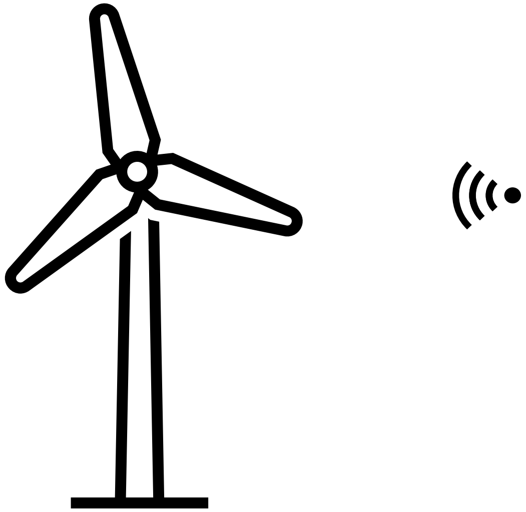
TOWARDS FULL-LIFECYCLE BEARING HEALTH STATE MONITORING: CHALLENGES AND OPPORTUNITIES

Cees Taal, IMC 2022

Future of Bearing Health Diagnostics and Prognostics

Digital Twin



Customer

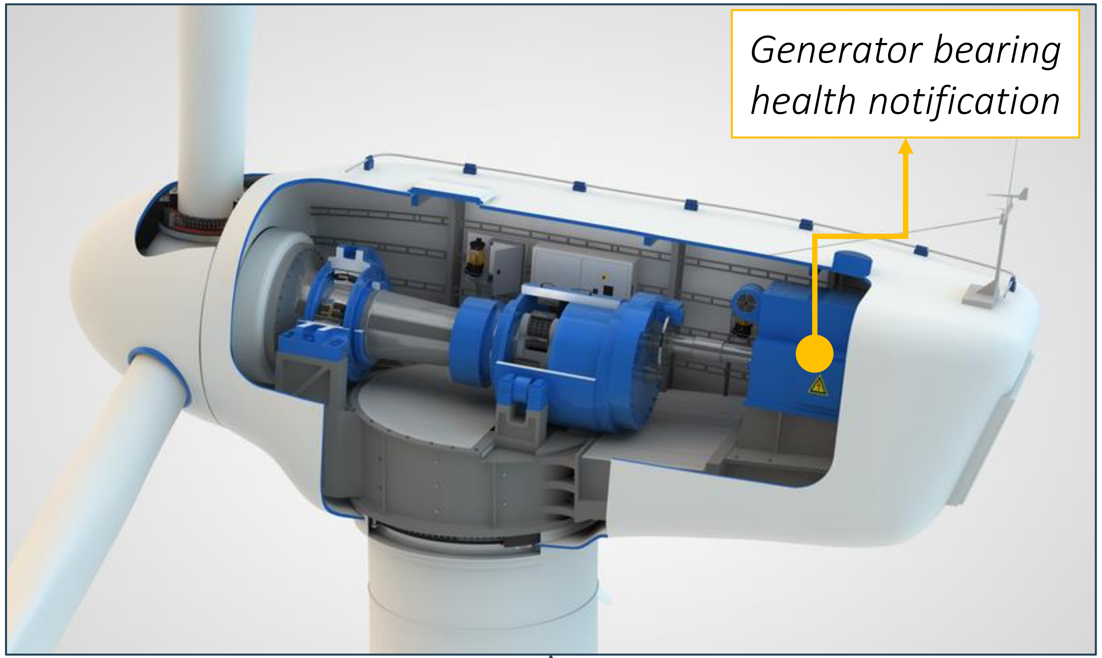
Maintenance advice

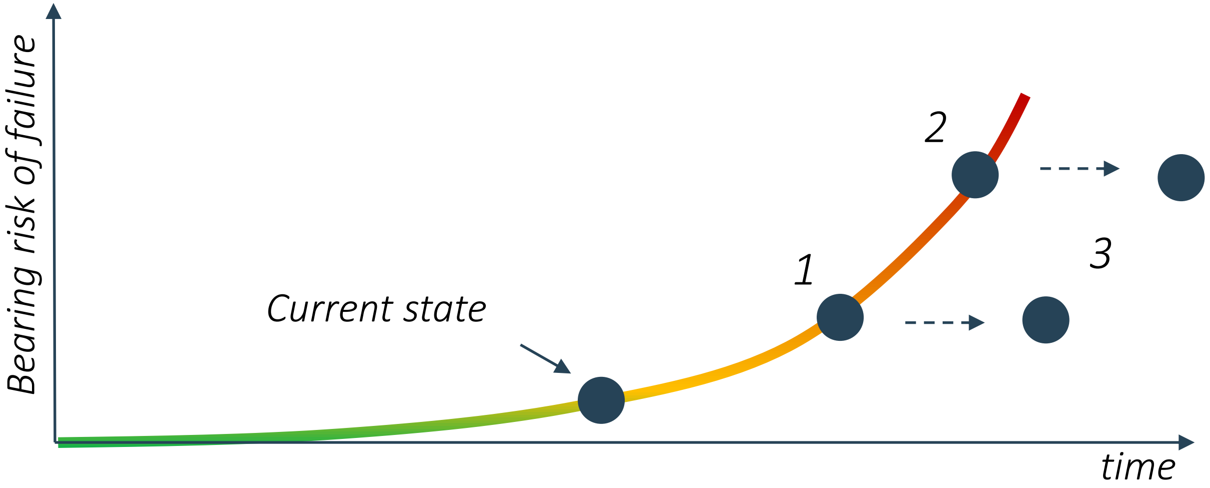
environmental impact

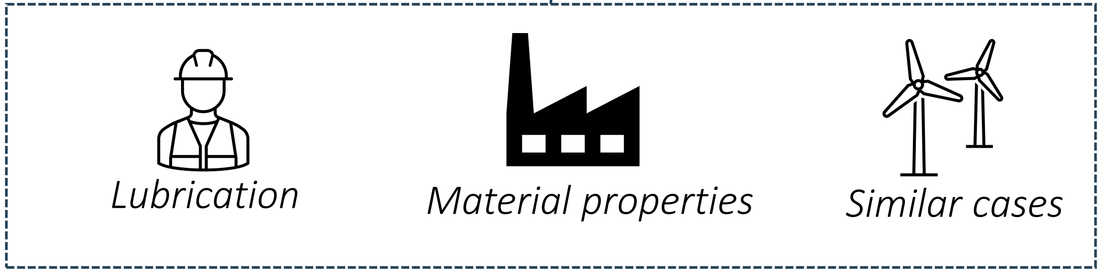
Risk

costs

Future of Bearing Health Diagnostics and Prognostics

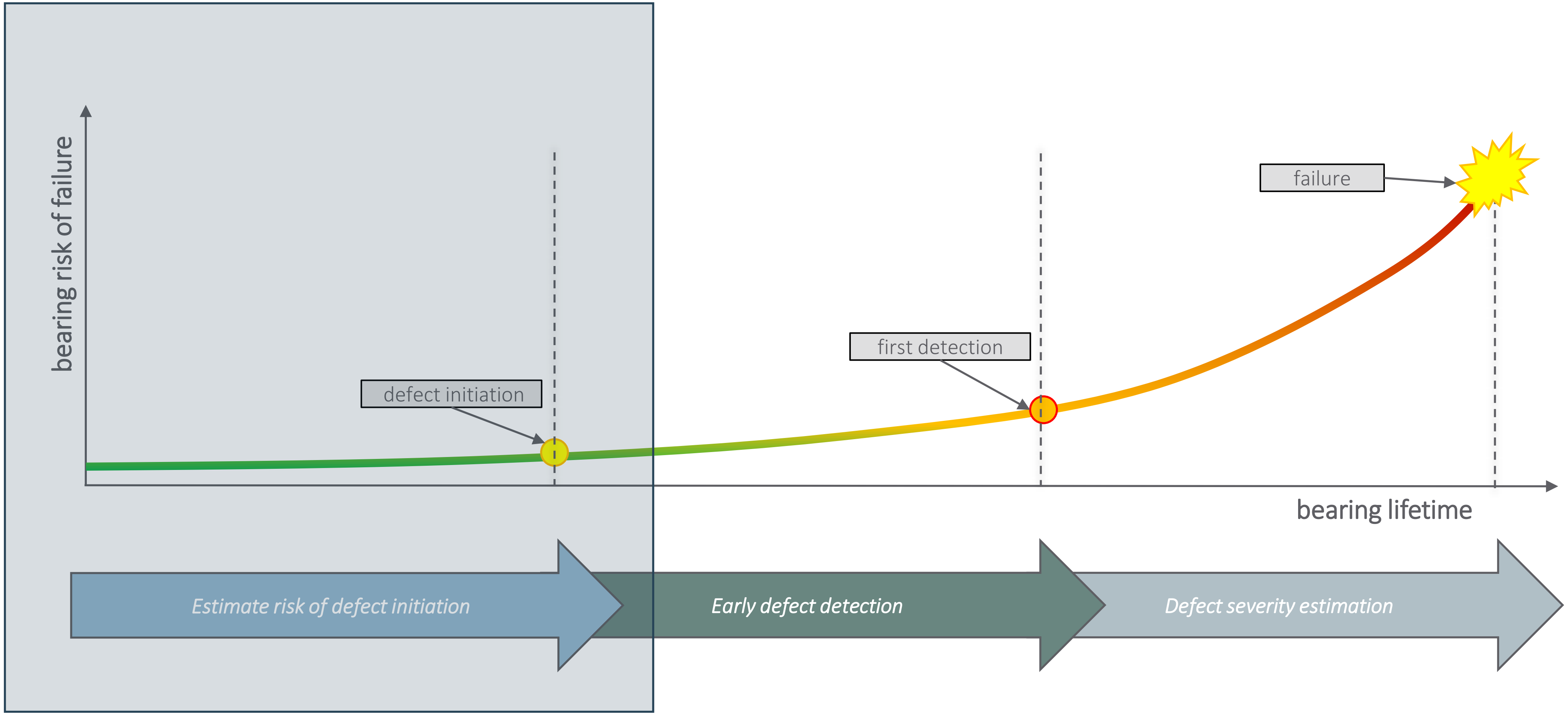




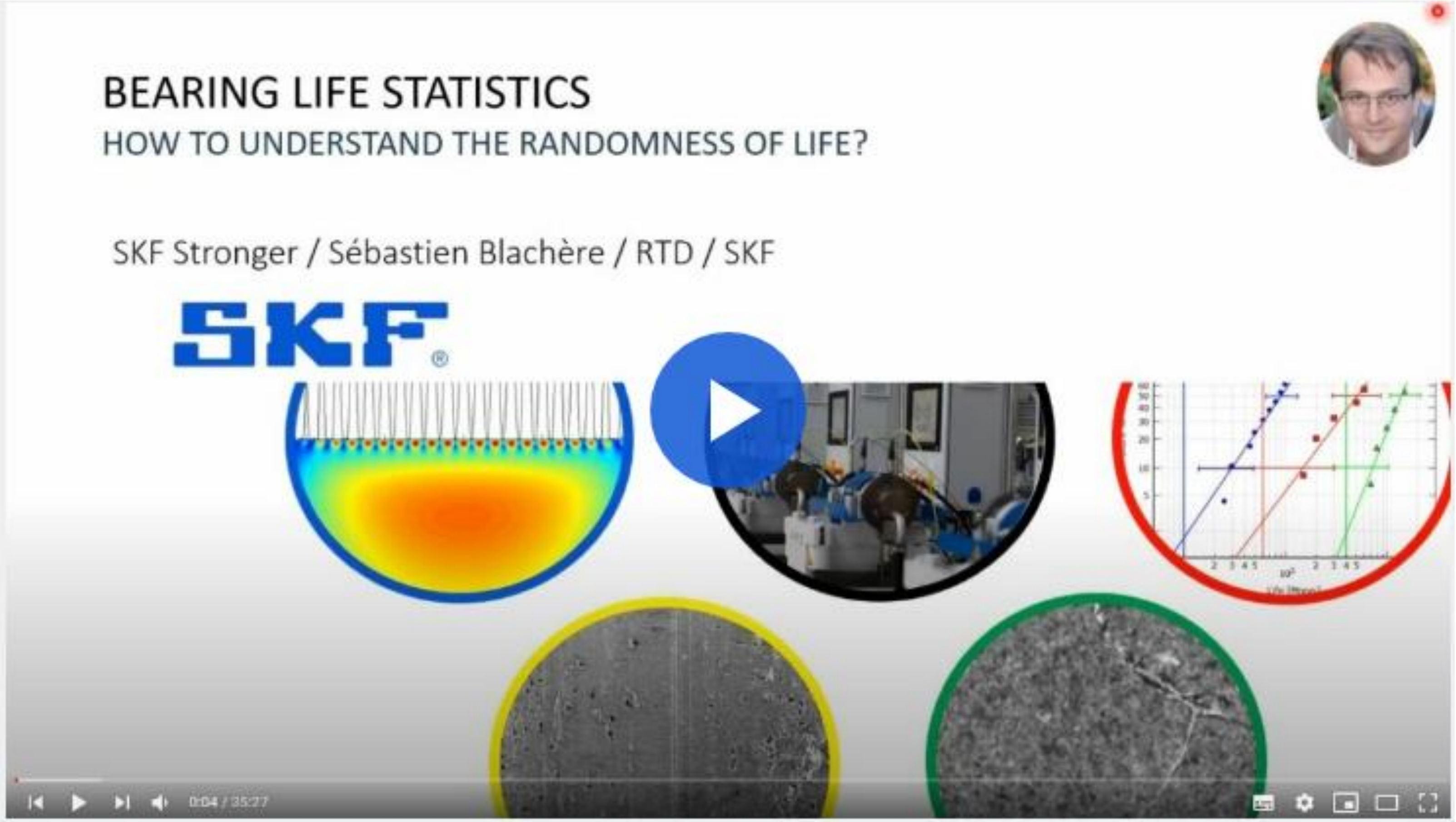


1. Remaining life for remanufacturing
2. Remaining useful life
3. Change load conditions to improve life

Full lifecycle bearing health state estimation

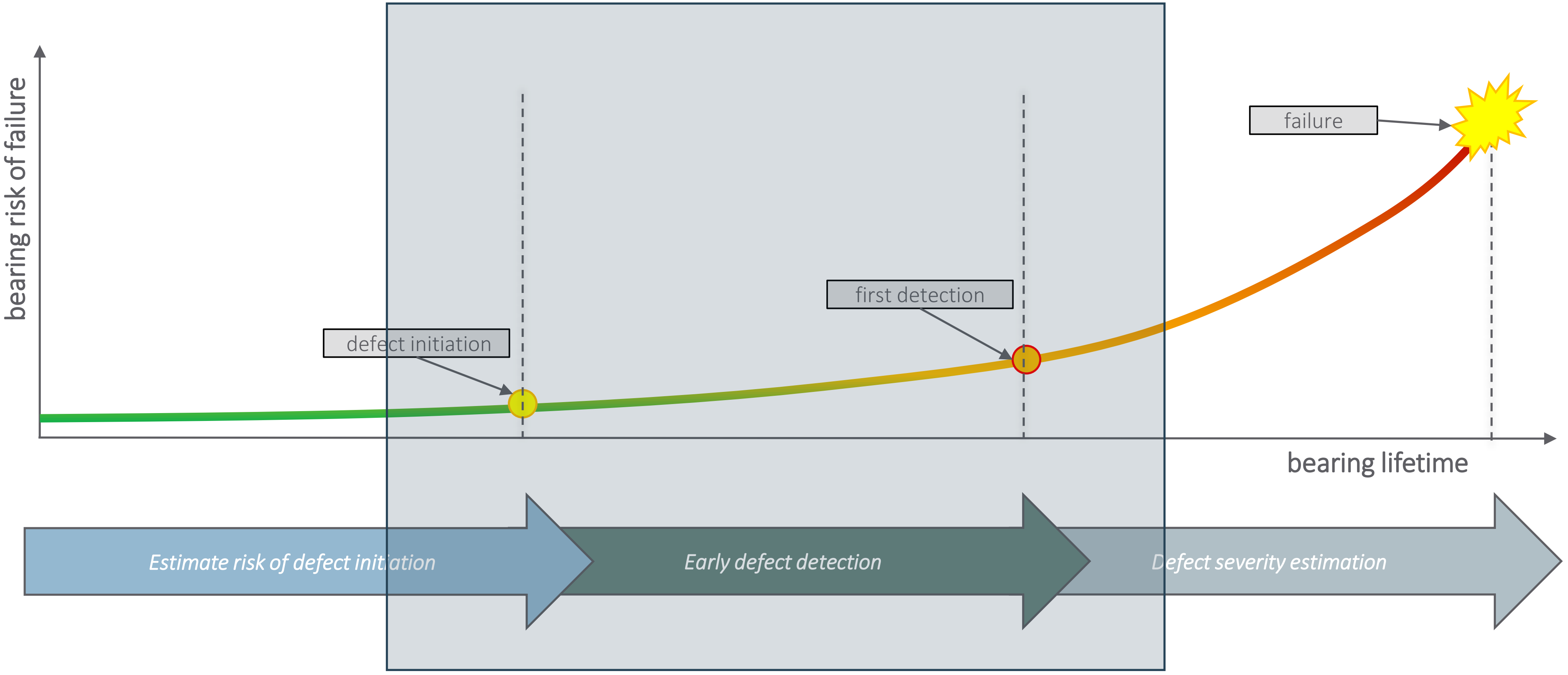


Defect initiation



https://evolution.skf.com/bearing-life-statistics/

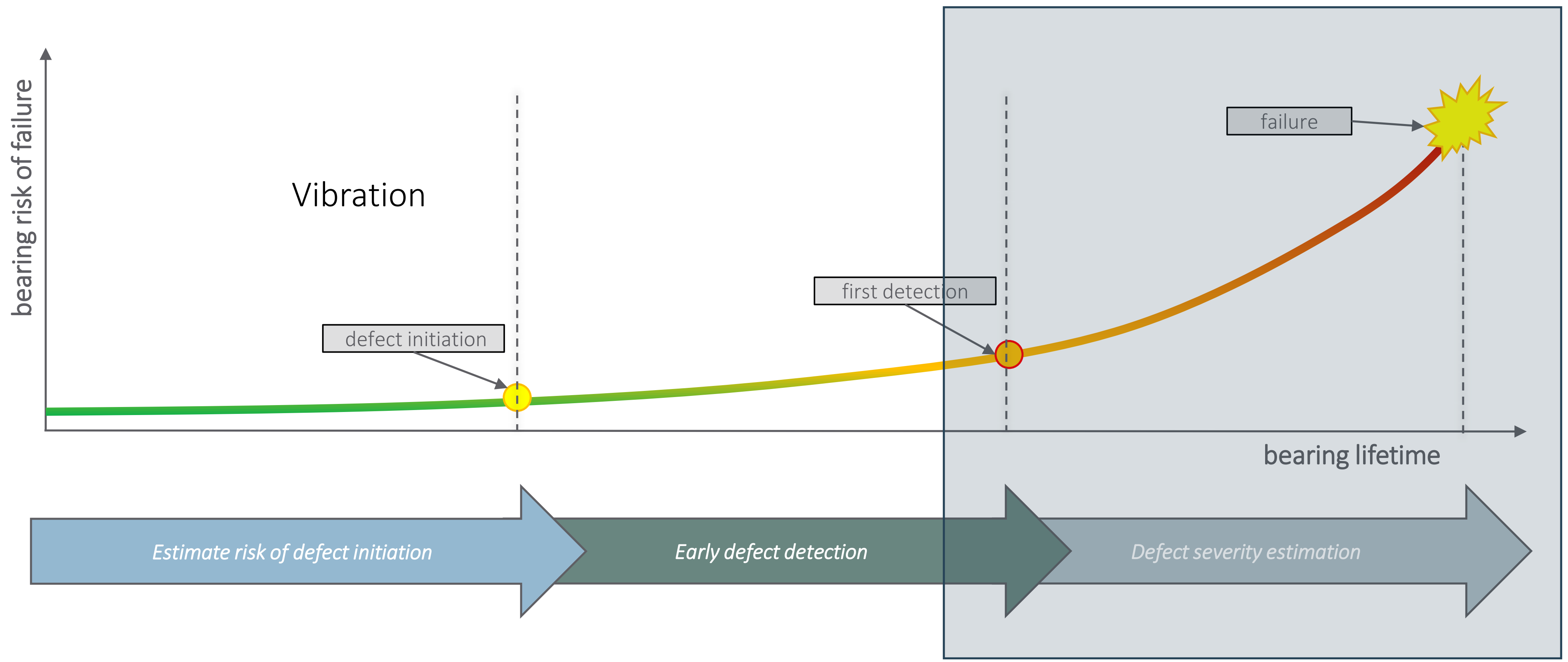
Full lifecycle bearing health state estimation



Beyond vibration: the sensor roller

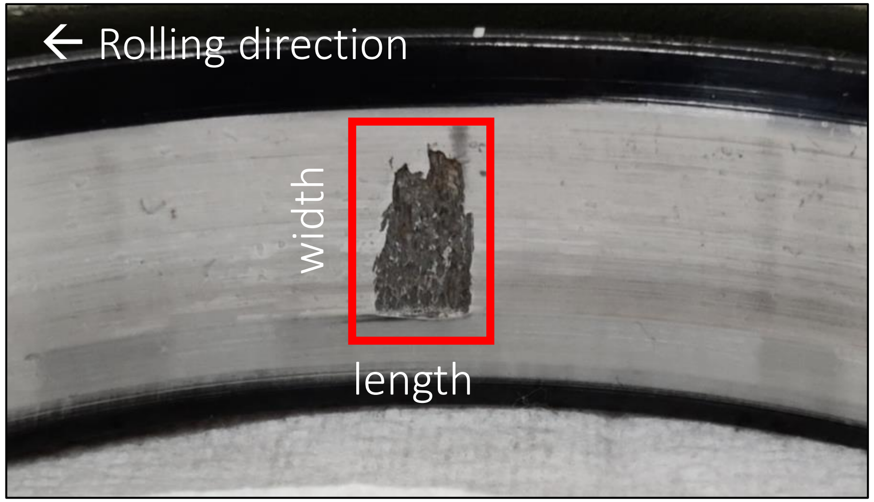
https://evolution.skf.com/raising-the-bar-for-collecting-bearing-data/

Full lifecycle bearing health state estimation

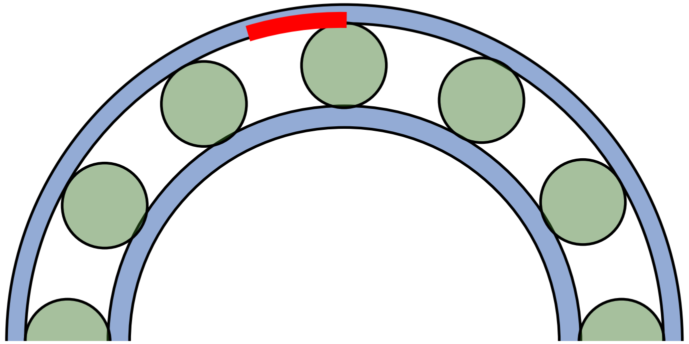


DEEP LEARNING & VIBRATION ANALYSIS: CHALLENGES AND OPPORTUNITIES

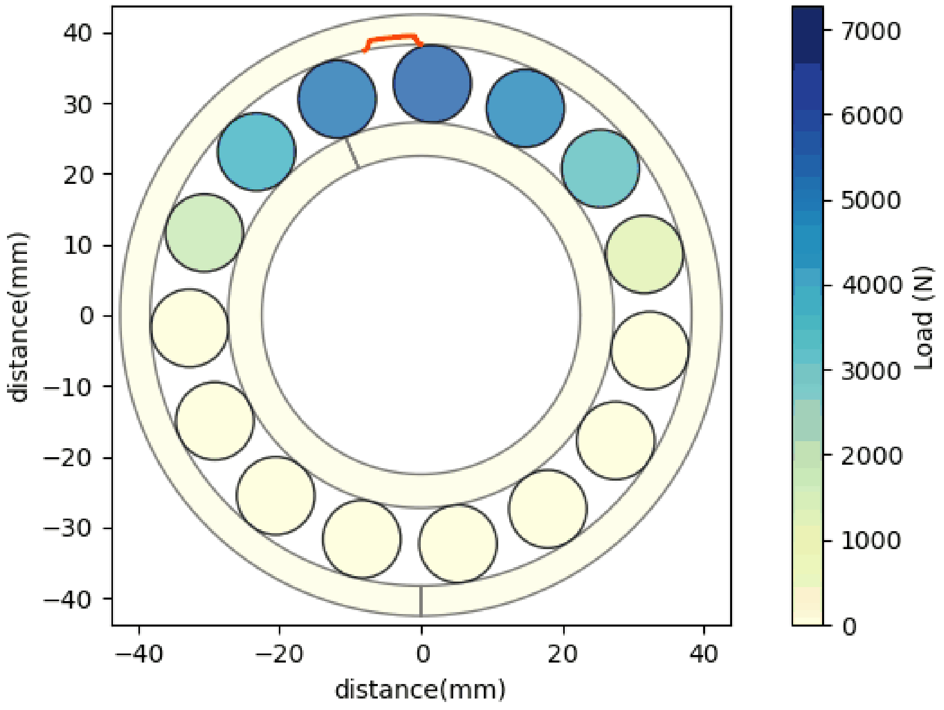
Vibration-based damage severity estimation

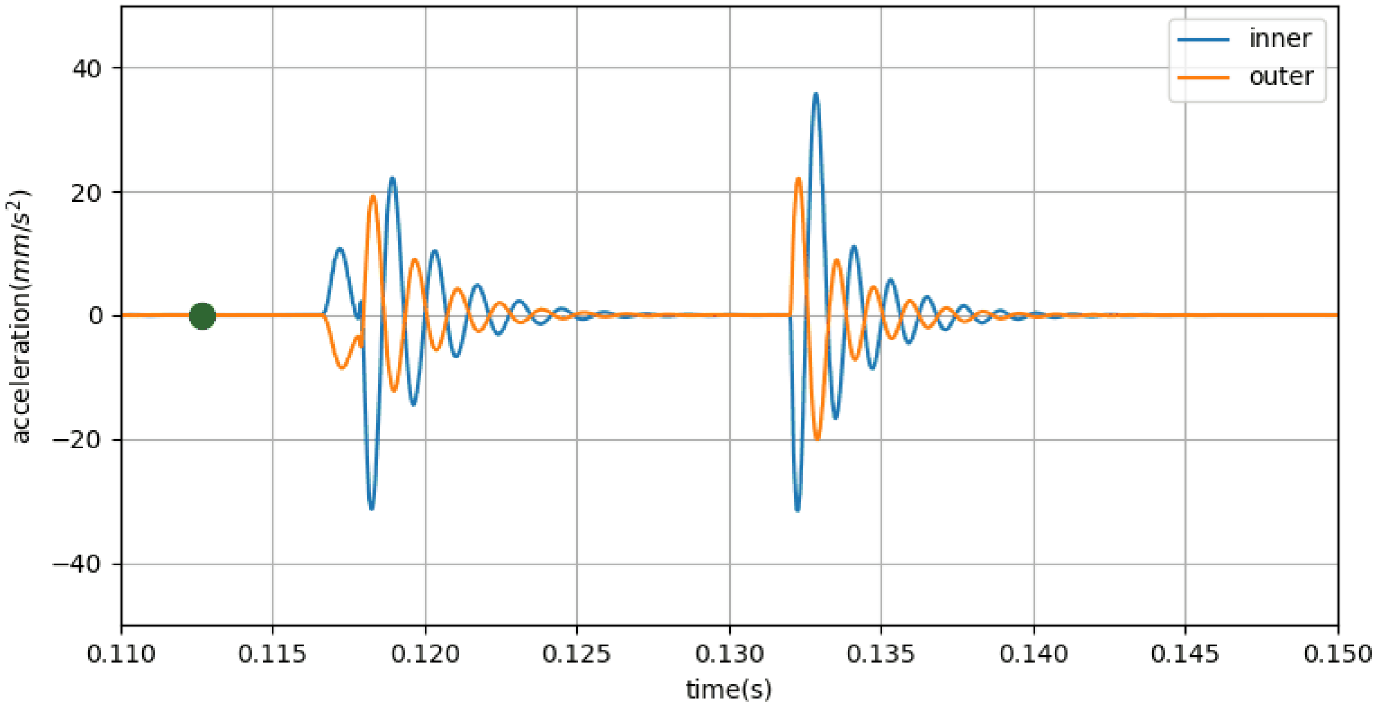


- Can we estimate the spall size based on vibration signals?
  - Many applications can tolerate large spalls
  - Spall growth is steady, small step to prognostics
  - Vibration sensors are sensitive in this range



Challenge with vibration-based spall size estimation





- Two clear separate pulses for rolling in/out based on dynamic modeling
- However, these events are hardly visible in customer applications!

Potential of deep learning

TABLE 3. **Comparison of classification accuracy on case western reserve university bearing dataset with different DL algorithms.**

Reference	Feature extraction algorithms	No. hidden layers	Classifier	Characteristics	Training sample percentage	Average accuracy
[104]	Adaptive CNN	3	Softmax	Predict fault size	50%	97.90%
[106]	CNN	4	Softmax	Noise-resilient	90%	92.60%
[107]	CNN	4	Softmax	Sensor fusion	70%	99.40%
[108]	CNN based on LeNet-5	8	FC layer	Better feature extraction	83%	99.79%
[109]	Deep fully connected CNN	8	Connectionist temporal classification	Validation with Actual filed test data	78%	99.22%
[110]	Multi-scale deep CNN	9	Softmax	Reduce training time	90%	98.57%
[111]	CNN with training interface	13	Softmax	Adapt to load change	96%	95.50%
[112]	IDS-CNN	3	Softmax	Adapt to load change	80%	98.92%
[113]	CNN-based LiftingNet	6	FC layer	Adapt to speed change	50%	99.63%
[114]	PSPP-CNN	9	Softmax	Adapt to speed change	67%	99.19%
[115]	AOCNN with SF	4	Softmax	Reduce training set %	5%	99.19%
[122]	SAE	3	ELM	Adapt to load change	50%	99.61%
[123]	SAE	3	ELM	Reduce training time	50%	99.83%
[124]	Stacked denoising AE	3	N/A	Noise-resilient	50%	91.79%
[125]	SDAE	3	Softmax	Noise-resilient	80%	99.83%
[127]	Ensemble deep AE	3	Softmax	Better feature extraction	67%	99.15%
[128]	Deep wavelet AE	3	ELM	Reduce training time	67%	95.20%
[129]	Stack sparse AE	2	N/A	Data compression	N/A	97.47%
[130]	SAE-local connection network	2	Softmax	Shift-invariant features	25%	99.92%
[131]	SAE	3	SVM	Online diagnosis	N/A	95.10%
[132]	SDAE	8	Gath-Geva (GG)	Noise-resilient	N/A	93.30%
[133]	Winner-take-all AE	2	Gath-Geva (GG)	Noise-resilient	N/A	97.27%
[137]	dual-tree complex wavelet	5	N/A	Adaptive DBN	67%	94.38%
[138]	DBN	2	Softmax	Adapt to load change	N/A	98.80%
[139]	DBN with ensemble learning	4	Sigmoid	Accurate & robust	N/A	96.95%
[145]	CNN-LSTM	3	Softmax	Accurate	83%	99.60%
[146]	Deep RNN	3	N/A	Accurate	60%	94.75%
[150]	DCGAN	8	SVM	Data augmentation	96%	86.33%
[152]	CatAAE	11	Softmax	Adapt to load changes	91%	90.68%
[153]	A2CNN	27	Softmax	Domain adaptation	N/A%	99.21%
[154]	GAN+SDAE	8	Softmax *et al.*	Data augmentation	50-78%	99.20%

Zhang et al. **Deep Learning Algorithms for Bearing Fault Diagnostics—A Comprehensive Review**, 2020, *IEEE Access* , Vol. 8

- Very good performance on CWRU-dataset
  - CWRU dataset lacks clear roll in-out features
  - What are these methods learning?

Interpretation of Deep Learning Models in Bearing Fault Diagnosis

- We used attention visualization (Grad-CAM) and signal transformations to investigate what the model learns*

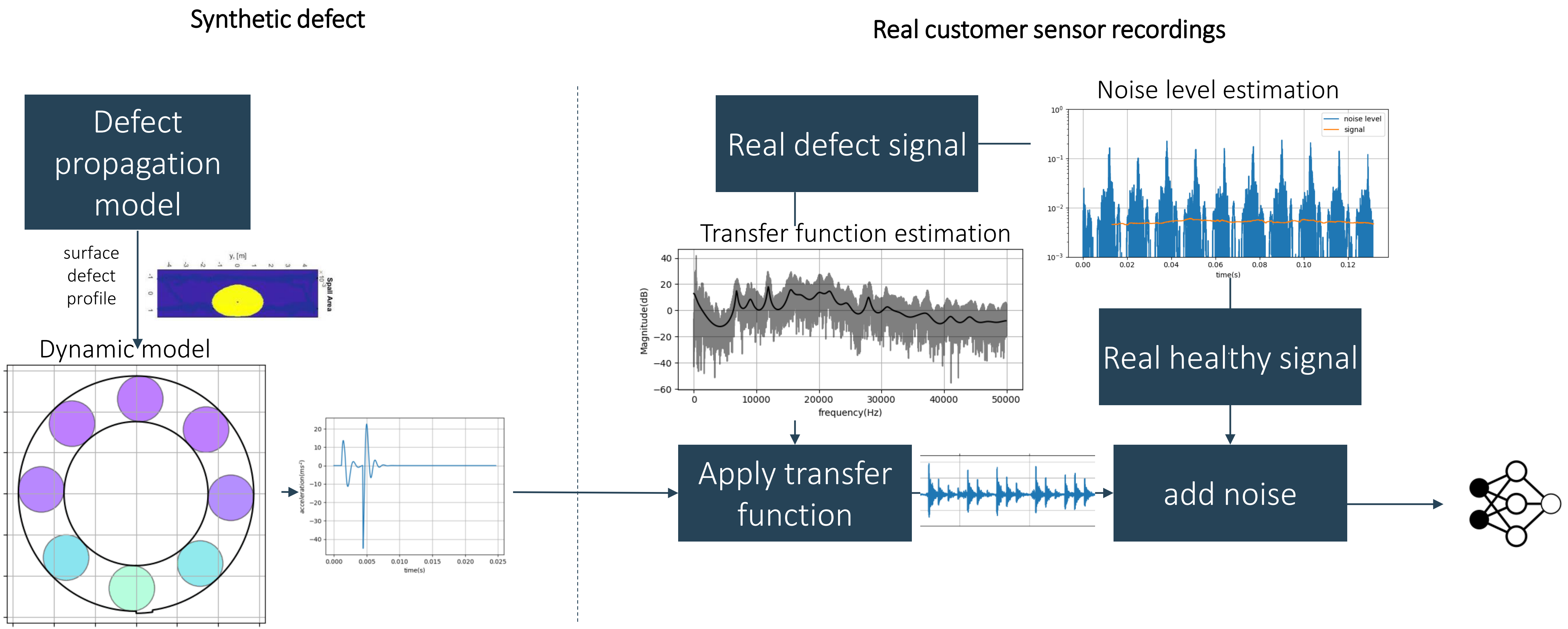
*Selvaraju et al. Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization , 2019, International Journal of Computer Vision

- **Conclusion:**
  - All temporal information can be removed without major impact on results
  - Transfer function is used for classification
  - Methods are not expected to generalize

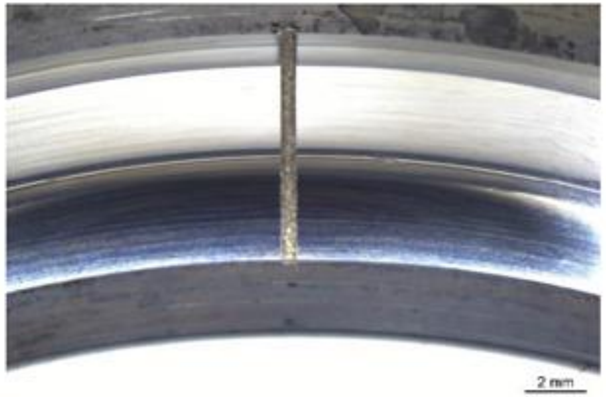
- Can we get better datasets?
  - Not so easy
  - Synthetic data?

*Liefstingh at al. "Interpretation of Deep Learning Models in Bearing Fault Diagnosis", 2021, Annual Conference of the PHM Society

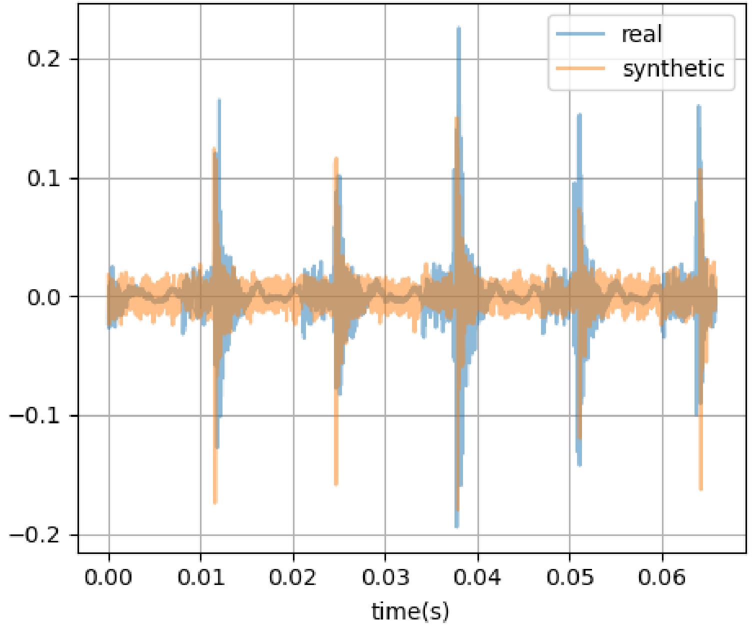
Synthetic defect data augmentation framework



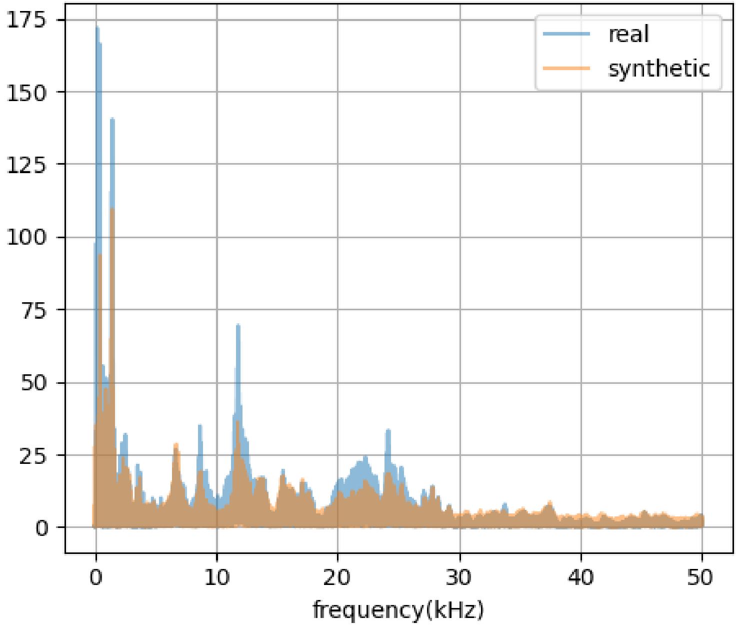
Example



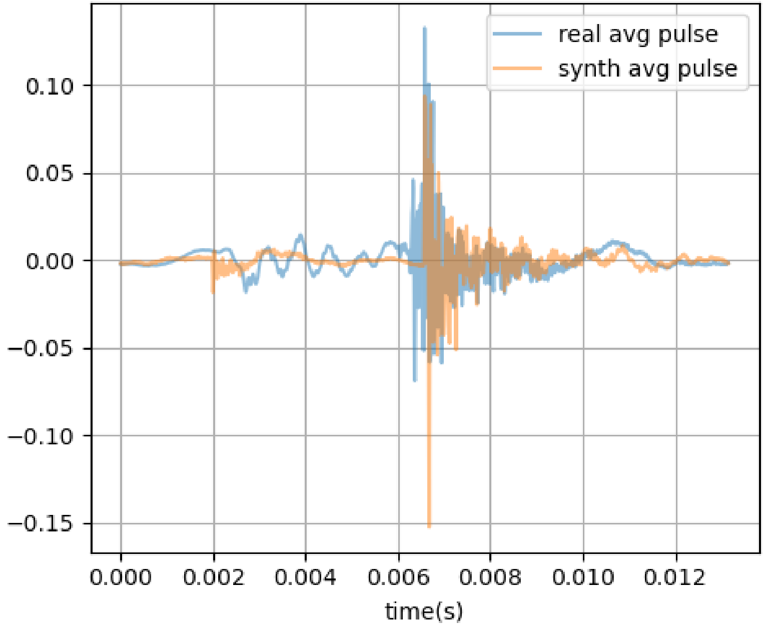
Outer ring groove in 6202 ball bearing



Time domain

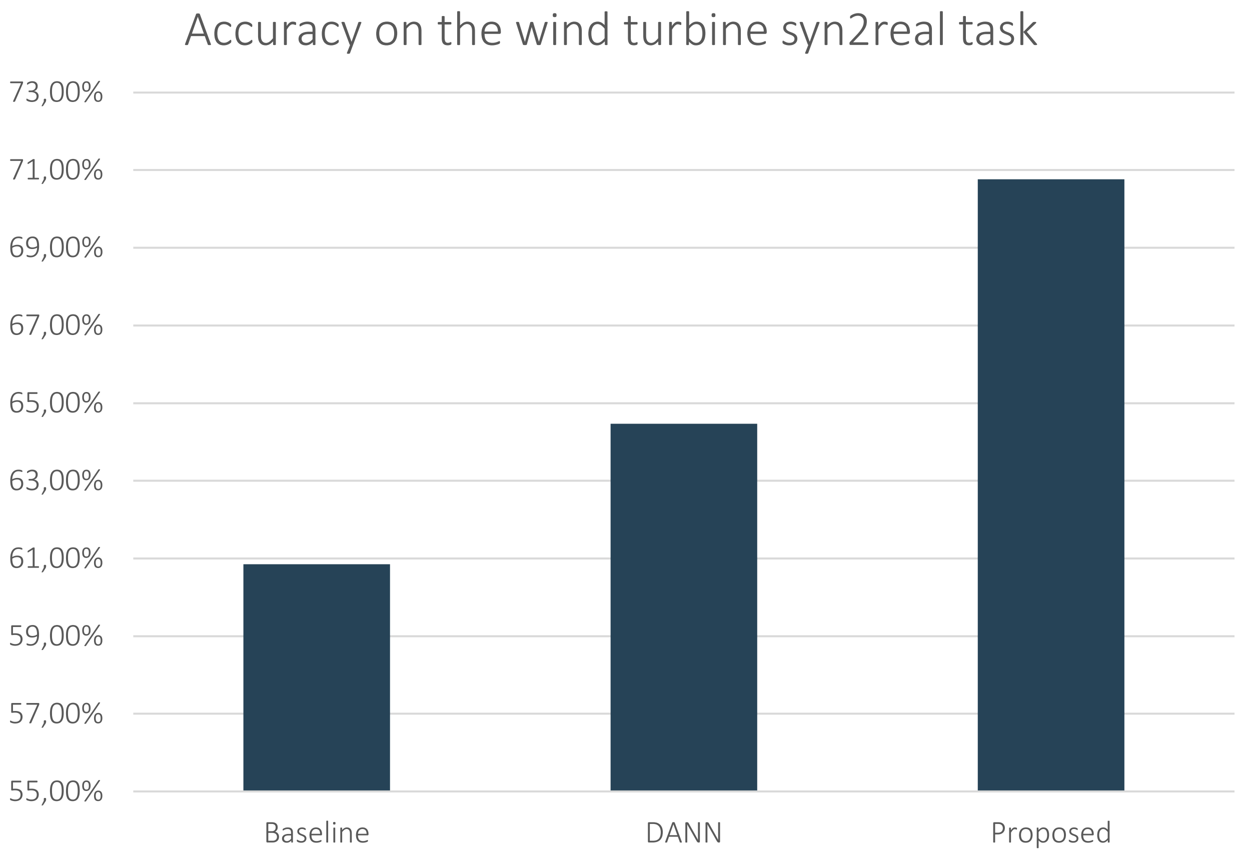


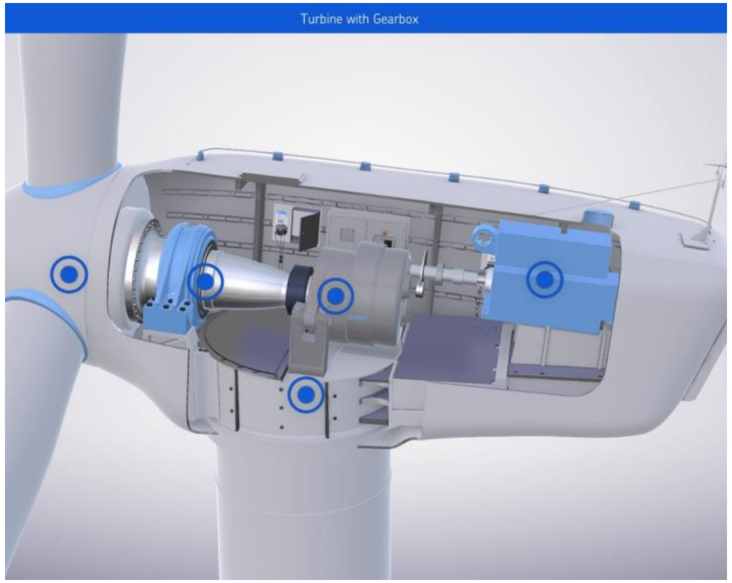
Frequency domain



Rolling element interaction with defect (average time)

Customer data (Wind): Bearing defect **identification**





Baseline
Training using only synthetic data

Proposed
Domain adaptation with conditional alignment

Note: This method predicts defect class, not severity yet.

*Wang, Qin, Cees Taal, and Olga Fink. "Integrating expert knowledge with domain adaptation for unsupervised fault diagnosis." *IEEE Transactions on Instrumentation and Measurement* 71 (2021): 1-12.

SUMMARY AND FUTURE WORK

Summary and future work

- Vibration-based severity estimation outside “the lab” is challenging
- Rolling in/out features not clearly present in “real” customer data
- Deep learning methods are sensitive for learning spurious correlations
- Augmenting clean sensor data with synthetic defects looks promising
- Need of transfer learning methods to close domain gap between real-synthetic
- Future: Extend to severity estimation

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