University of Stuttgart
Institute of Machine Components
Reliability Department

# A Machine Learning Approach to Enhance the Information on Suspensions in Life Data Analysis

Probabilistic Safety Assessment and Management
PSAM 16
June 27, 2022, Honolulu, Hawaii
Tamer Tevetoğlu, M.Sc

IMA
UNI STUTTGART

# Outline

1. Motivation and Goals 
2. Simulation Setup 
3. Results and Discussion 
4. Summary and Outlook 

icons: [1]

# Outline

1 Motivation and Goals 

2 Simulation Setup 

3 Results and Discussion 

4 Summary and Outlook 

# Motivation

**Motivation**:
- Budget and time constraints
- Small sample sizes and censoring:
  - Biased estimates
  - Low coverage probabilities

**State of the art**
- Countermeasures:
  - Maximum likelihood estimation (MLE):
    → takes failures and suspensions into account
  - Bias-correction methods
- Most research focuses on analytical studies with an infinite population

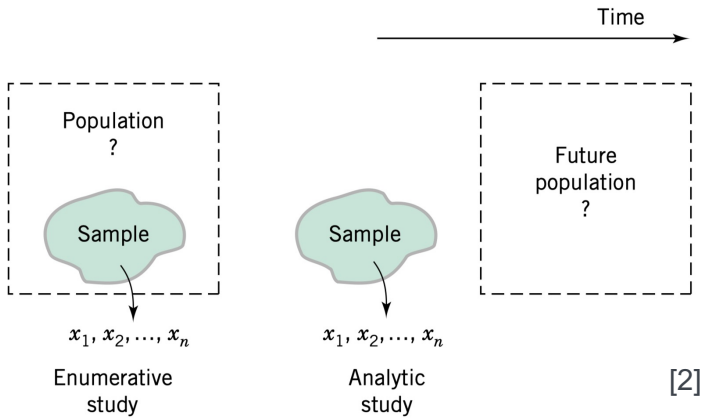
**Focus of this paper**
- Enumerative study with finite population
- Using machine learning to enhance the existing information (failures & suspensions):
  - Extending the Weibull analysis
  - Analyzing the practicality and performance
  - Simulation study

# Case Study

**Finite Population** (Turbofan Engine Degradation Simulation Data Set)
→ time-series data until end-of-life

**Enumerative** study

Weibull Time To Event Recurrent Neural Network (**WTTE-RNN**)
→ predicting the RUL of suspensions




[2]


Can we generally use WTTE-RNN to predict RULs in life data analyses, and if so, does it help to obtain more accurate confidence bounds?

# Outline

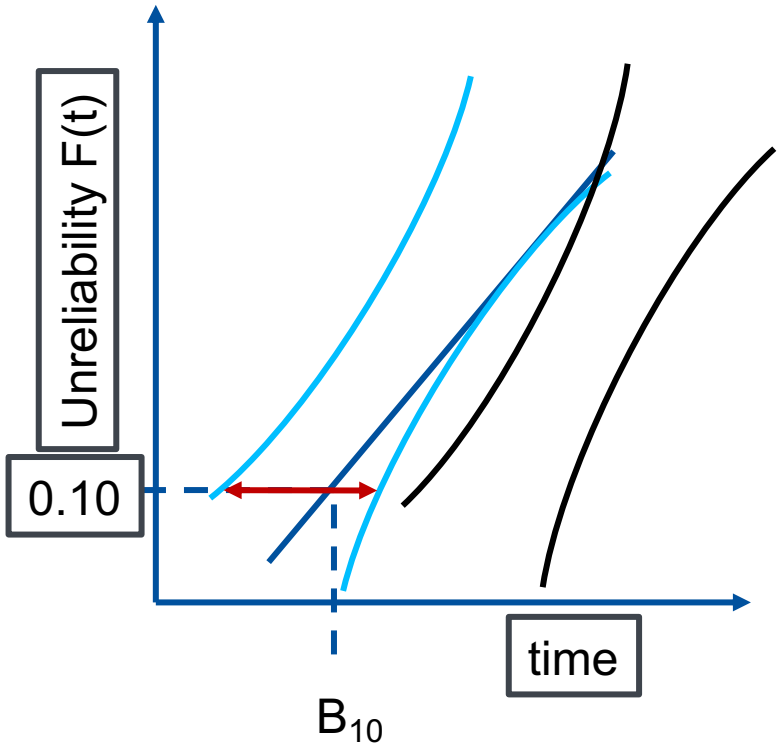
# Assessment Criteria

## Coverage Probability (CP)

- Frequentist probability that the confidence interval contains the true $B_{10}$-life
- Monte-Carlo approximation:

$$CP = \frac{n_b}{n_t}$$

- Adequate: CP = 0.89…0.91



# Dataset
## Turbofan engine degradation simulation data set

- Simulation was carried out using **C-MAPSS** (Commercial Modular Aero-Propulsion System Simulation)
- Dataset being used: **FD001**
  - 100 turbines
  - 1 failure mode (HPC Degradation)
  - 21 sensors (e.g. temperature, pressure, …)
  - end-of-life available

| TURBINE ID | CYCLE | SETTING 1 | … | SETTING 3 | SENSOR 1 | … | SENSOR 21 |
|---|---|---|---|---|---|---|---|
| 1 | 1 | -0,0007 | … | 100 | 518,67 | … | 234.190 |
| 1 | 2 | 0,0019 | … | 100 | 518,67 | … | 234.236 |
| 1 | 3 | -0,0043 | … | 100 | 518,67 | … | 233.442 |
| | | | | ⋮ | | | |
| 1 | 190 | -0,0027 | … | 100 | 518,67 | … | 230.675 |
| 1 | 191 | 0,0000 | … | 100 | 518,67 | … | 231.295 |
| 1 | 192 | 0,0009 | … | 100 | 518,67 | … | 229.649 |

Ground Truth:

| $B_{10}$ | Weibull Shape Parameter $\beta$ | Weibull Scale Parameter $\eta$ |
|---|---|---|
| 135.06 cycles | 4.41 | 225.03 cycles |

# Bias-Corrections

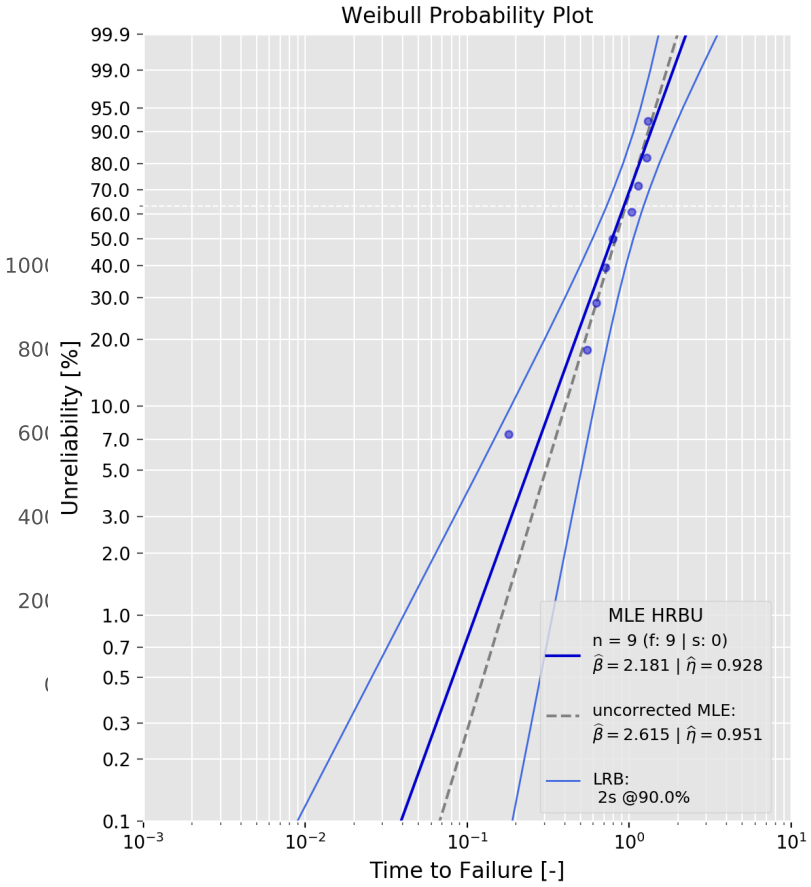
## Hirose and Ross method

- Mean correction
- Considers right-censored data

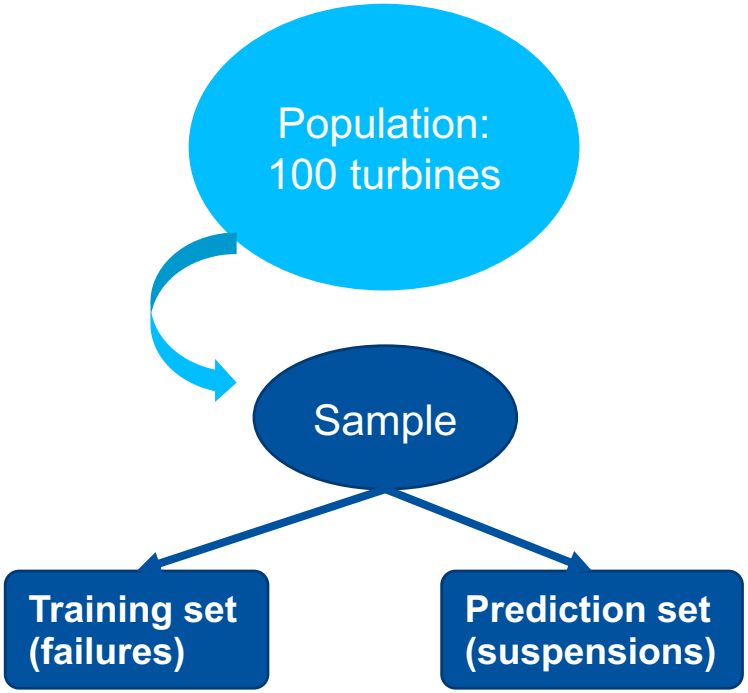
$$\hat{\beta}_{HRBU} = \frac{\hat{\beta}_{MLE}}{1.0115 + \frac{1.278}{df} + \frac{2.001}{df^2} + \frac{20.35}{df^3} - \frac{46.98}{df^4}}$$

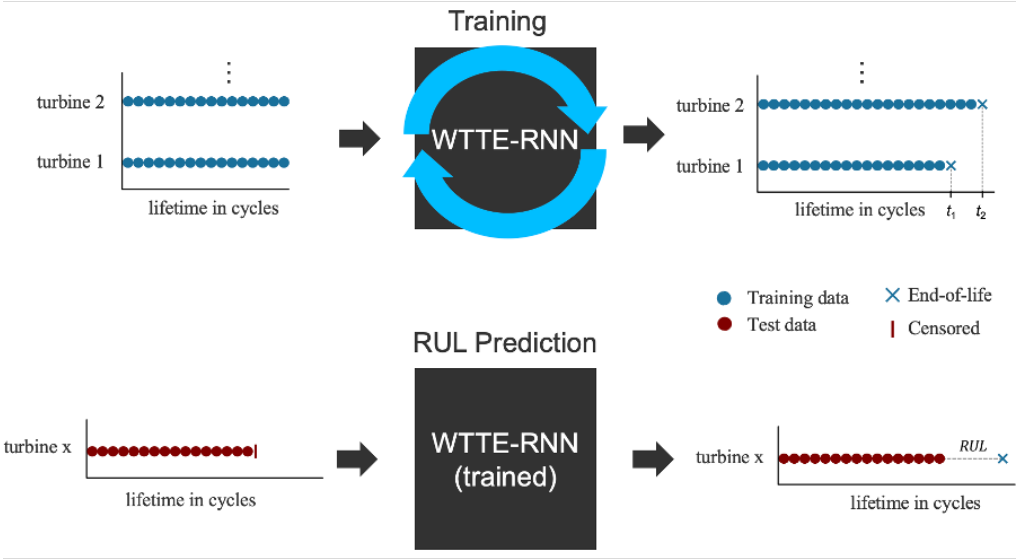
$$\hat{\beta}_{HRBU} = \frac{\hat{\beta}_{MLE}}{1 + \frac{1.37}{df - 1.92} \cdot \sqrt{\frac{n}{df}}}$$

*df*: failures
*ds*: suspensions

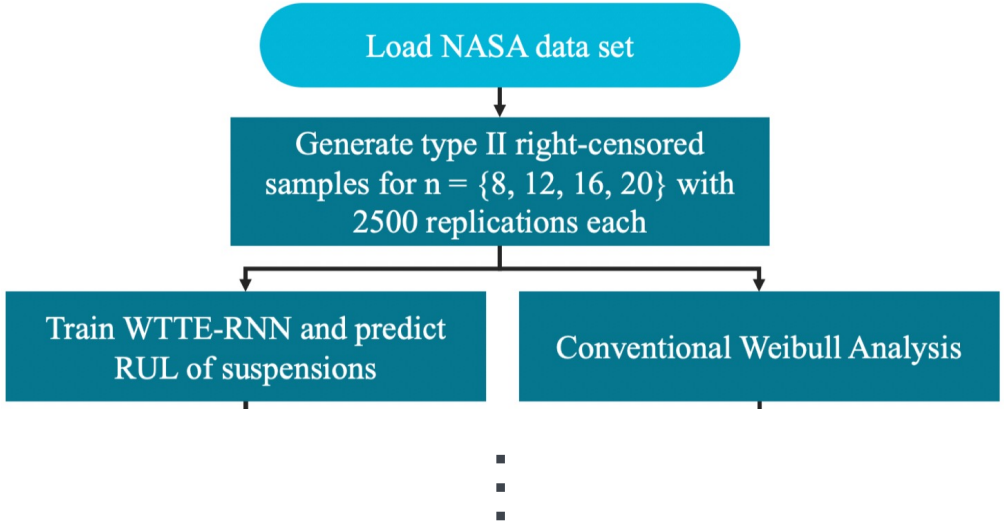


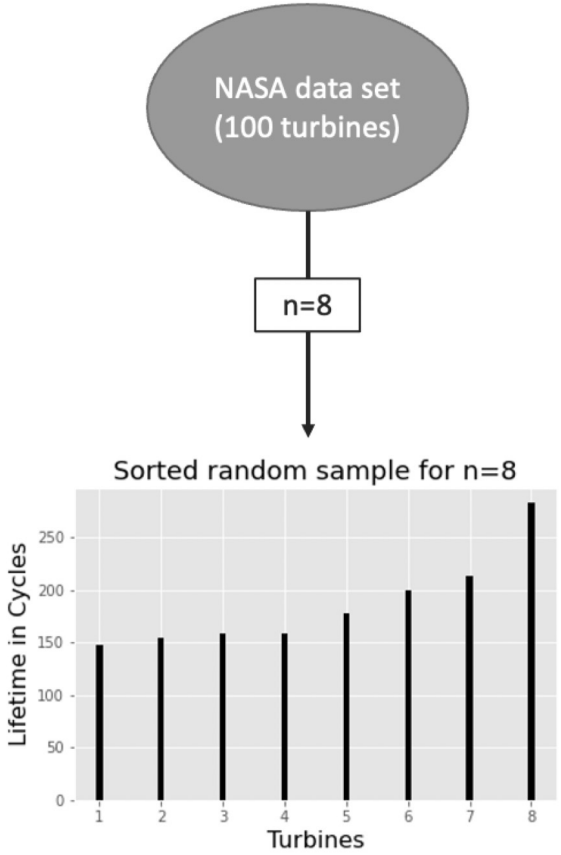
# WTTE-RNN


Population:
100 turbines
Sample
Training set
(failures)
Prediction set
(suspensions)

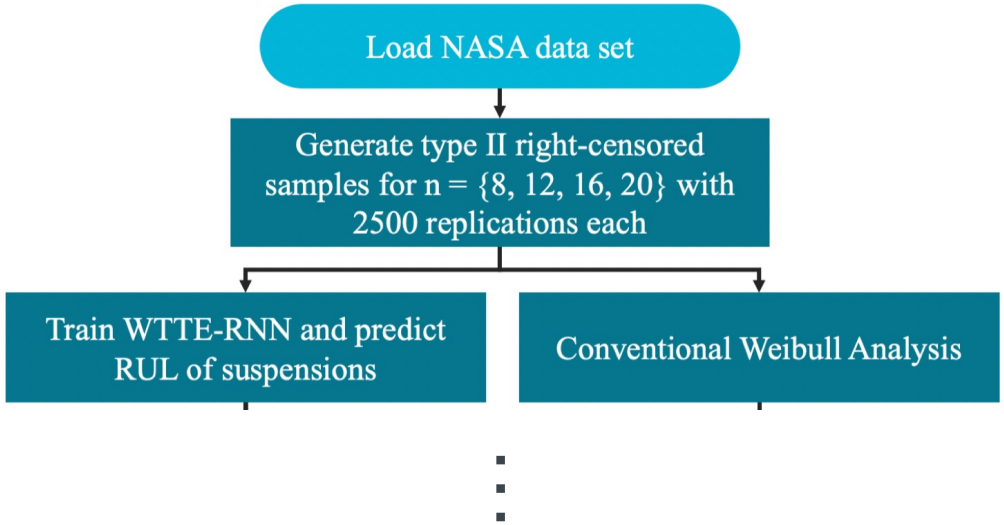

Training
turbine 2
turbine 1
lifetime in cycles
WTTE-RNN
turbine 2
turbine 1
lifetime in cycles
$t_1$
$t_2$
Training data
Test data
End-of-life
Censored
RUL Prediction
turbine x
lifetime in cycles
WTTE-RNN
(trained)
turbine x
RUL
lifetime in cycles

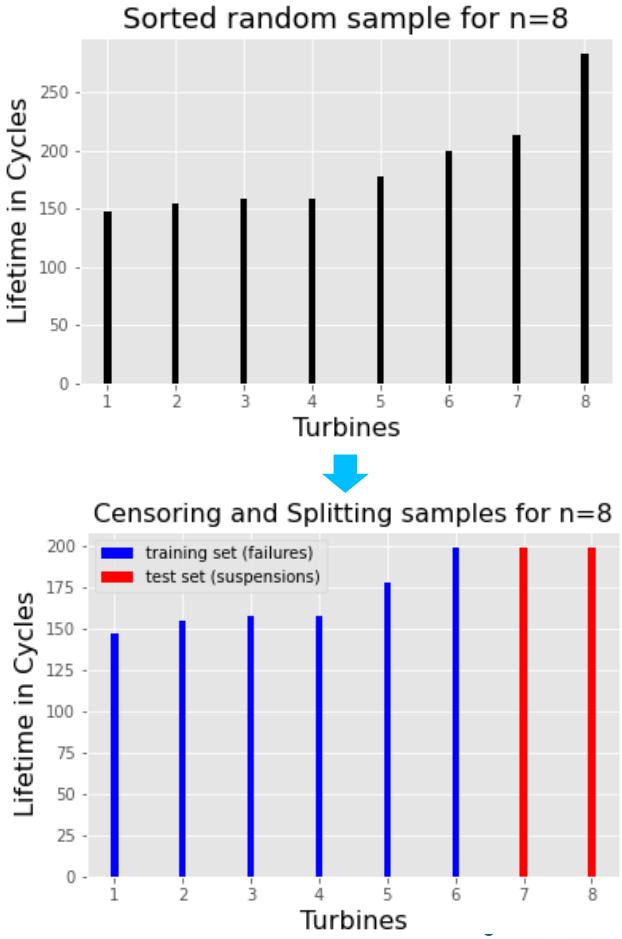
# Simulation Setup



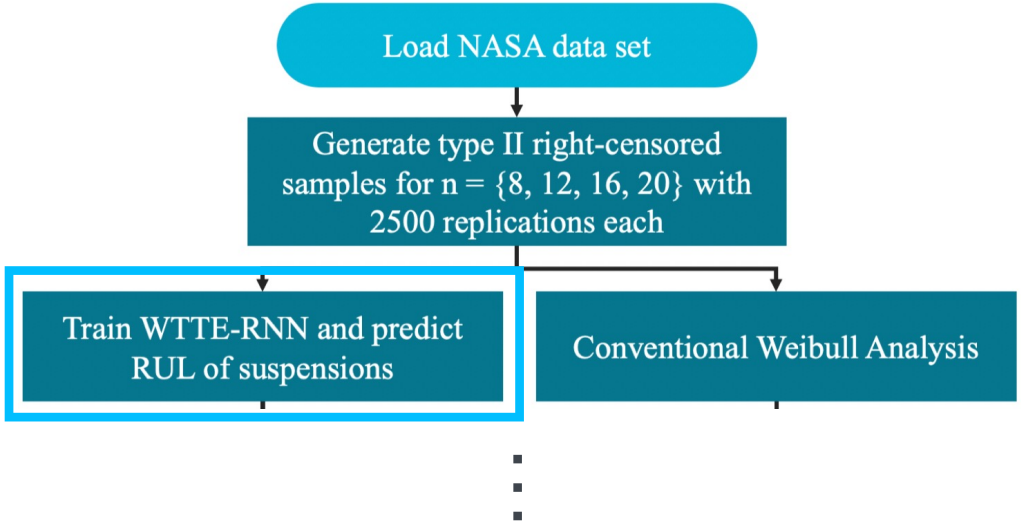



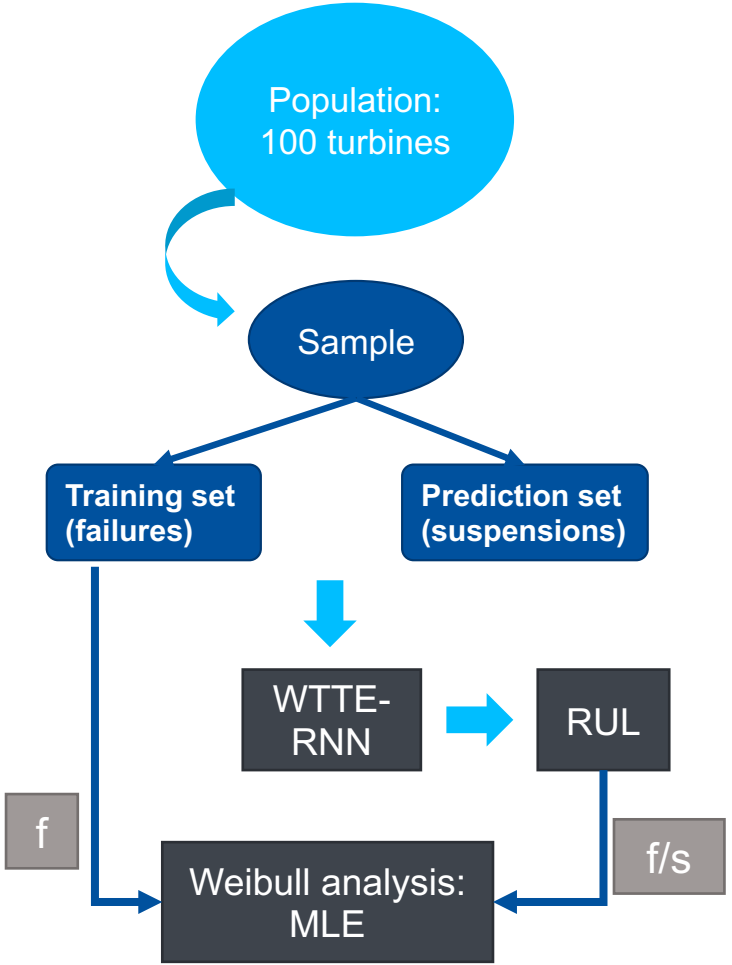
# Simulation Setup



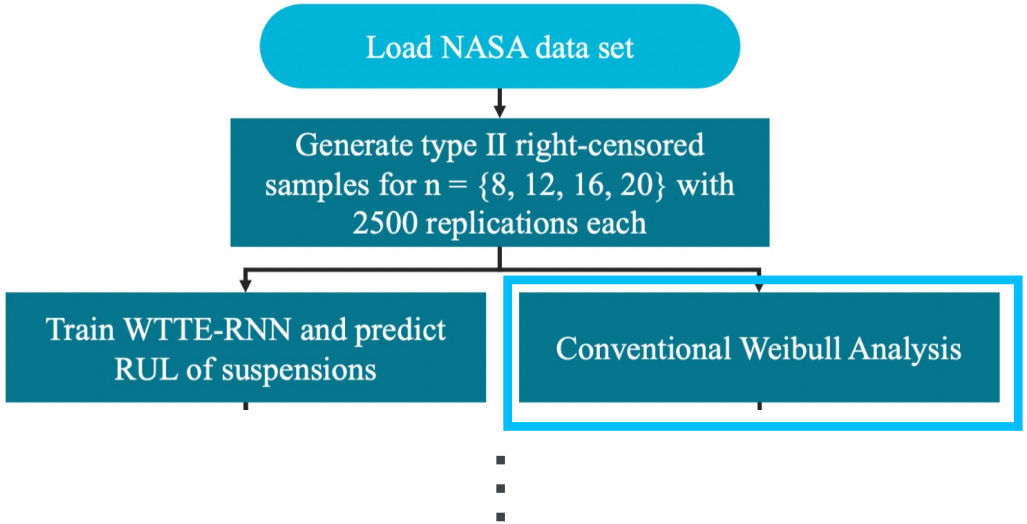



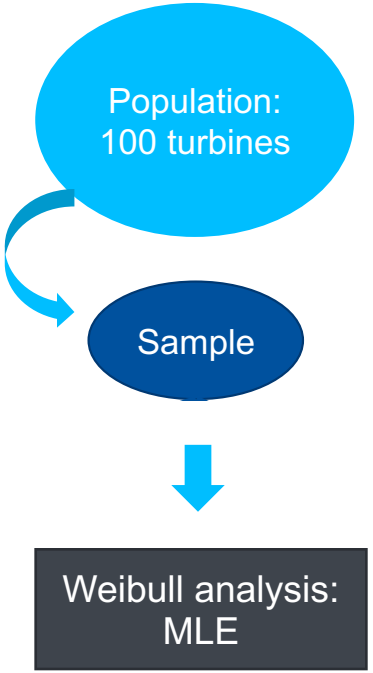
# Simulation Setup



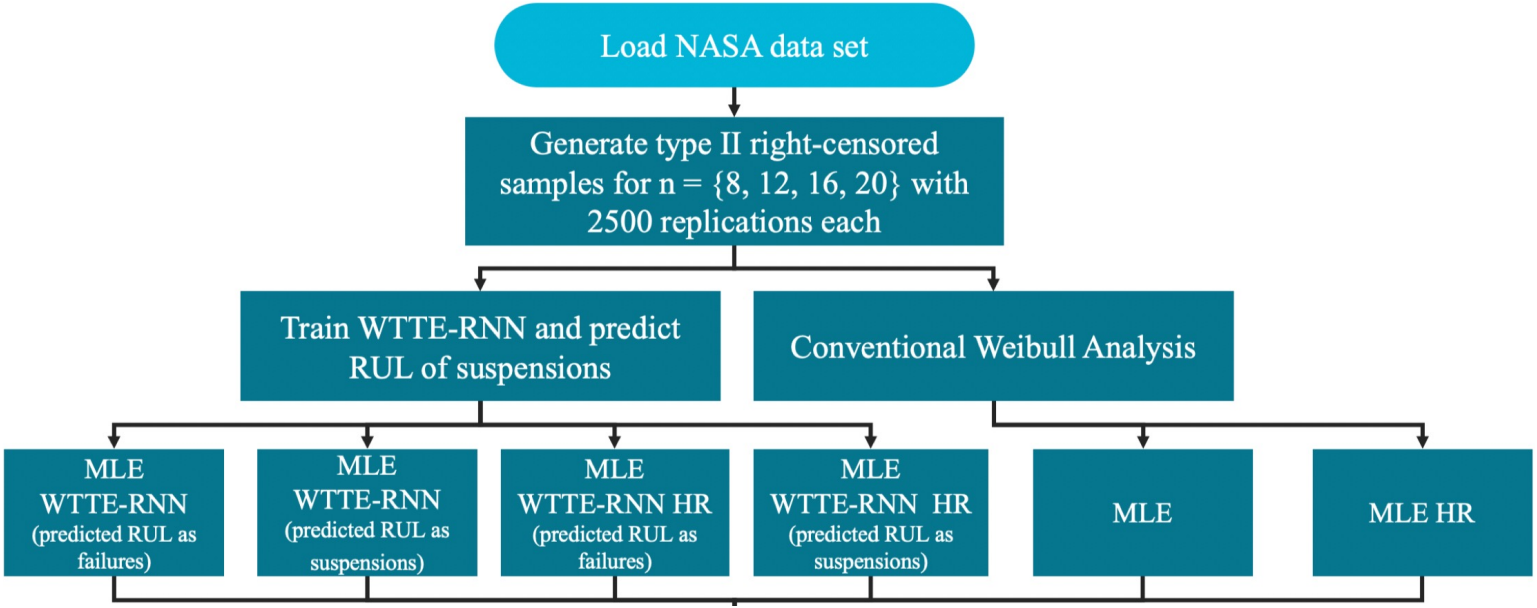



# Simulation Setup

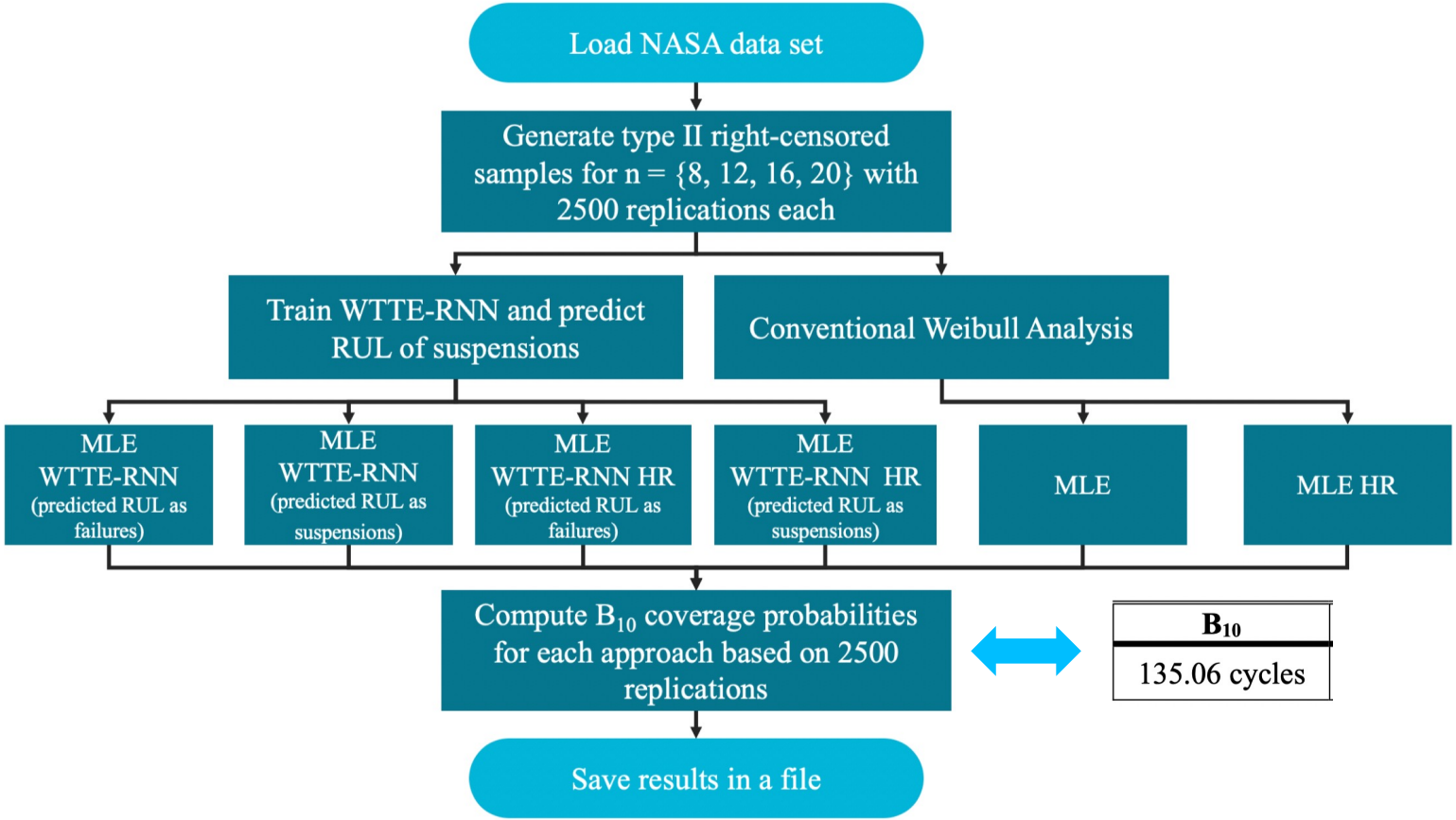


# Simulation Setup



# Simulation Setup



# Outline

1 Motivation and Goals 

2 Simulation Setup 

3 **Results and Discussion** 

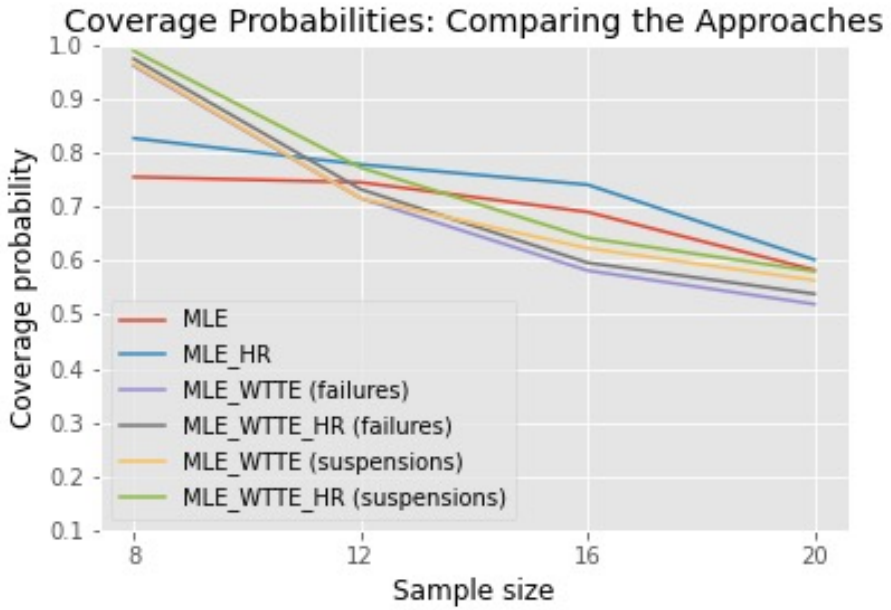
4 Summary and Outlook 



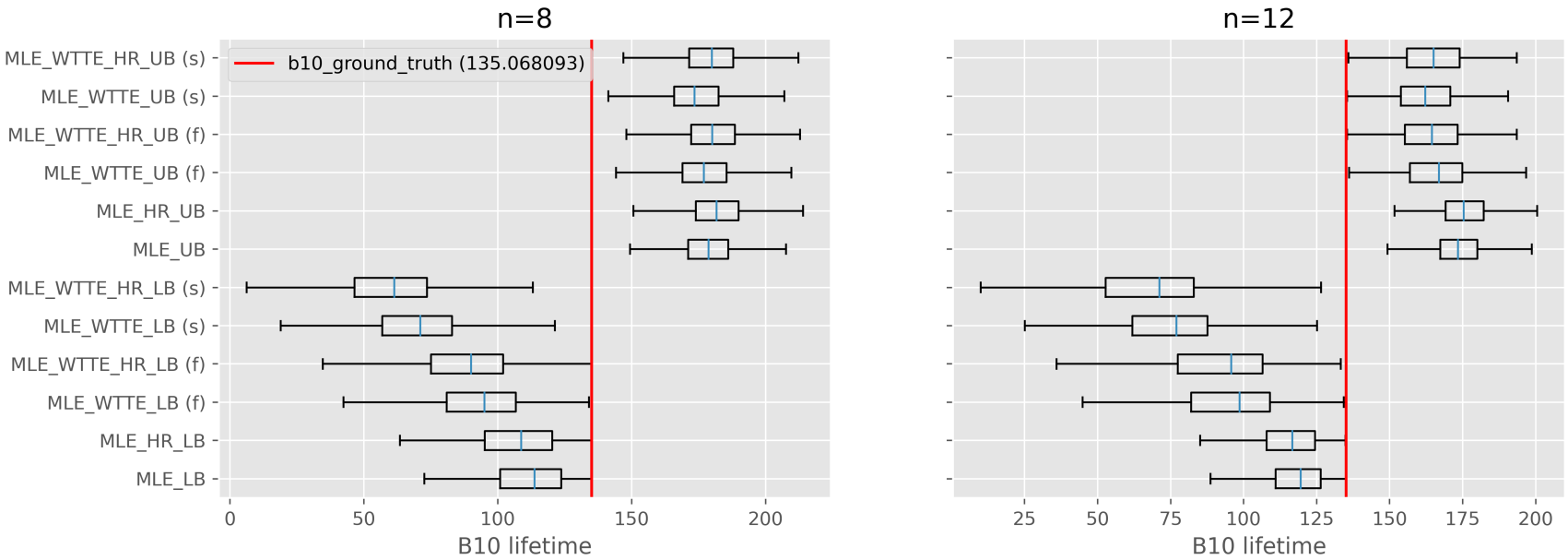
UNI STUTTGART

# Results

- All WTTE_RNN perform better than the conventional approaches for n = 8
- Bias-corrected conventional Weibull analyses result in a higher coverage probability than non-corrected ones
- Using the predicted RUL as suspensions rather than as failures in the MLE performs better
- For n = 12: All approaches perform about the same
- For n=16 and n = 20: Conventional approaches perform better

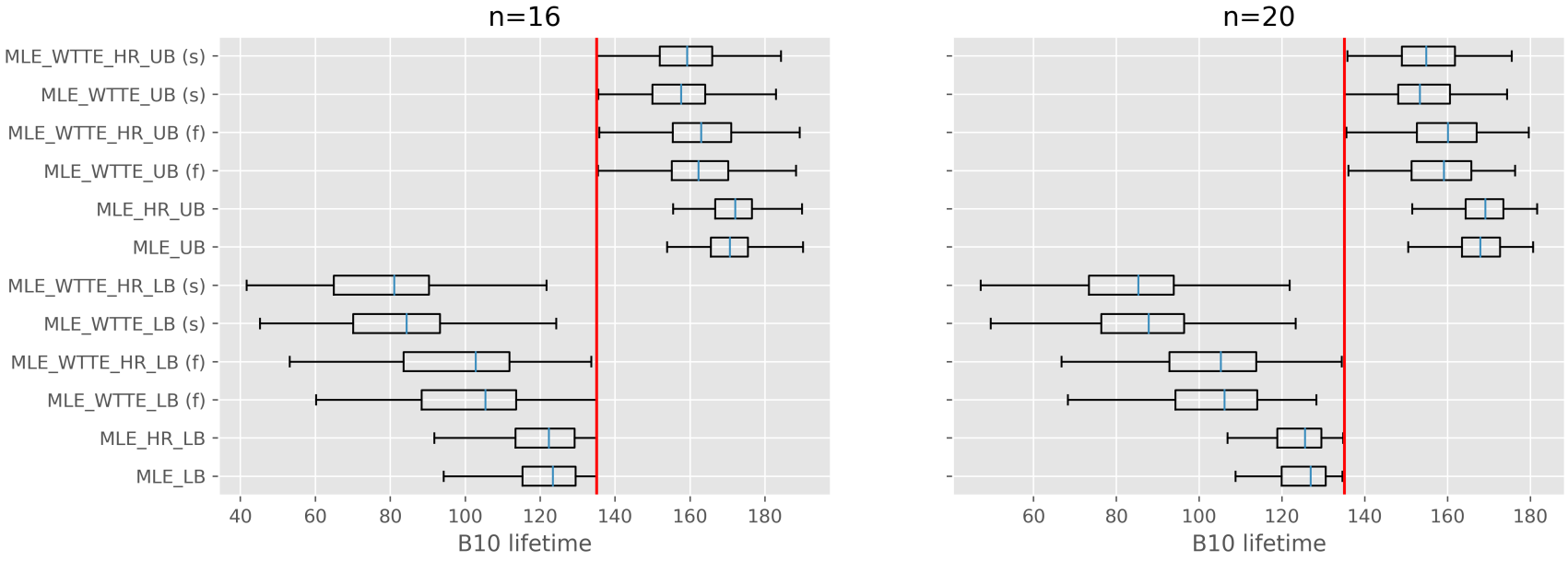


# Results




UB: upper bounds LB: lower bounds

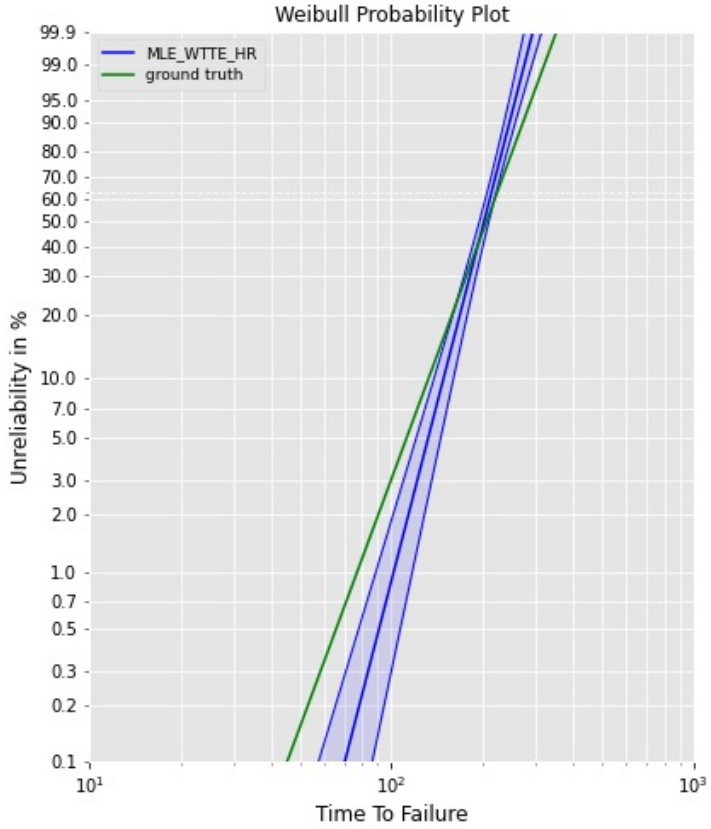
# Results




UB: upper bounds LB: lower bounds

# Discussion

- WTTE-RNN (f) using predicted RUL as actual failure data are significantly closer to the ground truth than WTTE-RNN (s)
- Overall, conventional approaches have less deviating lower and upper bounds
- The data shows that using the predicted RUL as suspensions rather than as failures in the MLE performs better
- **Bias-variance tradeoff:**
  - Green line: n = 100 failures.
  - Blue line: n = 80 (60 failures, 20 suspensions)



# Conclusion

- Study type (enumerative or analytical) and population type (focus of this paper: finite) are very important regarding the coverage
- The CP decreases for a finite population in an enumerative as the sample size increase → contrary to infinite populations
- WTTE-RNN can help to increase the CP for small sample sizes
- Predicted information (RUL) as enhanced information on suspensions is recommended

# Outline

1 Motivation and Goals 

2 Simulation Setup 

3 Results and Discussion 

4 Summary and Outlook 

## Summary

- The data shows that…

  …using the predicted **RUL as suspensions** rather than as failures in the MLE performs better

  …the **type of study** (enumerative or analytical) and **type of population** are very important regarding the coverage probability

- The CP decreases for a finite population in an enumerative as the sample size increases
- WTTE-RNN can help to increase the CP for small sample sizes

## Outlook

- High potential in optimizing data-driven approaches for Weibull analyses
- Future data-driven models in life data analysis should find the sweet spot between prediction accuracy and variance
- Conduct more simulation studies with available data

# Bibliography


| ID | Source |
|---|---|
| [1] | www.flaticon.com |
| [2] | Engineering Statistics 5th Edition – Montgomery et al. |
| | |
| | |
| | |
| | |
| | |
| | |


UNI STUTTGART