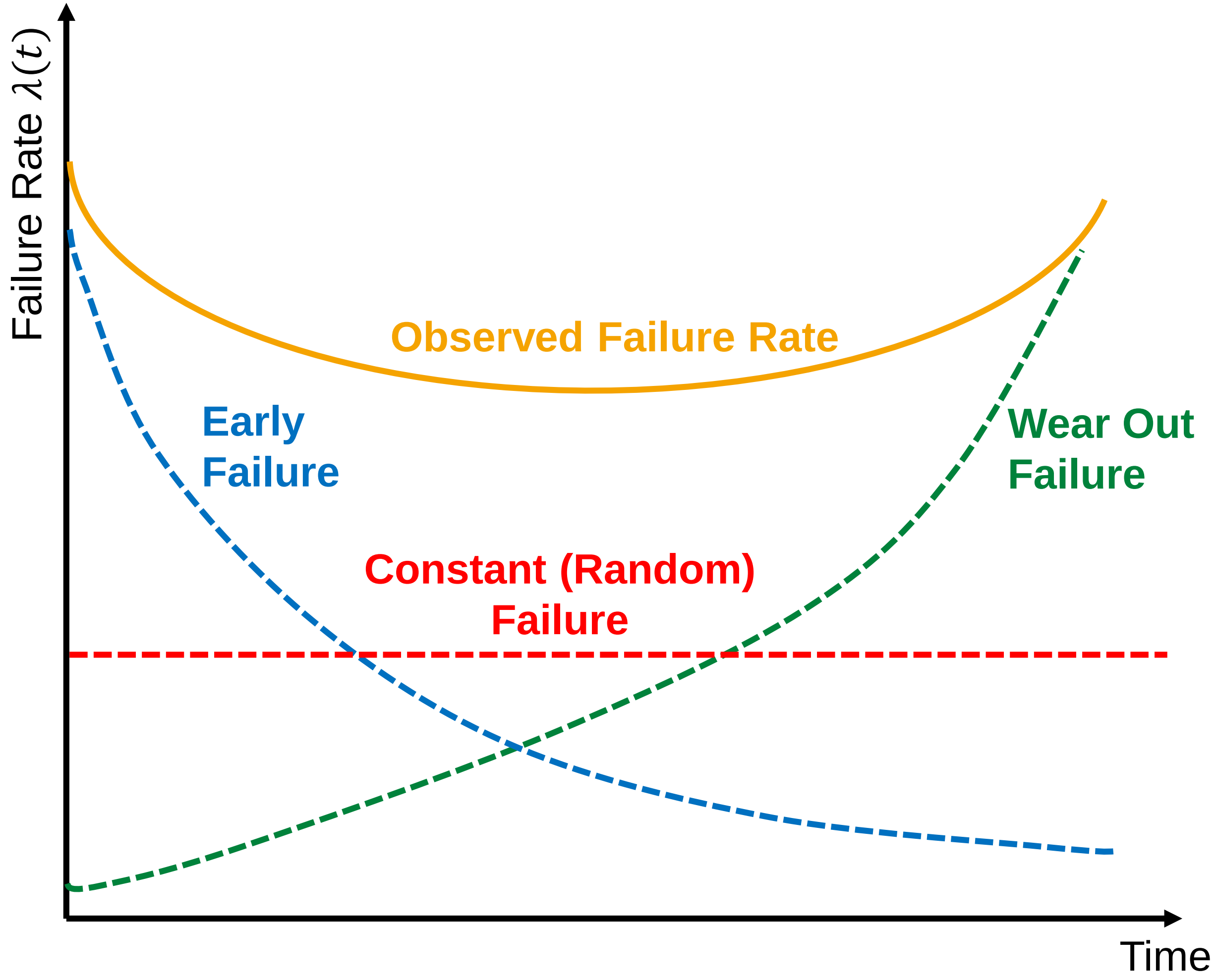
[gruenderszene.de]



[capital.com]

Prognosis of component's health is not always technical feasible

- **Early Failure**
  - Production quality
  - Wrong design
  - → Any component
- **Wear Out Failure**
  - Aging of a component
  - Degradation of component
  - → Typically mechanical components
- **Constant (Random) Failure**
  - **Unpredictable** cause
  - → Typically electronic components

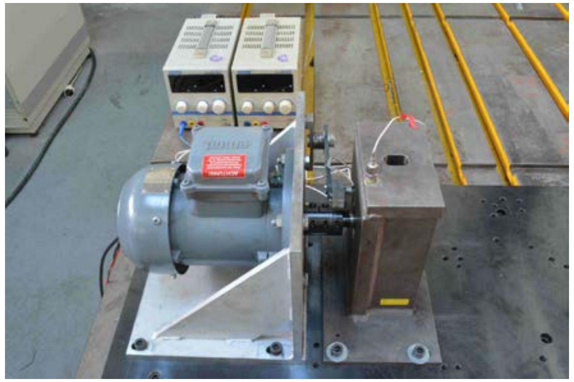


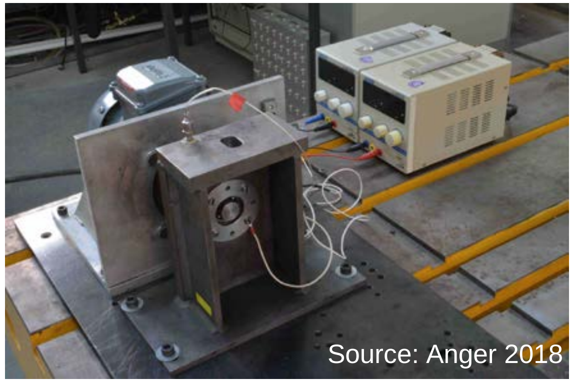
HOW TO ASSES A COMPONENT‘S HEALTH

A test rig can be used to generate run-to-failure curves

Bearing degradation

- Rotation from induction machine
- Current through bearing to accelerate degradation

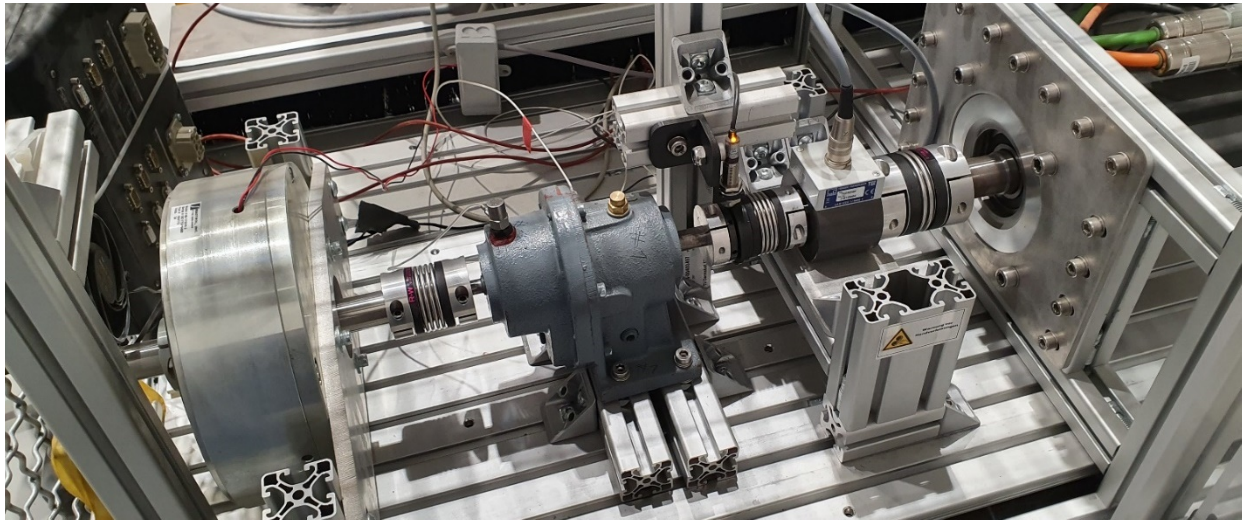




Source: Anger 2018

Gearbox degradation

- Motor for rotation
- Hysteresis brake to apply different loads

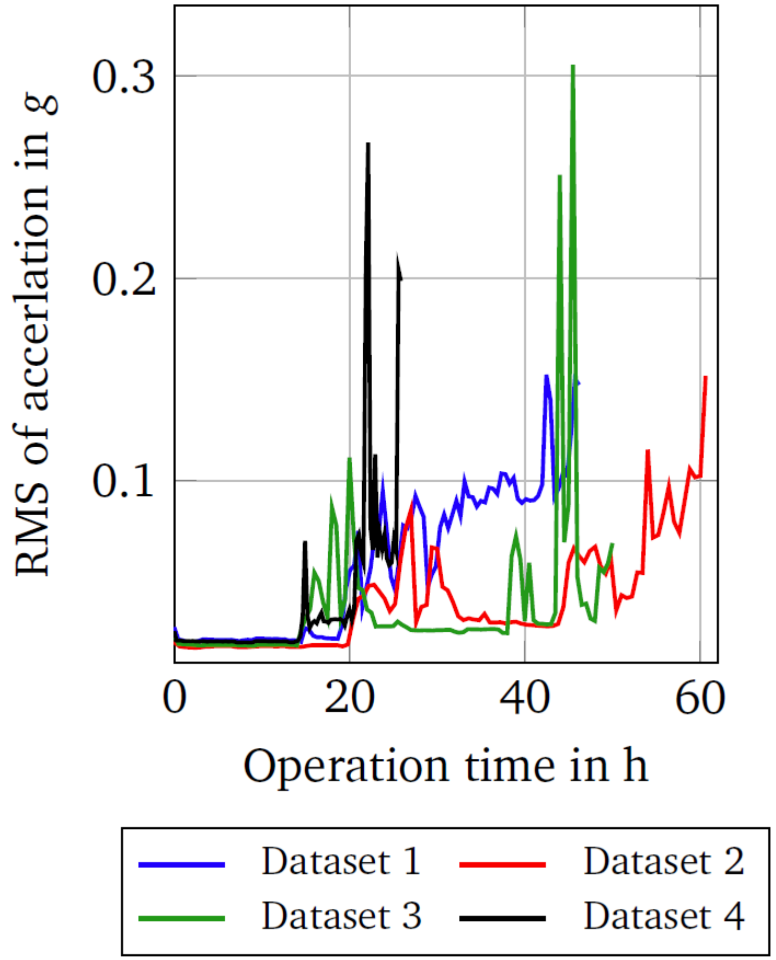


Different values of a feature may indicate a component's break down

- Operation time until breakdown differs between components
- RMS value of acceleration might differ when component actually fails
- RMS values might decrease again
  → pseudo repair

➔ Determine a component specific feature value baseline

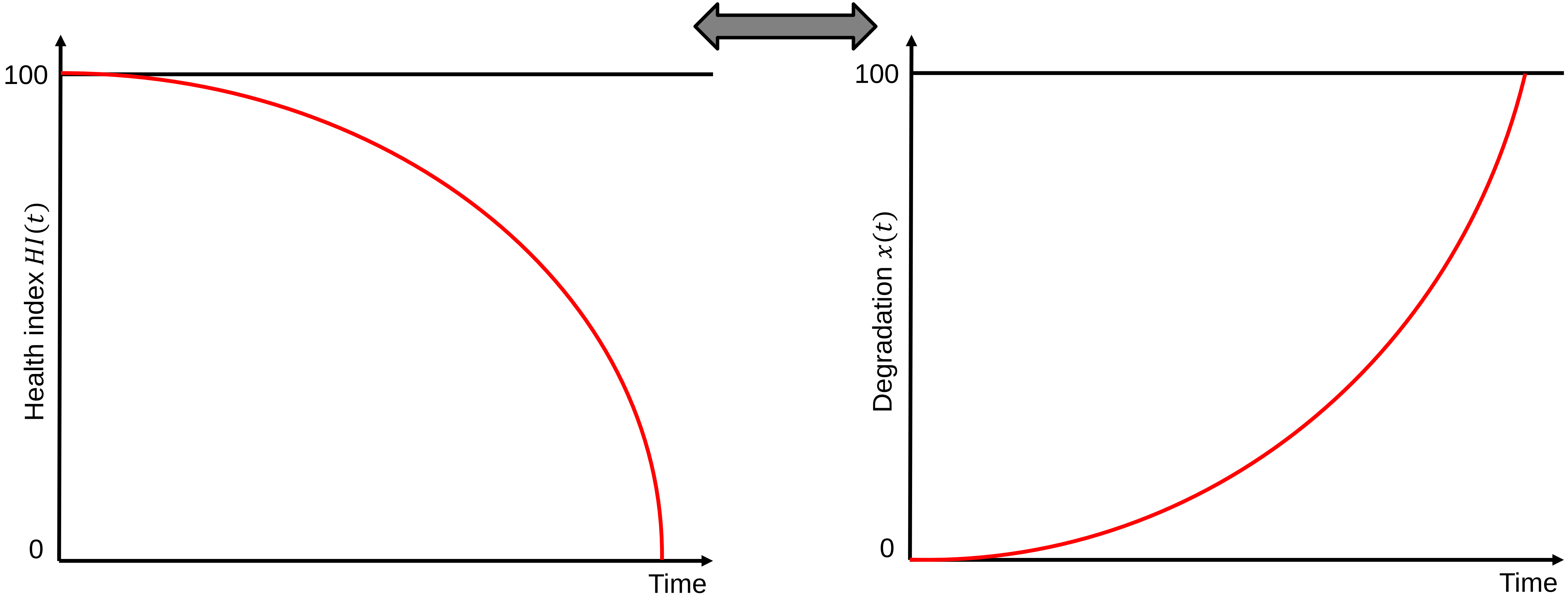
➔ Normalize values to predefined range (e.g. [0,1])



Source: Anger 2018

Health index or degradation value can be used to describe wear-out

$$x(t) = 1 - HI(t)$$



HOW TO PREDICT A COMPONENT'S REMAINING USEFUL LIFE

There are four assumptions that are ideally considered for prognosis

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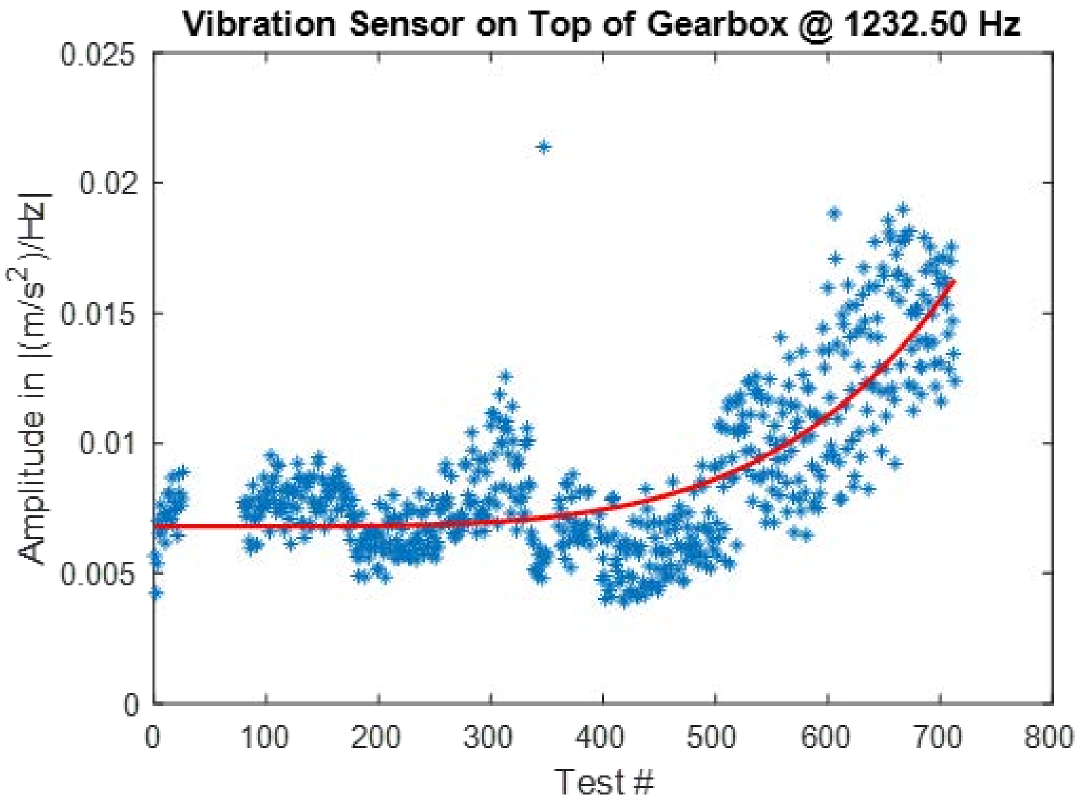
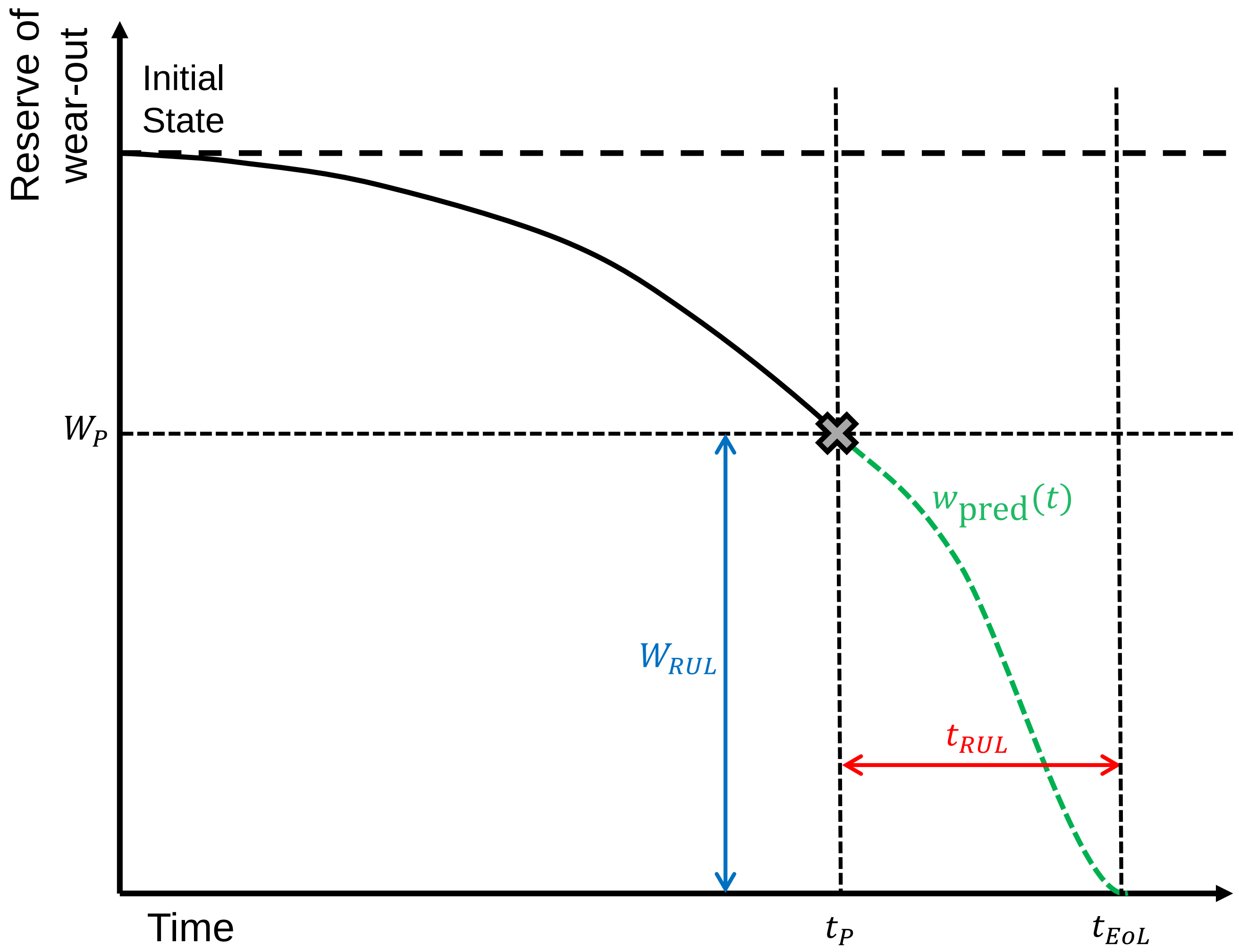
1. The monitored system **degrades** as a function of **use**, **time** and **environmental conditions**
2. The **aging** and **damage accumulation** is a **monotonic process**
3. Signs of **aging** are **visible before** the **failure** of the system occurs
4. Signs of **aging** can be **fitted** to a **model** to estimate the remaining useful life



Remaining Useful Life describes the remaining wear out/time/… reserve

- Remaining Useful Life (RUL) can be interpreted in different ways
  - t_{RUL} remaining useful life-time
  - W_{RUL} remaining useful life-wear-out
- Use case dependent what to predict
  - t_{RUL} if you want to know the time until a component fails → most cases
  - $w_{\text{pred}}(t)$ if you want to know how the wear-out will develop over the time



Regression that maps degradation solely over time is no prediction

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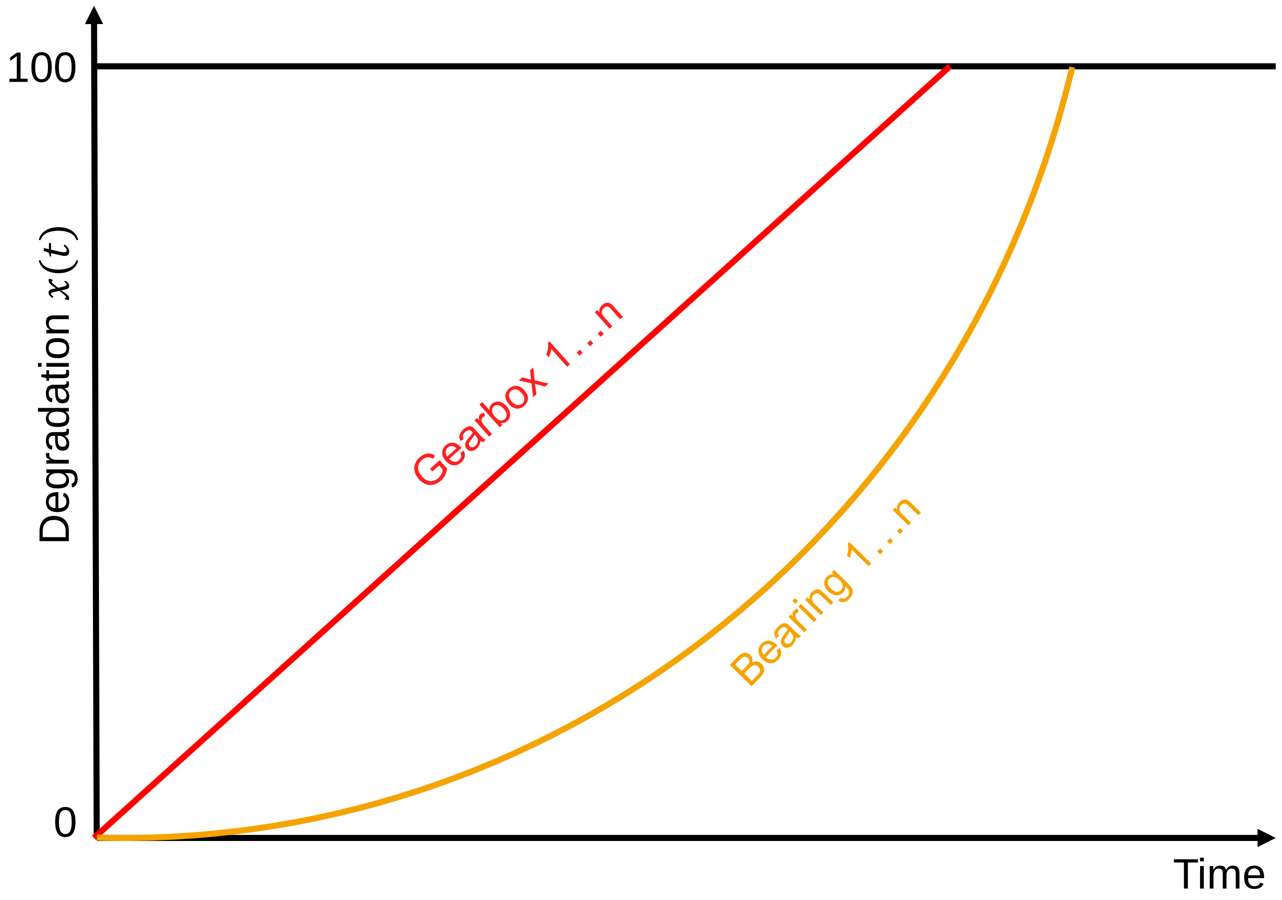
- Simple regression when each component behaves in the same way
- $x_1(t) = x_2(t) = \cdots = x_n(t)$
- It does not matter which type of function $x(t)$ represents (linear, exponential,…)

➔ Since all functions are the same, there is no real prediction model

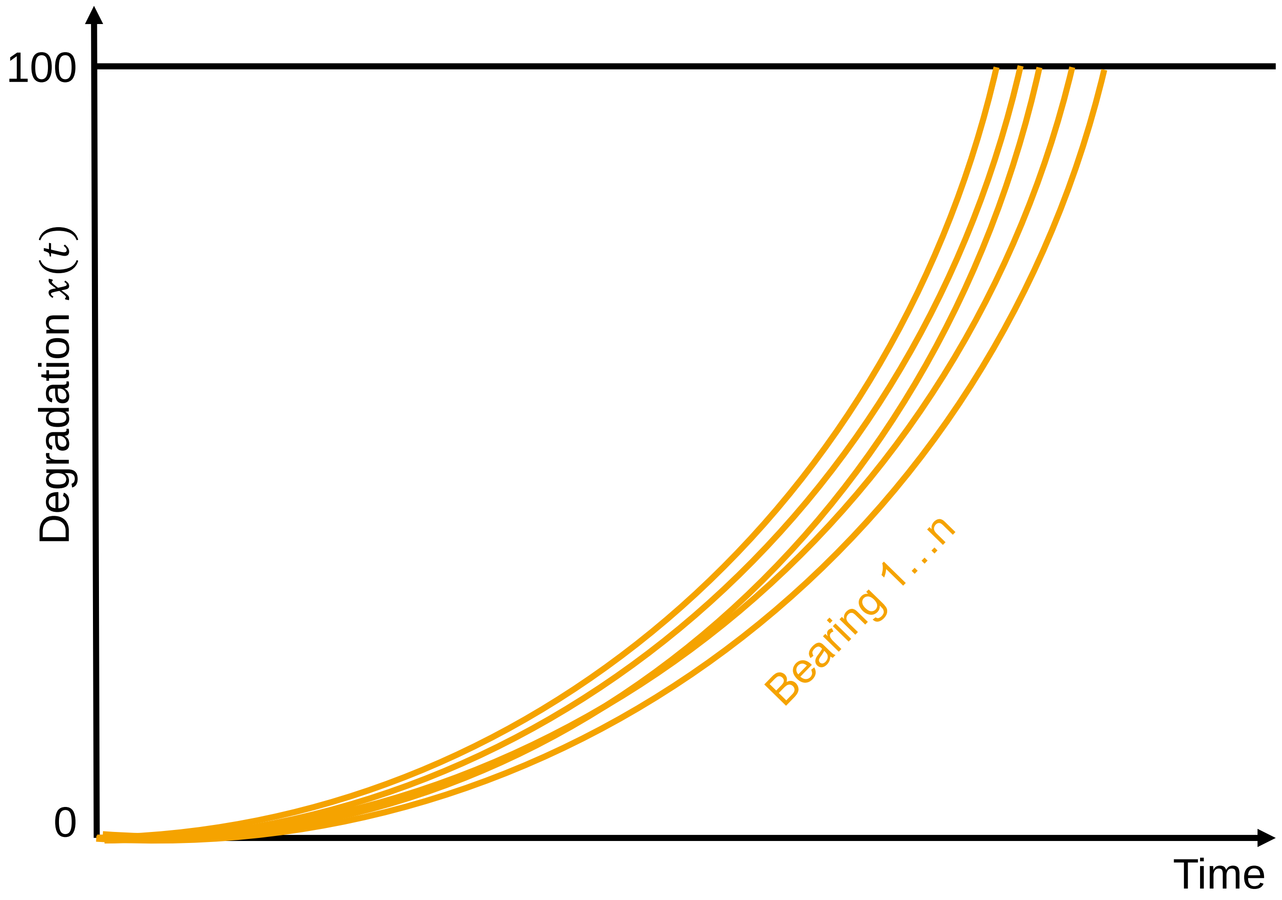


FSR

Prognosis algorithm copes with different behavior of components

- Each gearbox degrades differently
- $x_1(t) \neq x_2(t) \neq \cdots \neq x_n(t)$
- Prognosis algorithm has to incorporate further information
  - Component's degradation history
  - Further sensor values

➔ Since all functions differ, a *complex* model is necessary for prediction



Prognosis learns behavior of components and predicts at different time steps

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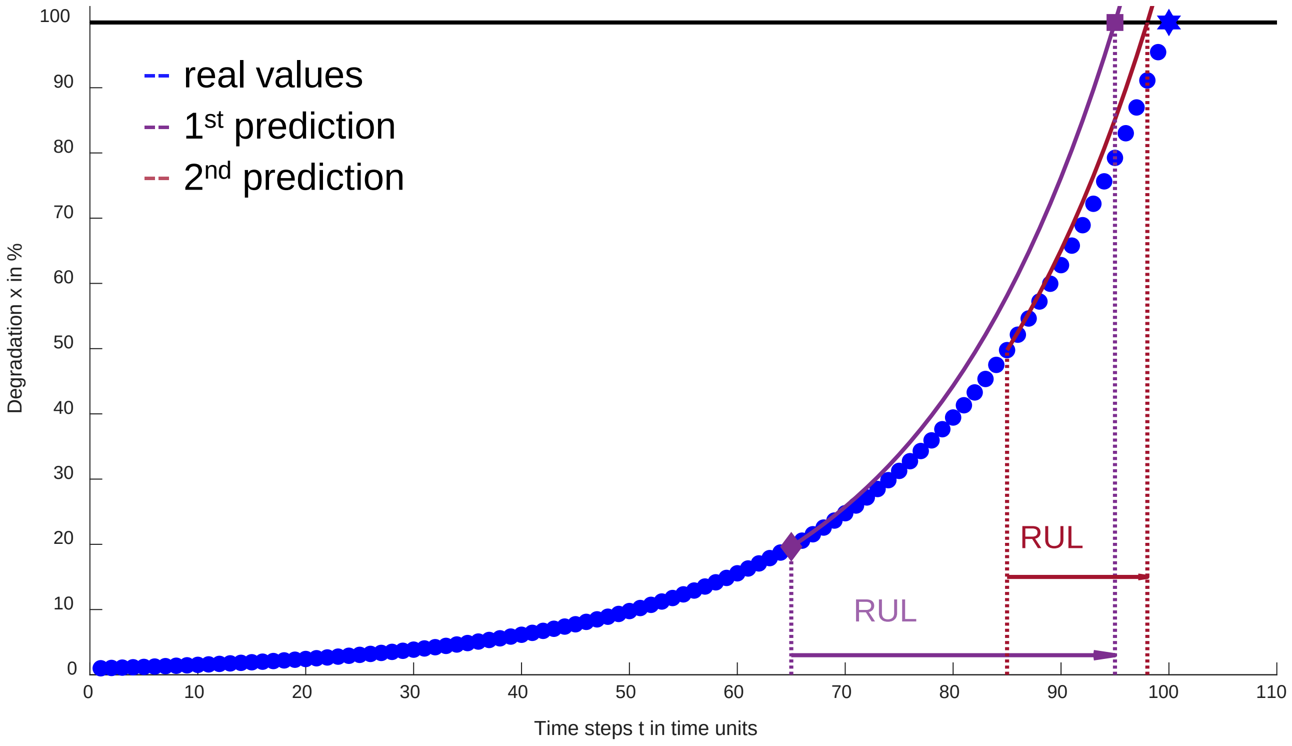
- Typically predictions are not accurate
- Typically later predictions tend to be closer to real end of life



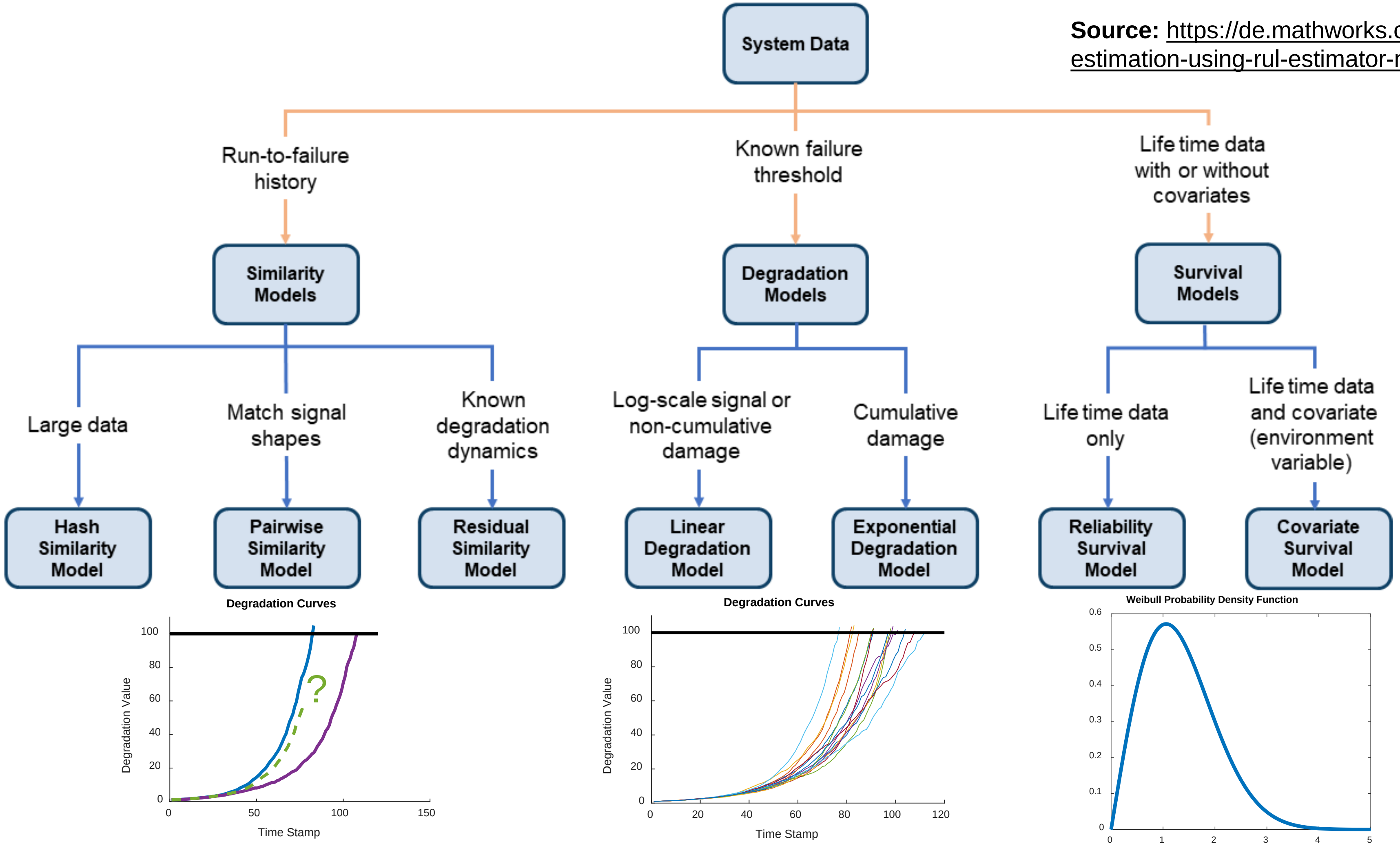
t_{EoL} → End of life time (reality)

t_{p} → Start time of prediction

t_{EoP} → End time of prediction

Different approaches according to available (historic) system data

Source: https://de.mathworks.com/help/predmaint/ug/rul-estimation-using-rul-estimator-models.html



Let‘s have a look on Gaussian Process Regression (GPR) mathematics

- Gaussian Distribution $N(\mu, \Sigma)$ ←→ Gaussian Process $GP(m(x), k(x, x'))$
- k is covariance function that is represented by a so called kernel function

$$k_{SE}(x, x') = e^{-1/2|x-x'|^2}$$

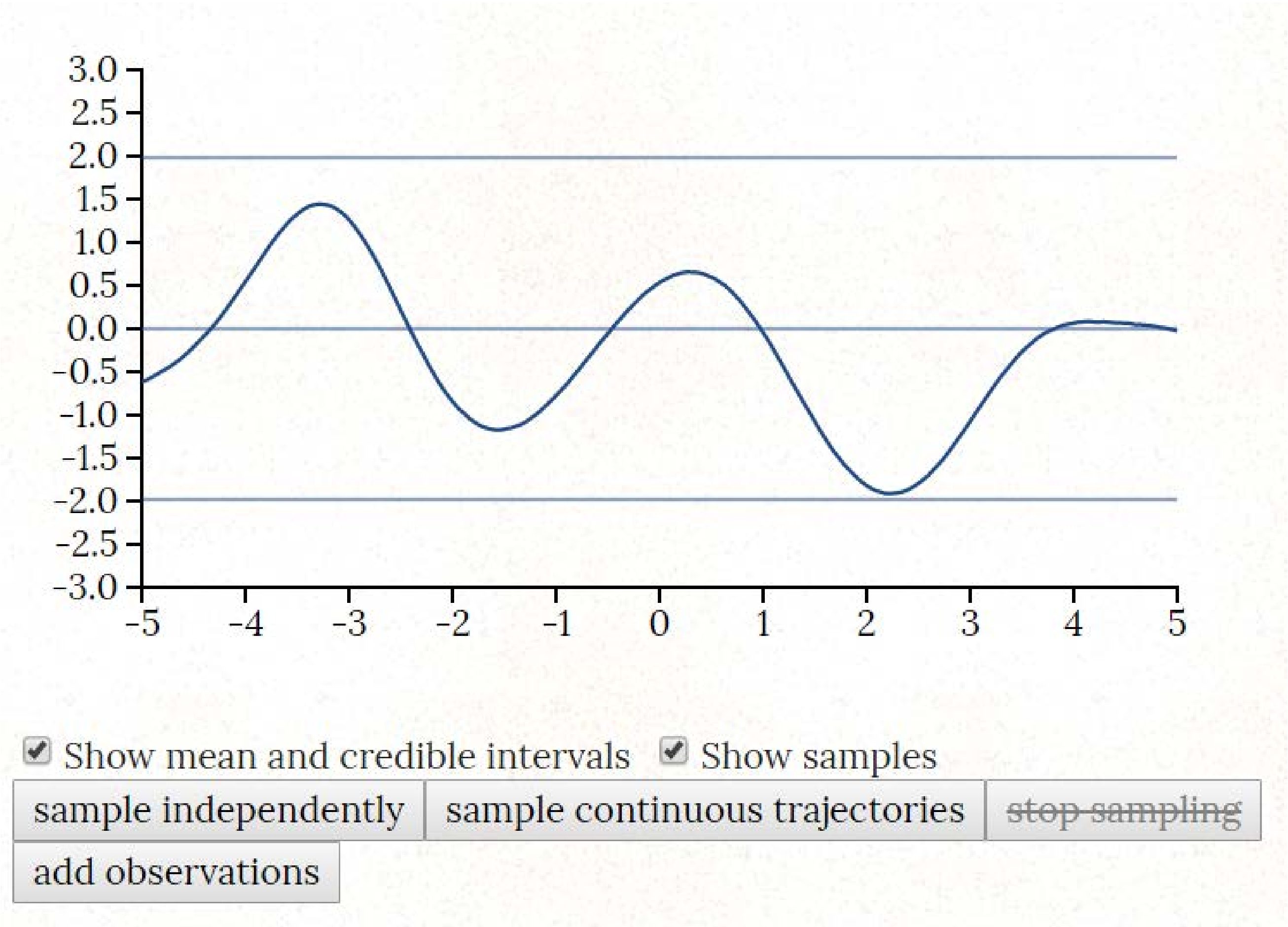
➔Gaussian Process is a random distribution of functions

➔Gaussian Process is non-parametric: inputs are compared to training data

$$f(x) \coloneqq \text{observation} \qquad f_*(x_*) \coloneqq \text{unknown}$$

$$\begin{pmatrix} f \\ f_* \end{pmatrix} \sim N\left(0, \begin{pmatrix} k(x, x) & k(x, x_*) \\ k(x_*, x) & k(x_*, x_*) \end{pmatrix}\right)$$

Let's see a demonstration of GPR fitting process

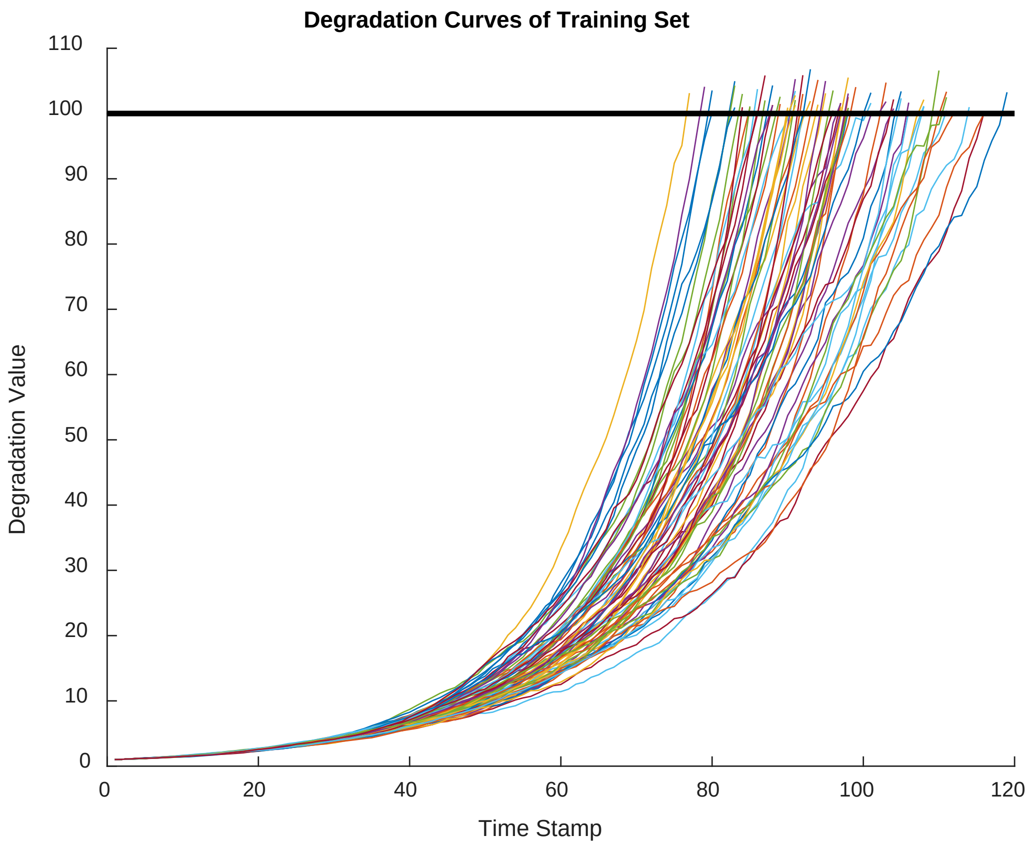


http://www.tmpl.fi/gp/

The GPR is applied to a simple degradation prognosis

- Random exponential degradation curves with noise
- Fit a gaussian process regression that has as input:
  - Current degradation: $x(t_k)$
  - Last degradation: $x(t_{k-1})$
  - Second last degradation: $x(t_{k-2})$

  and outputs:
  - Next degradation: $x(t_{k+1})$



In MATALB you need only one command to train a GPR

➔ Let‘s have a look into MATLAB

```
fitrgp(table2array(SimData.train.gprInputTable),SimData.train.gprOutputTable.nextDeg,...
                           'FitMethod','sd',...
                           'PredictMethod','exact',...
                           'KernelFunction',conf.gpr.KernelFunction,...
                           'BasisFunction',conf.gpr.BasisFunction,...
                           'Verbose',conf.gpr.verbose);
```

Exemplary results of an iterative GPR prediction until threshold is reached

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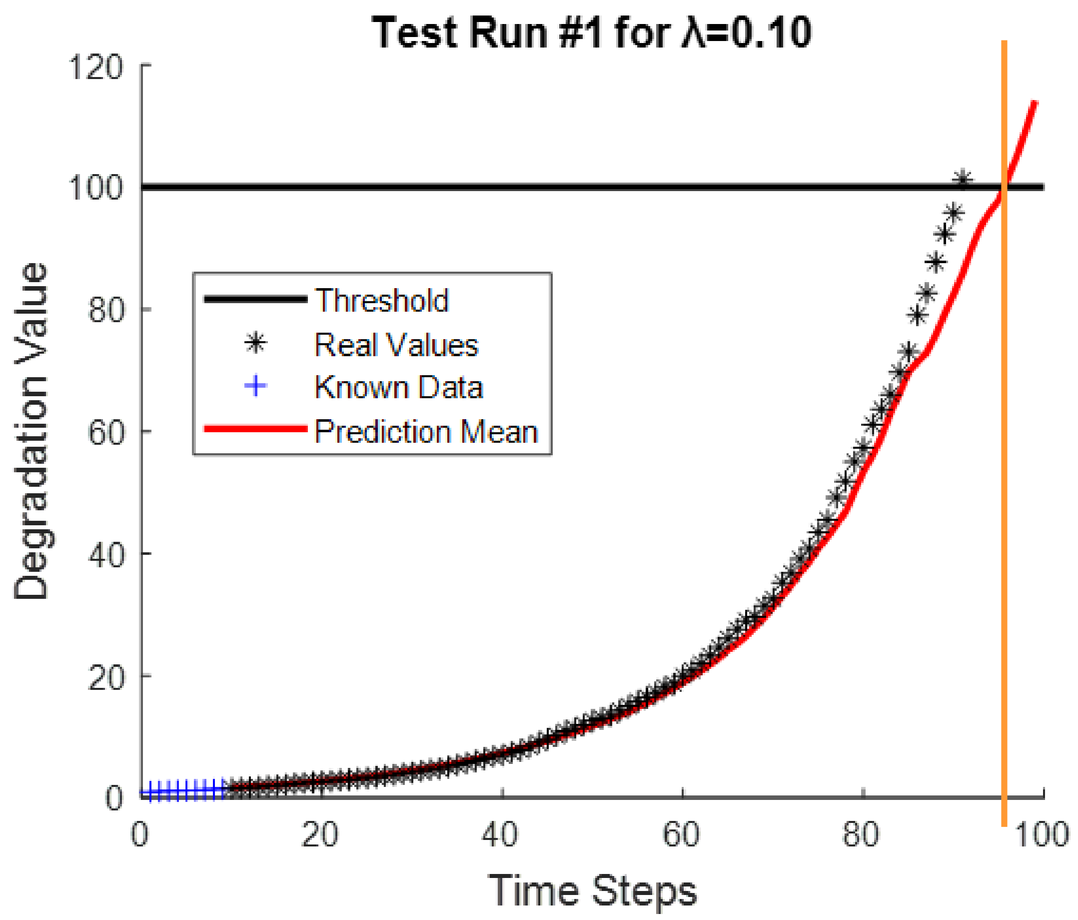

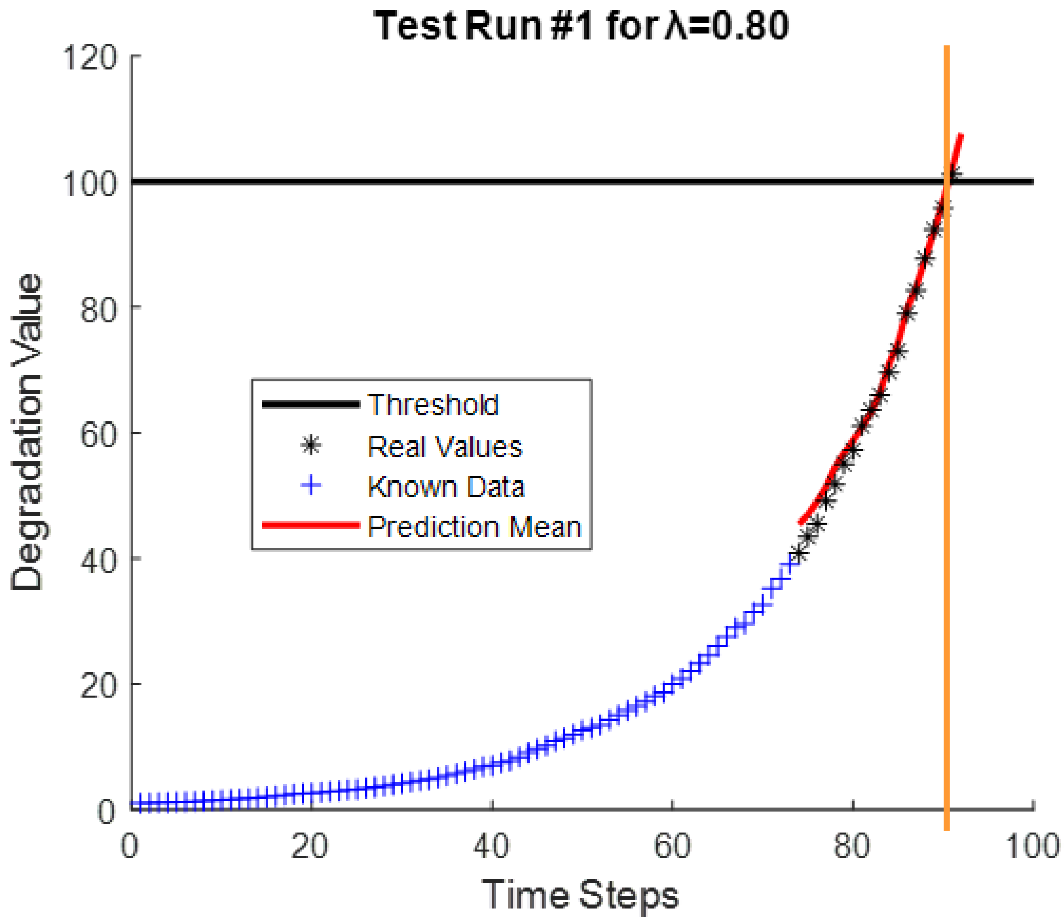

UNCERTAINTY IN PREDICTION

A look into the future never gives a certain answer

- Phenomena of any prognosis like weather forecasts, stock forecasts, etc.
- Input uncertainty
  - Material properties → the reason to test more than one component
  - Initial or boundary conditions → the environment has an influence
  - Sensor uncertainty → the reason for sensor calibration
- Discretization uncertainty
  - Time steps (sample rate) → real world is continuous – information between samples is lost
  - Floating-point number precision → conversion of analog values to discretized values
- Model uncertainty
  - Representation of the real world problem → algorithm output vs. real world output

Each prognosis needs to be expressed as a probability

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- Each prognosed degradation at time t_k is a probability distribution for $x(t_k)$
- The probability of failure is expressed as a cumulative distribution function (CDF)

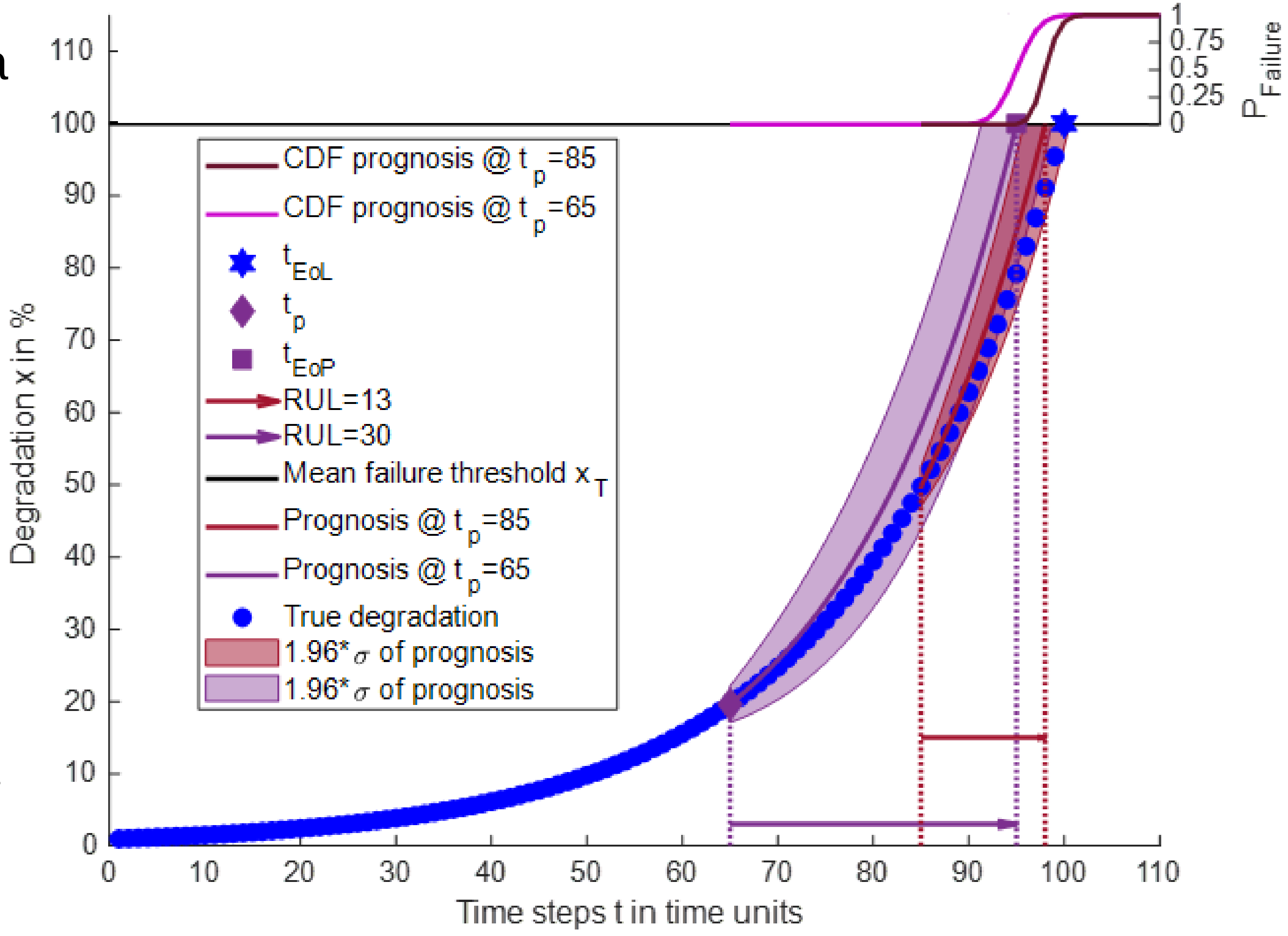
→ Reaching the threshold at time t_k is given with a probability

→ How to calculate the RUL?

  → Mean of CDF reflects the expectation value of discrete distribution

  → Median of CDF reflects a probability of 50 % that a component will have failed until that time

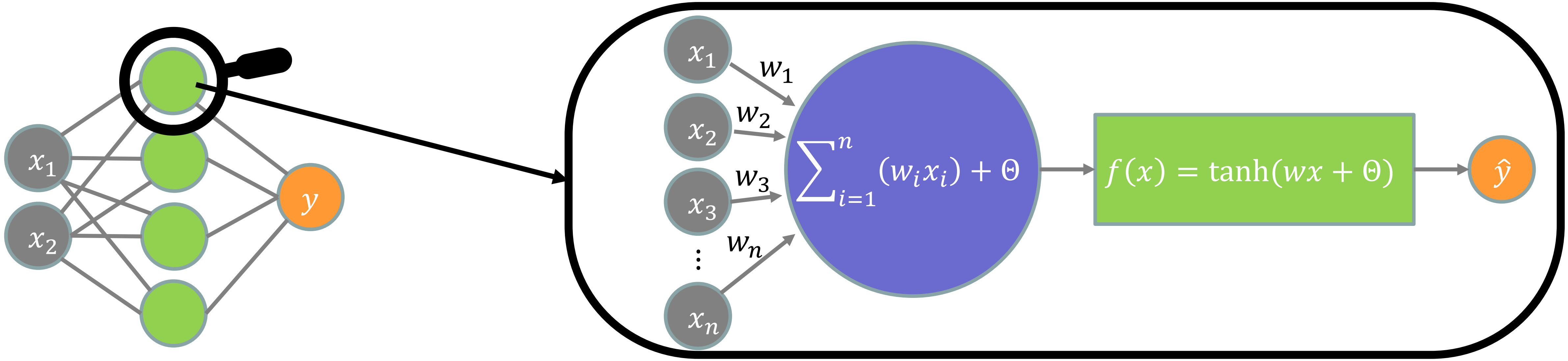
  → Specify a distinct probability value for the CDF



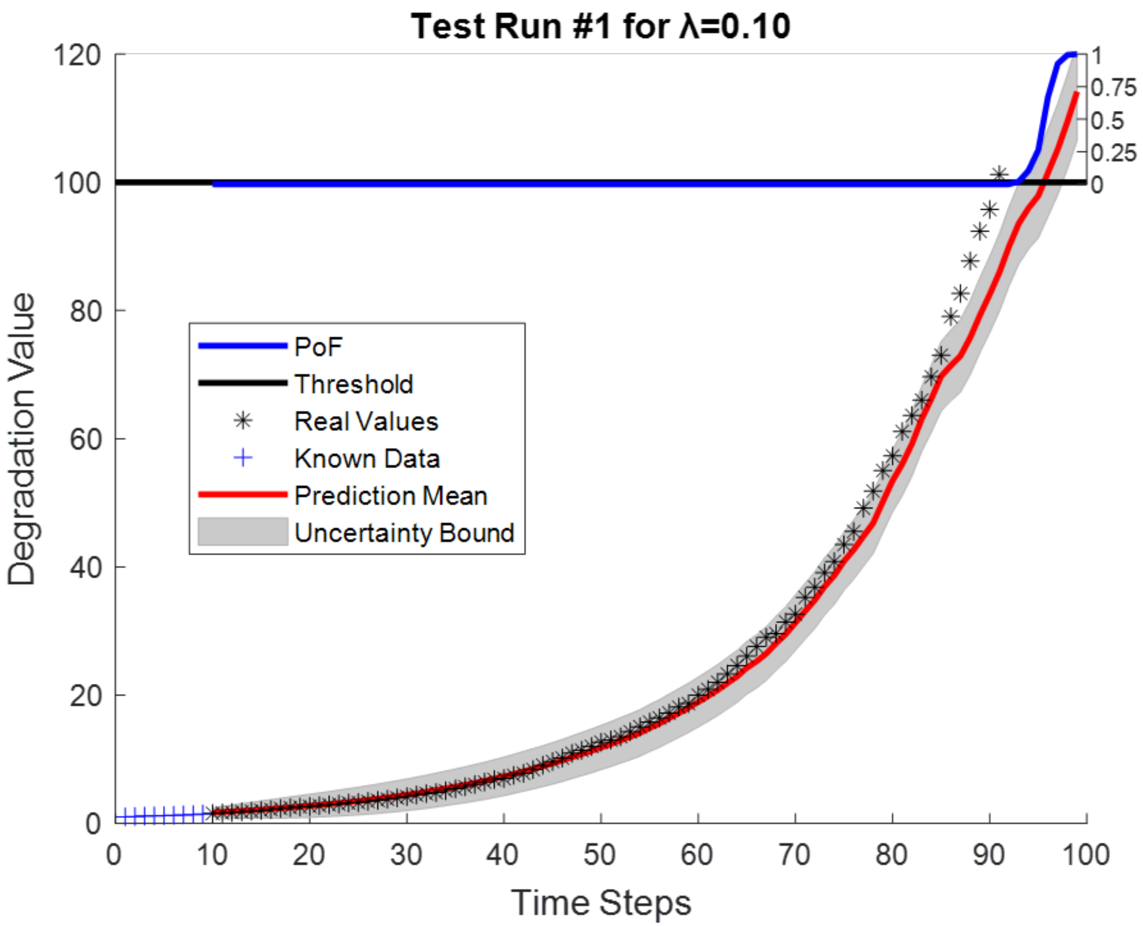
GPR inherently outputs an uncertainty boundary, but not all methods do

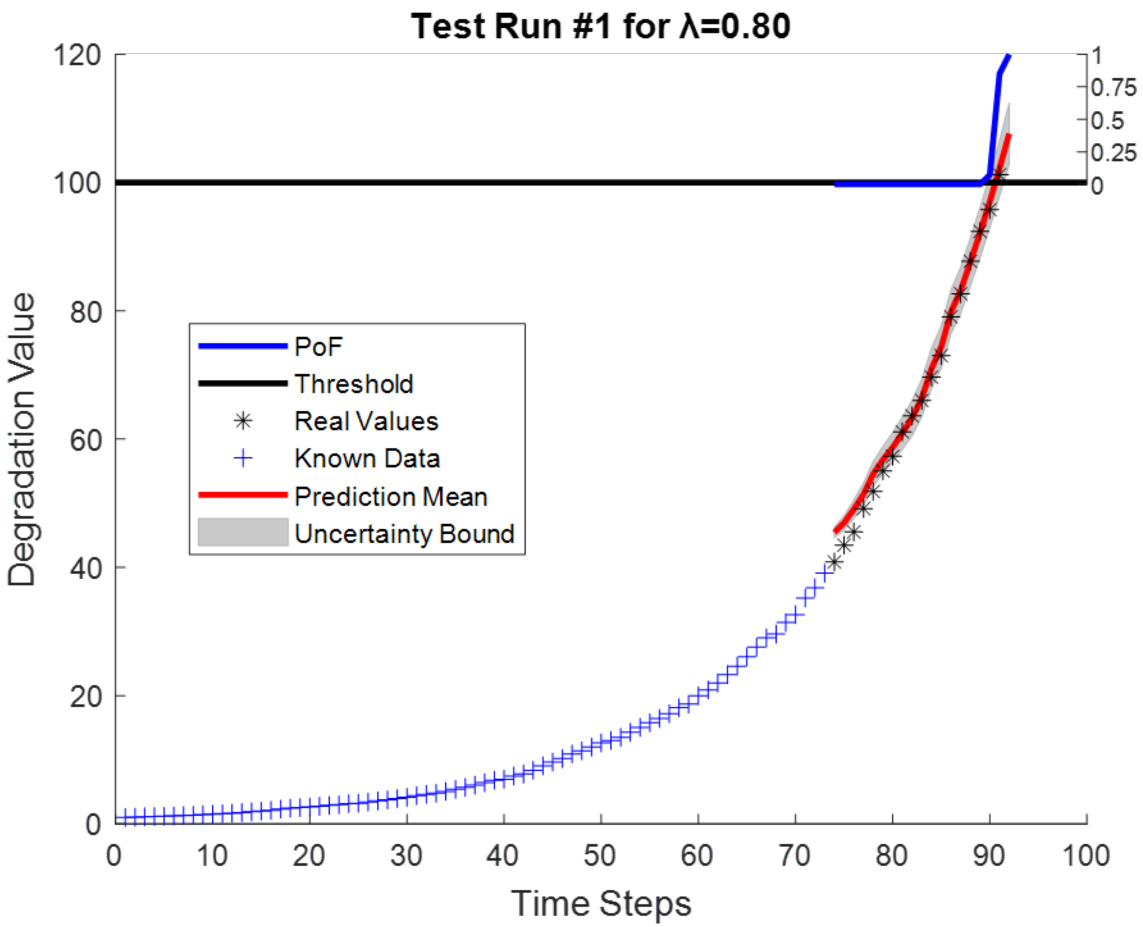
- Covariance function delivers uncertainty $\begin{pmatrix} f \\ f_* \end{pmatrix} \sim N\left(0, \begin{pmatrix} k(x,x) & k(x,x_*) \\ k(x_*,x) & k(x_*,x_*) \end{pmatrix}\right)$
- Not all methods output uncertainty

→ Use additional methods: Bootstrapping, Particle Filter, Monte Carlo,…



The same degradation curves as previously but with uncertainty

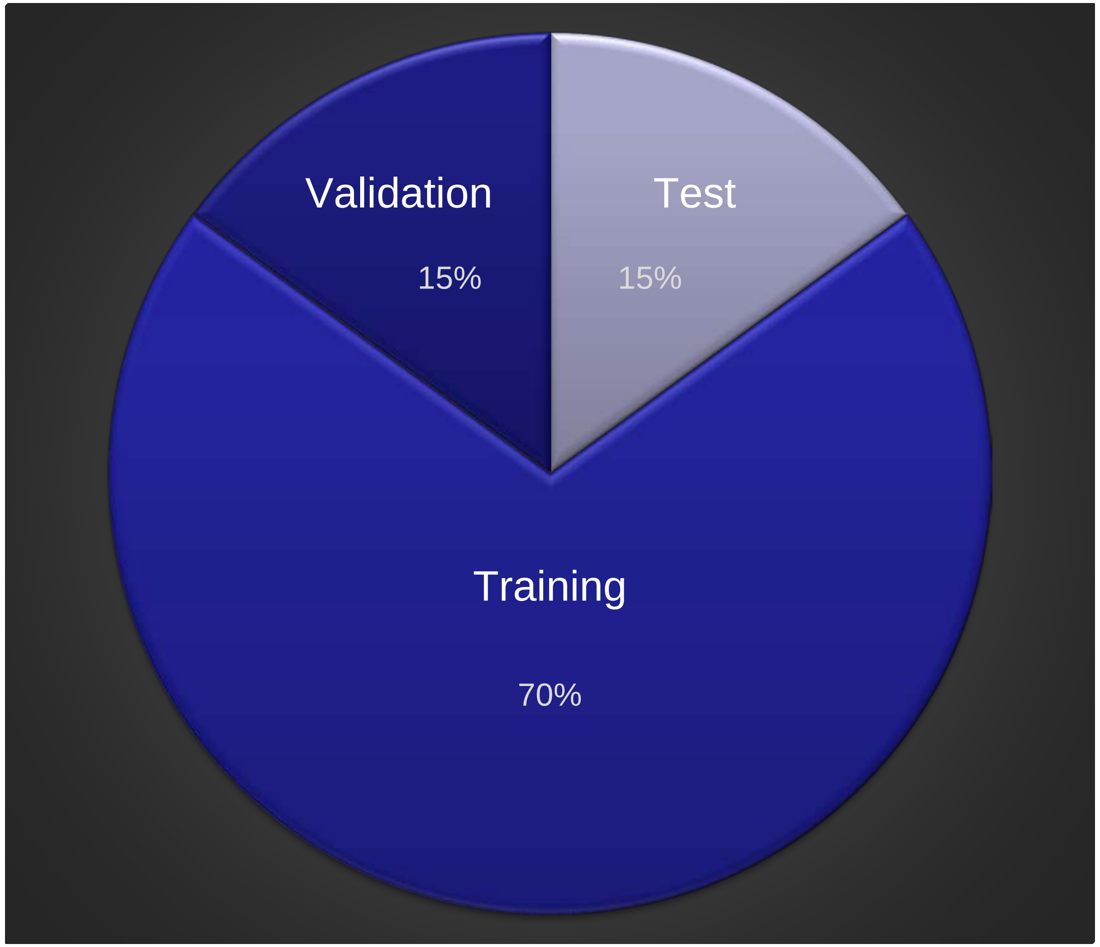




HOW TO EVALUATE THE PROGNOSTIC PERFORMANCE

The dataset is split into training, validation and testing

- **Training:** the data that is used to train an algorithm (e.g. Neural Network)
- **Validation:** the data that is used to optimize the parameters
- **Test:** the data that is used to test the trained model – never seen by the algorithm before



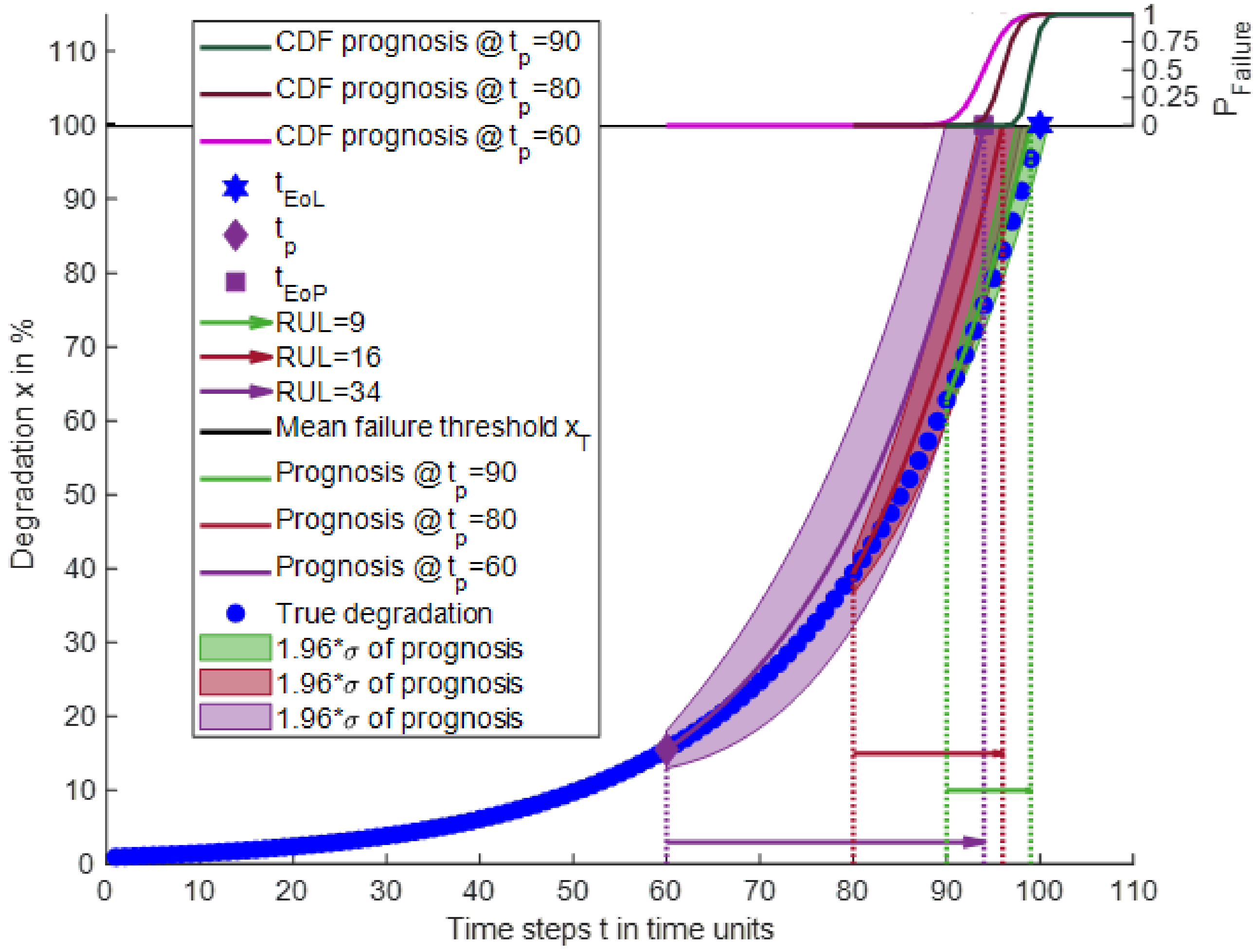
Test data is used to predict from different time steps

- For simplification and comparison reason normalized time steps are used

$$\lambda = {t_P}/{t_{EoL}}$$

- Normalization equalizes the different lifetimes
- Typical values are

$$\lambda = 0.1, 0.2, \dots, 0.9$$



Different performance metrics exist to compare prognostic's accuracy and precision

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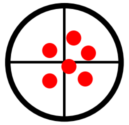


Accuracy based metrics

- **Error** $\Delta(i) = r_*(i) - r(i)$

  $r(i)$: RUL estimate at time t_i

  $r_*(i)$: True RUL at time t_i

  → represents the deviation

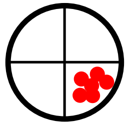
- **Mean absolute percentage error**

  $$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{100\Delta(i)}{r_*(i)}\right|$$

  → unit free metric

  → weighs small errors differently to big errors

  → heavier penalty on forecasts that exceed the actual than on those that are less



Precision based metrics

- **Sample standard deviation**

  $$SSD = \sqrt{\frac{\sum_{i=1}^{N}(\Delta(i)-\mu_\Delta)}{N-1}} \quad \text{with } \mu_\Delta\text{: mean of errors}$$

  → measures dispersion/spread of the error

  → normal distribution is assumed

- **Mean absolute deviation**

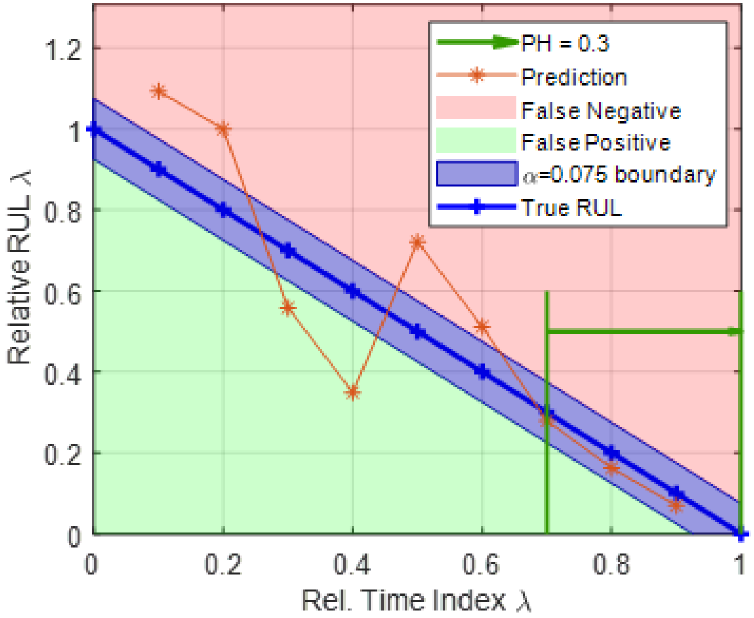
  $$MAD = \frac{1}{N}\sum_{i=1}^{N}\left|\Delta(i) - \text{median}\big(\Delta(i)\big)\right|$$

  → estimator of dispersion/spread of the error

  → can be used for small number of data

Different performance metrics exist to compare prognosis results

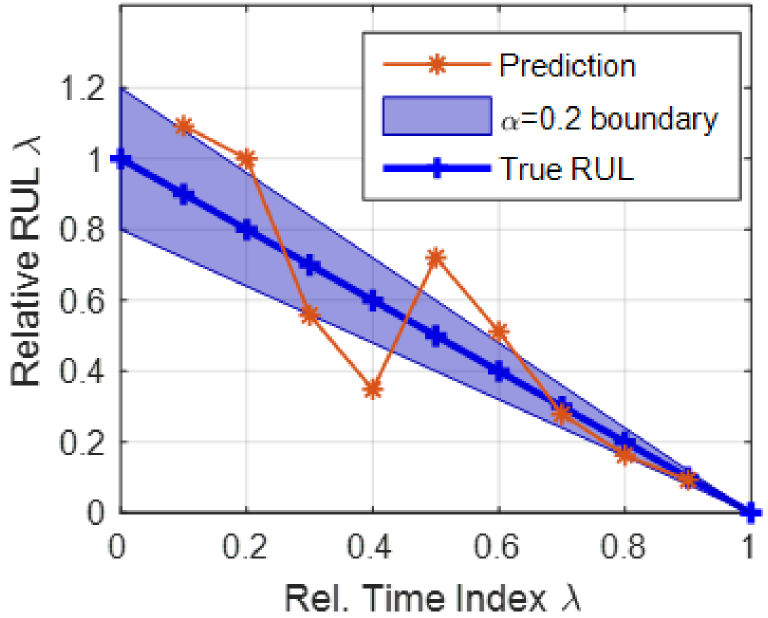
Prognostic Horizon



→ $1 - \lambda$ when the predictions stay inside boundary

- **False Positive:** unacceptable early predictions
- **False Negative:** unacceptable late predictions

$\alpha - \lambda$ Accuracy



→ Similar to Prognostic Horizon metric

→ Cone shape penalizes big errors for later predictions

→ Cone shape considers convergence

The performance of predictions can vary between test runs

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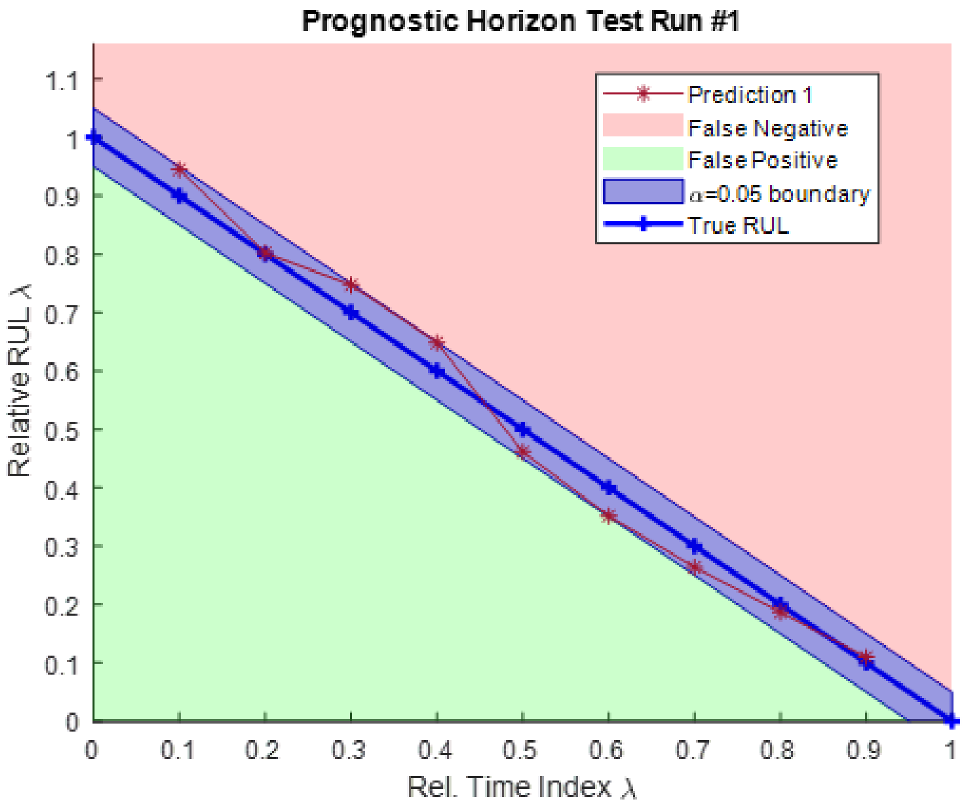
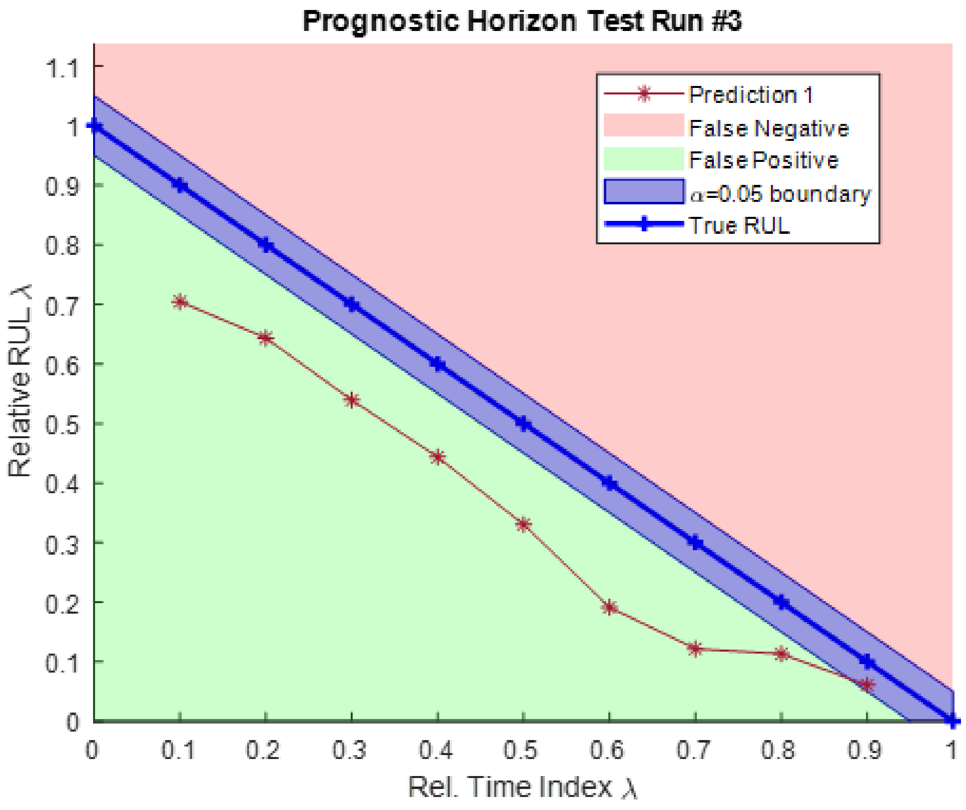


- Accurate prediction (PH = 0.5)
- Good result



- Prediction is inaccurate (PH = 0.1)
- Bad result
- **Safe result** (False Positive)

The function *predict* in MATLAB performs a prediction step

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➔ Let‘s have a look into MATLAB

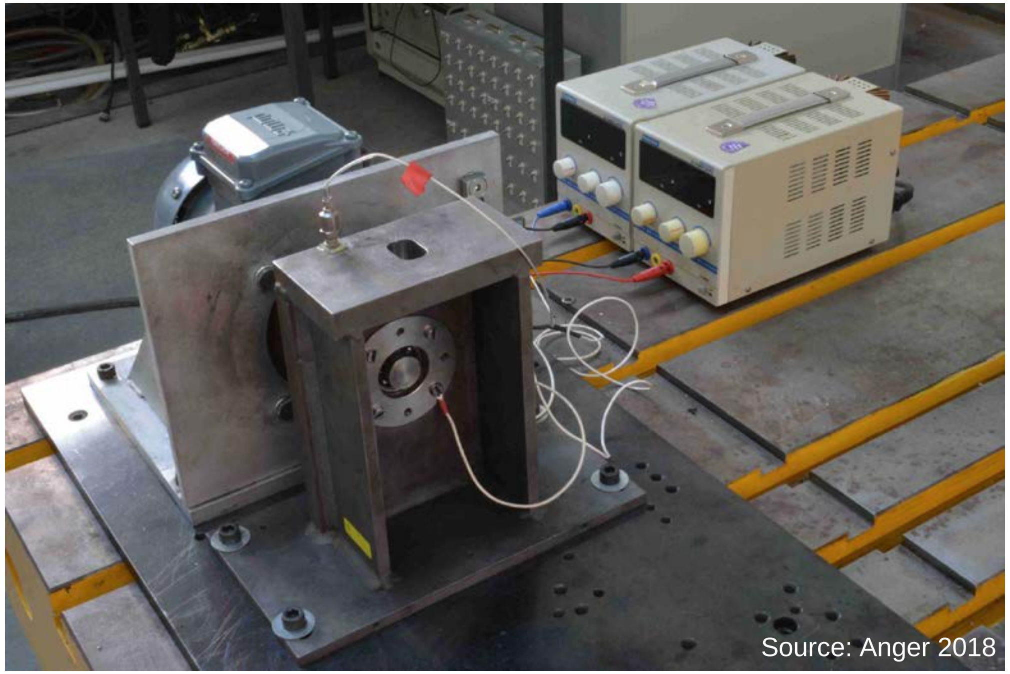
```
%% do the prediction
[y_predict(end+1,:), y_predictStdCurr] = predict(gprMdl.gprMdl,x_predict(end,:));
%% add up the variance of the prognosis
if isempty(y_predictStd)
        y_predictStd(1,:) = sqrt(y_predictStdCurr.^2 + conf.prog.baseStd.^2);
else
        y_predictStd(end+1,:) = sqrt(y_predictStd(end,:).^2 + y_predictStdCurr.^2);
end
```

CHALLENGES IN REAL WORLD APPLICATION

Prediction in laboratory environment is easier than in real world application

Laboratory environment

- Run-to-failure → accelerated degradation
- Controlled environment
- Different algorithms developed and approved



Source: Anger 2018

Real environment

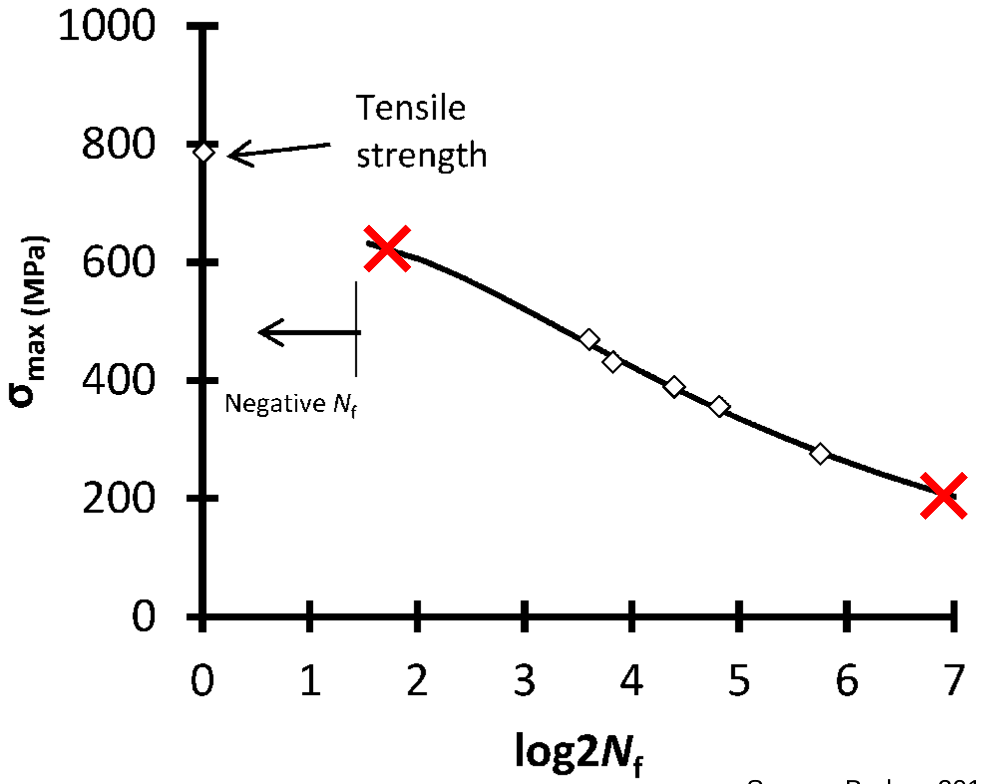
- No run-to-failure → limited data
- Environmental influences (vibration, weather,…)
- Algorithm transfer from labor is challenging

Source: EnBW

The higher the load, the higher the wear and vice versa

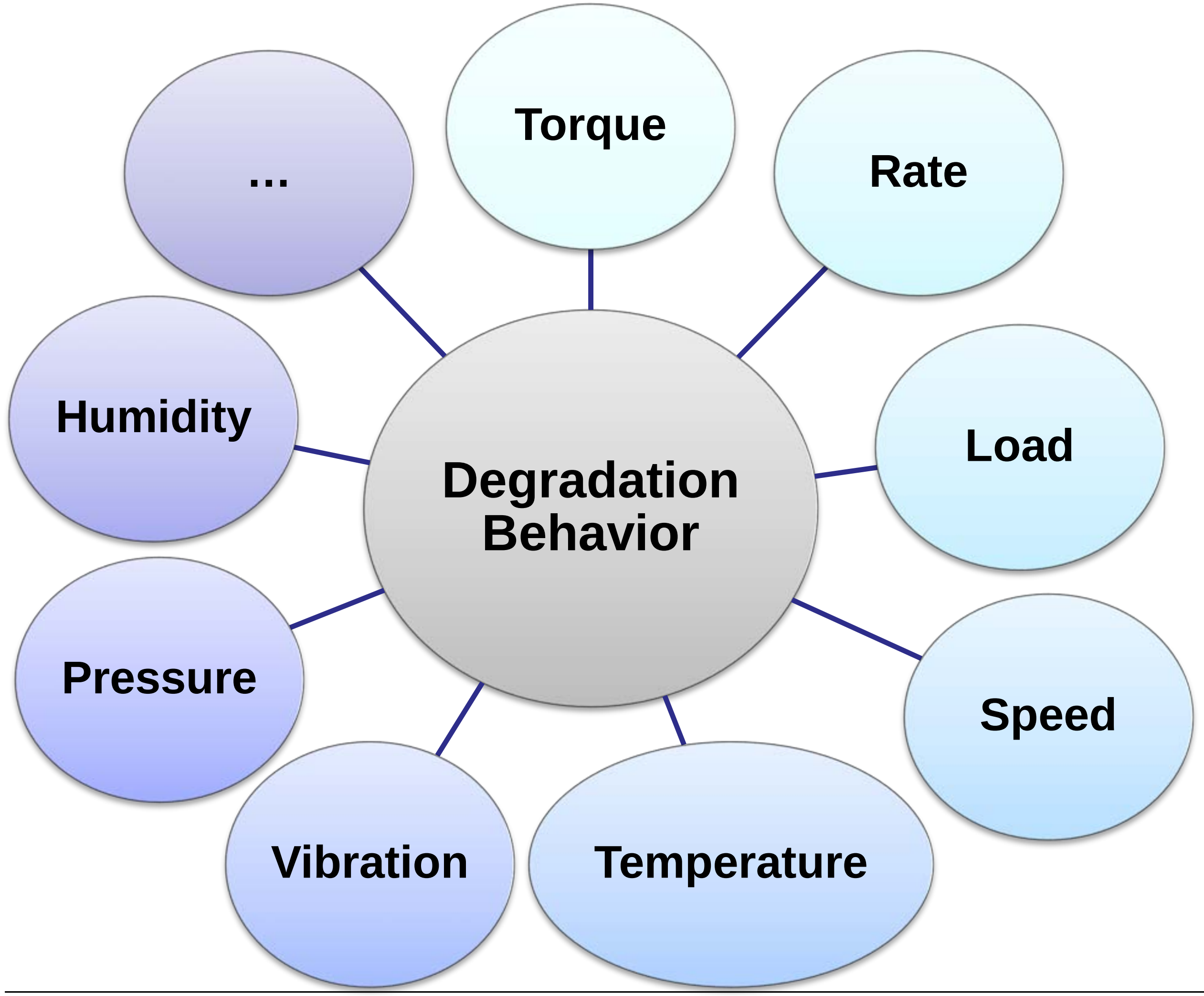
- Applied load determines the maximum number of cycles
- Well known from typical robustness models
  - Wöhler curve
  - Miner‘s rule
  - …

Wöhler-Curve



Source: Burhan 2018

There is a wide range of parameters that can effect degradation



- Parameter‘s relevance depends on usage scenario
- In case influence of parameter variation should be considered, additional measurement is required
- Planned conditions need to be known for a degradation prediction

What to take with you?

LEARNING OUTCOMES

Key Findings

- Prognosis only makes sense for components that show degradation behavior
- Creating a Health Indicator can be challenging
- RUL is typically interpreted as a time
- Different approaches are available to predict the RUL / degradation
- Consideration of the uncertainty is essential
- There are common metrics that can be used to evaluate the prognosis performance
- Application of prognosis algorithms in real world environment is challenging

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