Feasibility of machine learning algorithms for identification of structural damage in offshore wind jacket structures

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Outline

1. Introduction
2. Methodology
3. Damage and Datasets Definition
4. Detection Feasibility
5. Conclusions and Future Work

Introduction

1.1. Structural Damage Detection

State-of-the-art

Approach	Damage Indicator(s)	Installed sensor(s)	Resolut.	Detection approach	Cost
Inspection	Visual testing examination	-	-	**Practical assessments on site**	
Data-Driven	Natural frequencies and/or mode shapes	Accelerometers	≥ 20 Hz	**Vibration-based**	
	Fatigue loads (DEL)	• Strain gauge (direct measur.)	≥ 20 Hz	**Machine learning** Monitoring of DEL via regression and/or anomaly detection approach	

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1.1. Structural Damage Detection

Scope of the analysis
(other possible approaches)

Approach	Damage Indicator(s)	Installed sensor(s)	Resolut.	Detection approach	Cost
Inspection	Visual testing examination	-	-	**Practical assessments on site**	
Data-Driven	Natural frequencies and/or mode shapes	Accelerometers	≥ 20 Hz	**Vibration-based**	
	Fatigue loads (DEL)	• Strain gauge (direct measur.)	≥ 20 Hz	**Machine learning** Monitoring of DEL via regression and/or anomaly detection approach	
		• SCADA (indirect measur.)	10-min		
	Anomaly in SCADA data	SCADA	10-min	**Machine learning** (1) Classification approach for identification of the damage indicator(s) (2) Monitoring of quantity via regression and/or anomaly detection approach	
	Anomaly in other measurable signals	• Strain gauges • Accelerometer • Inclinometer …etc.	10-min		

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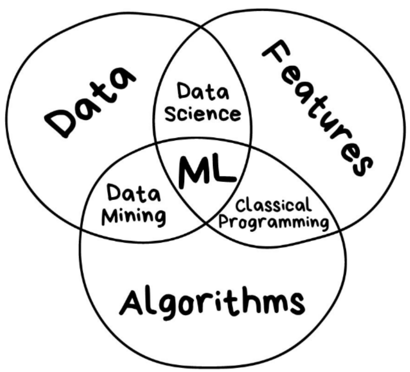
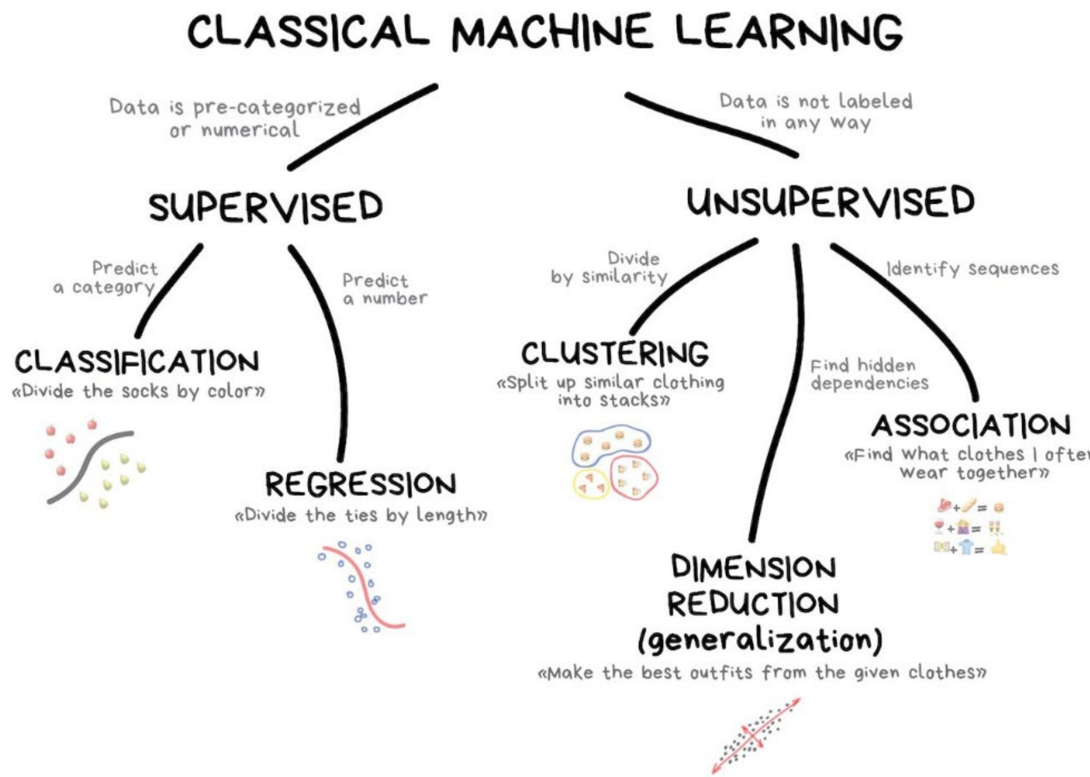
1.2. Brief on Machine Learning (ML)





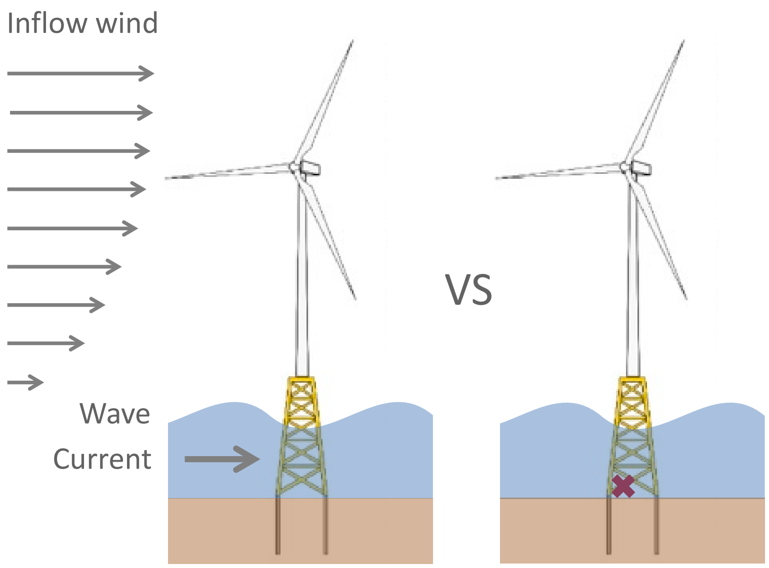
https://vas3k.com/blog/machine_learning/

Methodology

2.1. Causes of Changes in the Dynamics

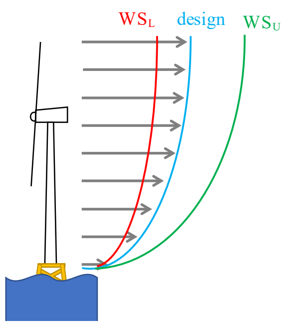
1 Integrity of the Structure

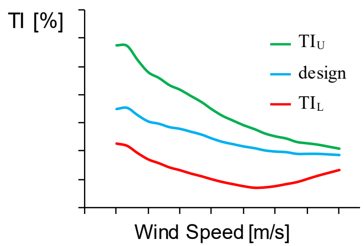
Healthy   Damaged



2 Environmental Operational Conditions (EOC)

- Inflow wind

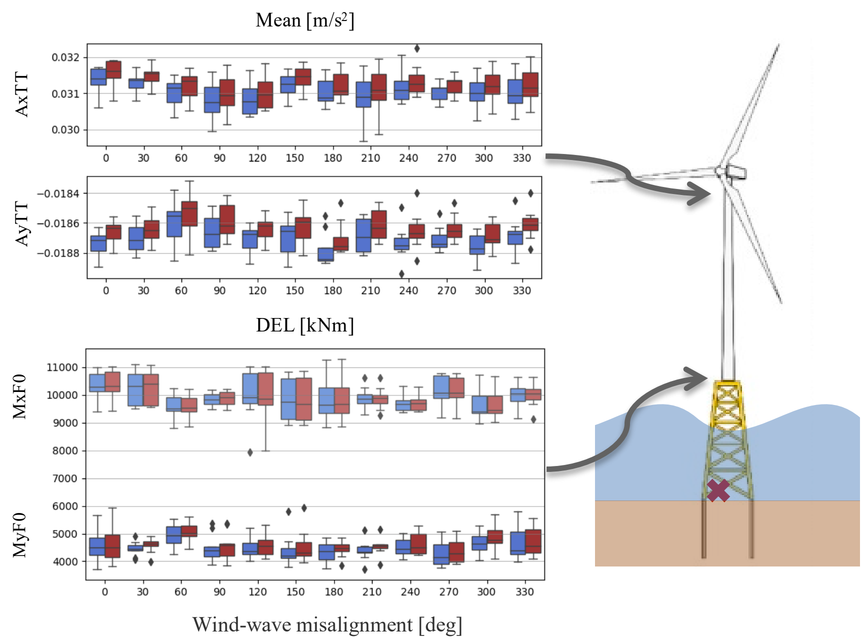




- Wave loads

2.2. Effect of structural integrity

Healthy VS Damaged



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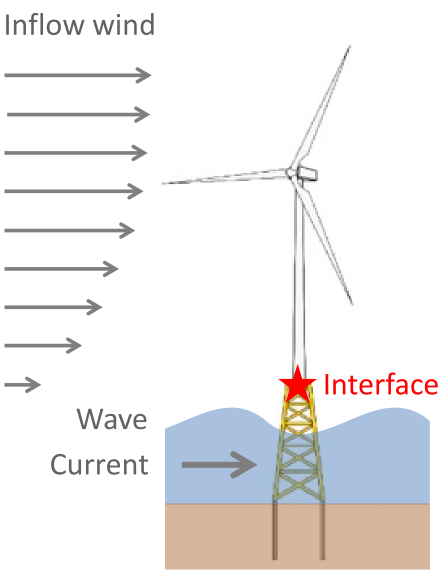
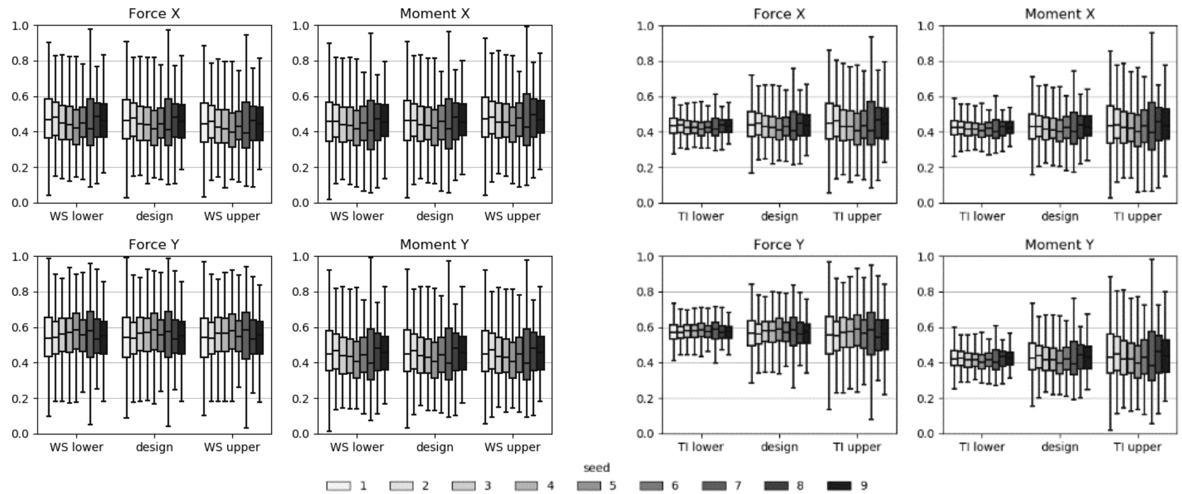
2.3. Effect of EOC



Wind shear

Turbulence intensity



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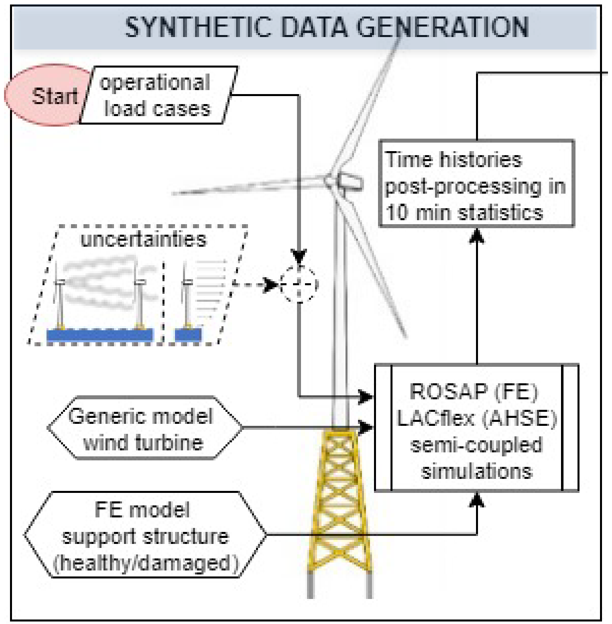
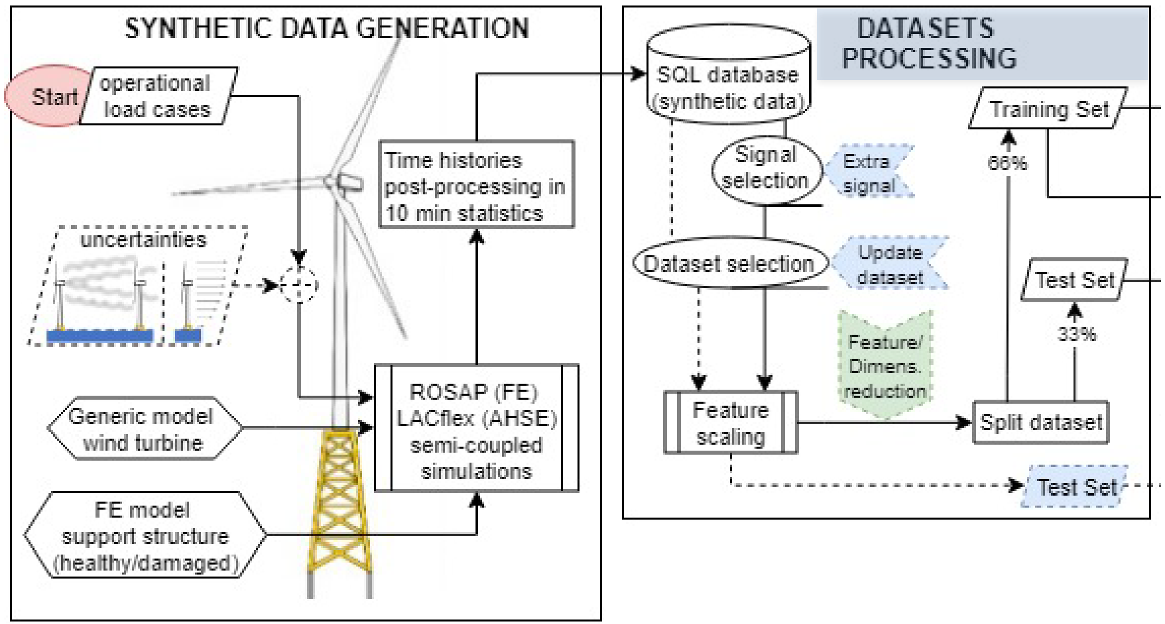
2.4. Detection Study Approach



- Need for **information from damaged status**
- Use of **simulation model** of turbine
- Consideration of variation in **environmental and operational conditions (EOC)**

2.4. Detection Study Approach



- Healthy VS damaged signals, and **identification of damage indicators**
- **What ML approach to select?**

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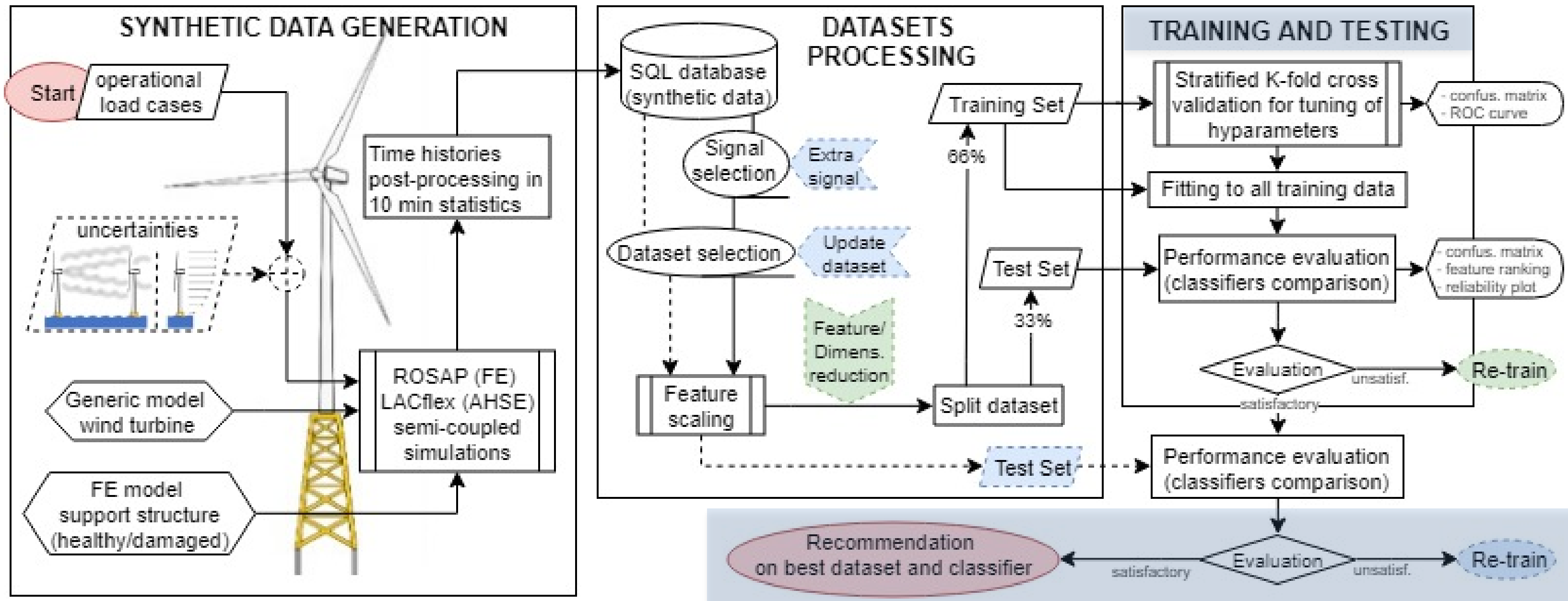
2.4. Detection Study Approach

- **Tuning and training**
- **Testing** the goodness of **damage detection VS EOC**



2.5. Classification algorithms and methods

- **Well-known classification algorithms**
- **Cross validation (CV)** on subsets of training set
  - tuning of hyperparameters
  - selection of solving methods
- **Testing set** for
  - stochasticity of the EOC (wind and wave)
  - uncertainties on the EOC (turbulence intensity)
- **Performance evaluation**
  - confusion matrix (acc, TDR, FDR)
  - confidence of prediction (reliability curves)

		Predicted	
		Healthy (0 or Negative)	Damaged (1 or Positive)
Actual	Healthy (0 or Negative)	True Healthy (TH)	False Damaged (FD)
	Damaged (1 or Positive)	False Healthy (FH)	True Damaged (TD)

$$\text{acc} = \frac{\text{TD+TH}}{\text{Total population}}$$

$$\text{TDR} = \frac{\text{TD}}{\text{FH+TD}}$$

$$\text{FDR} = \frac{\text{FD}}{\text{TH+FD}}$$

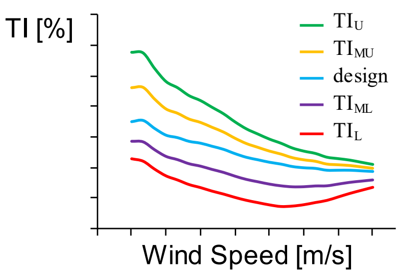
	acc/TDR	FDR
✖	below 60	above 40
!	(75;60]	(30;40]
✔	(90;75]	(10;30]
●	[100;90]	[0;10]

TDR: damage detection rate
FDR: false alarm rate

Damage and Datasets Definition

3.1. EOC load cases and Datasets

- DLC 1.2
  - 6 average wind speeds
  - 4 wind directions
  - 12 wave angles
- Turbulence



- 9 seedings (stochasticity)

	Acronym	Loading conditions	N. simulations
Training Datasets (D)	D0	design	**5,904**
	D1	design + TI_U	11,808
	D2	design + TI_L	11,808
	D3	design + TI_U + TI_L	17,712
Testing Datasets (T)	T33	-	33% D#
	T1	TI_U	**5,904**
	T2	TI_L	**5,904**
	T3	TI_{MU}	**5,904**
	T4	TI_{ML}	**5,904**

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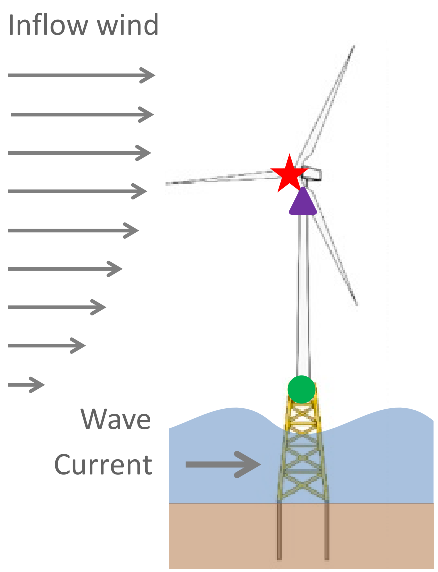
3.2. Sensor setups



Sensor type	Measurement	Signal acronym	Unit	Sensor set up			
				S0	S1	S2	S3
SCADA	Nacelle direction	YawPos	[deg]	x	x	x	x
	Wind direction	WDir	[deg]	x	x	x	x
	Yaw angle (misalign. error)	YawErr	[deg]	x	x	x	x
	Wind speed	Whub	[m/s]	x	x	x	x
	Power	Pow	[kW]	x	x	x	x
	Rotor speed	RotSpd	[rpm]	x	x	x	x
	Pitch angle (Collective)	PiPos1	[deg]	x	x	x	x
Accelerometer	2D Tower top acceleration	AxTT AyTT	[m/s^2]	x	x	x	
Inclinometer	2D Rotation at interface	UrxF UryF	[deg]		x	x	x
Strain Gauge	2D Bending moment at interface	MxF0 MyF0	[kNm]			x	

Detection Feasibility

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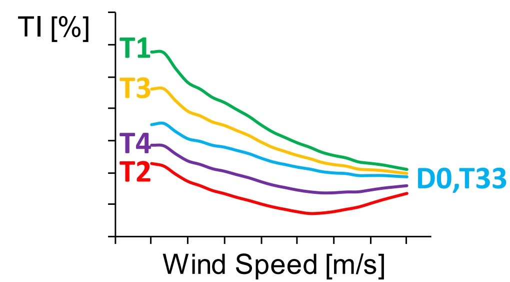
4.1. Preliminary results

Sensor type	Sensor set up			
	S0	S1	S2	S3
SCADA	x	x	x	x
Accelerometer	x	x	x	
Inclinometer		x	x	x
Strain Gauge			x	

	Acronym	Loading conditions
D	D0	design
	D1	design + TI_U
	D2	design + TI_L
	D3	design + TI_U + TI_L
T	T33	-
	T1	TI_U
	T2	TI_L
	T3	TI_{MU}
	T4	TI_{ML}

- **Acceptable classification**
  - Logistic regression (**LR**)
  - Support vector machine (**SVM**)
  - Random forest (**RF**)

  for below (BR) and above (AR) rated design cases



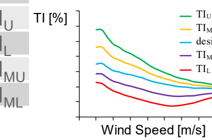
	Classifiers	CV	D0			T33			T1	T2	T3	T4
		acc.	acc.	TDR	FDR	acc.	TDR	FDR	acc.	acc.	acc.	acc.
BR	LR	70%	69%	!	✓	70%	!	✓	50%	50%	52%	52%
	SVM (poly)	70%	91%	●	●	71%	!	✓	50%	50%	53%	54%
	RF	85%	100%	●	●	86%	✓	✓	55%	68%	66%	72%
AR	LR	61%	61%	!	!	59%	✗	✗	50%	50%	52%	50%
	SVM (rbf)	64%	89%	✓	●	64%	!	!	50%	50%	52%	50%
	RF	70%	100%	●	●	69%	!	✓	56%	56%	60%	59%

- **Not acceptable for variation of EOC** (turbulence intensity)

4.2. Varying training dataset

Sensor type	Sensor set up			
	S0	S1	S2	S3
SCADA	x	x	x	x
Accelerometer	x	x	x	
Inclinometer		x	x	x
Strain Gauge			x	

	Acronym	Loading conditions
D	D0	design
	D1	design + TI_U
	D2	design + TI_L
	D3	design + TI_U + TI_L
T	T33	-
	T1	TI_U
	T2	TI_L
	T3	TI_{MU}
	T4	TI_{ML}



- **No satisfactory** results for **LR and SVM**
- **Improvements of RF** (see *table below*)

	Dataset	Sensor	CV	T33			T1			T2			T3			T4		
			acc	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR
BR	D1	S0	82%	85%	✓	✓				63%	✗	!	69%	!	✓	72%	!	!
BR	D2	S0	88%	91%	●	●	57%	!	✗				68%	!	●	80%	●	!
BR	D3	S0	67%	88%	●	●							73%	!	!	82%	!	✓
AR	D1	S0	68%	85%	!	!				63%	✗	✓	69%	!	✗	72%	✗	✓
AR	D2	S0	76%	91%	!	✓	57%	●	✗				68%	●	✗	80%	✓	!
AR	D3	S0	60%	88%	!	✓							73%	!	!	82%	✓	✗

4.3. Varying sensor setup

Sensor type	Sensor set up			
	S0	S1	S2	S3
SCADA	x	x	x	x
Accelerometer	x	x	x	
Inclinometer		x	x	x
Strain Gauge			x	

	Acronym	Loading conditions
D	D0	design
	D1	design + TI_U
	D2	design + TI_L
	D3	design + TI_U + TI_L
T	T33	-
	T1	TI_U
	T2	TI_L
	T3	TI_{MU}
	T4	TI_{ML}

- Investigation for **RF** (see *table below*)
- **Overall satisfactory performance for S3 setup**

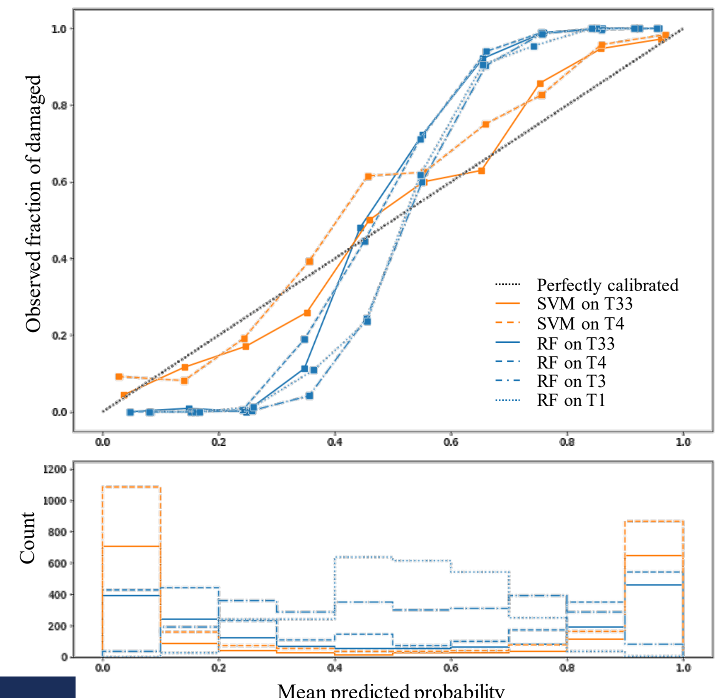
	Dataset	Sensor	CV	T33			T1			T2			T3			T4		
			acc	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR
BR	D1	S0	82%	85%	✓	✓				63%	✗	!	69%	!	✓	72%	!	!
	D2	S0	88%	91%	●	●	57%	!	✗				68%	!	●	80%	●	!
	D3	S0	67%	88%	●	●							73%	!	!	82%	!	✓
	D0	S1	94%	96%	●	●	66%	!	✗	80%	!	●	76%	●	!	84%	!	●
		S2	95%	96%	●	●	68%	!	!	81%	!	●	78%	●	!	85%	!	●
		S3	94%	95%	●	●	82%	✓	✓	86%	✓	●	90%	✓	●	91%	✓	●
AR	D1	S0	68%	85%	!	!				63%	✗	✓	69%	!	✗	72%	✗	✓
	D2	S0	76%	91%	!	✓	57%	●	✗				68%	●	✗	80%	✓	!
	D3	S0	60%	88%	!	✓							73%	!	!	82%	✓	✗
	D0	S1	91%	96%	✓	●	66%	●	✗	80%	✗	●	76%	●	!	84%	✗	●
		S2	92%	96%	●	●	68%	●	✗	81%	✗	●	78%	●	✓	85%	✗	●
		S3	91%	95%	●	✓	82%	●	!	86%	✗	●	90%	●	✓	91%	!	●

4.4. Optimal training set

Sensor type	Sensor set up S0	S1	S2	S3
SCADA	x	x	x	x
Accelerometer	x	x	x	
Inclinometer		x	x	x
Strain Gauge			x	

	Acronym	Loading conditions
D	D0	design
	D1	design + TI_U
	D2	design + TI_L
	D3	design + TI_U + TI_L
T	T33	-
	T1	TI_U
	T2	TI_L
	T3	TI_{MU}
	T4	TI_{ML}

- **Satisfactory detection for RF**
  - below and above rated
  - all level of turbulence intensity
- **Acceptable performance for SVM** for below rated and TI below 90th percentile curve



		CV	T33			T1			T3			T4		
		acc	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR
BR	RF	95%	97%	●	●	82%	✓	✓	91%	●	✓	96%	●	●
	SVM	90%	94%	●	●	53%	✗	!	64%	!	!	91%	✓	●
AR	RF	93%	97%	●	●	82%	●	✓	91%	●	✓	96%	✓	●
	SVM	74%	78%	✓	✓	53%	✓	✗	60%	✓	✗	52%	✗	!

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Conclusion and Future Works

SVM: support vector machine -based classifiers
RF: random forest -based classifiers

5.1. Conclusion

- **Feasibility of detection** of a member loss in offshore wind jacket structure via **low-resolution data** is proved
- **Tower top accelerometer** can give indication on the presence of the damage, but affected by varying level of TI
- **Tower bottom inclinometer** improves the prediction

5.2. Future Work

1) **Applicability** for a real exploitation of a machine learning detection approach based on the simulated data
2) **Detection other damages/levels**

	Loading conditions				Sensor setup				Perfromance on test set									
	D0	D1	D2	D3	S0	S1	S2	S3	T33		T1		T2		T3		T4	
SVM	X				X				B	A	B	A	B	A	B	A	B	A
		X			X				B	A			B	A	B	A	B	A
			X		X				B	A	B	A			B	A	B	A
				X	X				B	A					B	A	B	A
	X					X			B	A	B	A	B	A	B	A	B	A
	X						X		B	A	B	A	B	A	B	A	B	A
	X							X	B	A	B	A	B	A	B	A	B	A
			X					X	B	A	B	A			B	A	B	A
RF	X				X				B	A	B	A	B	A	B	A	B	A
		X			X				B	A			B	A	B	A	B	A
			X		X				B	A	B	A			B	A	B	A
				X	X				B	A					B	A	B	A
	X					X			B	A	B	A	B	A	B	A	B	A
	X						X		B	A	B	A	B	A	B	A	B	A
	X							X	B	A	B	A	B	A	B	A	B	A
			X					X	B	A	B	A	B	A	B	A	B	A

Overall performance: Satisfactory / Acceptable / Not acceptable

B: below rated
A: above rated

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Questions?

Thanks for your attention!

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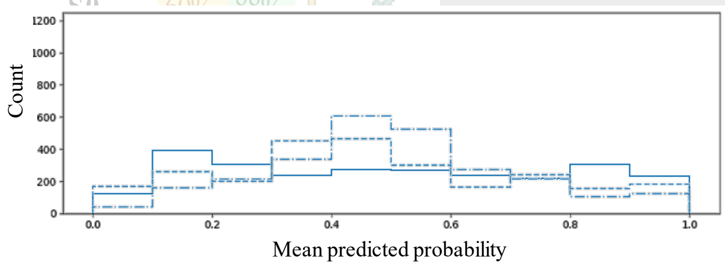
4.2. Varying training dataset

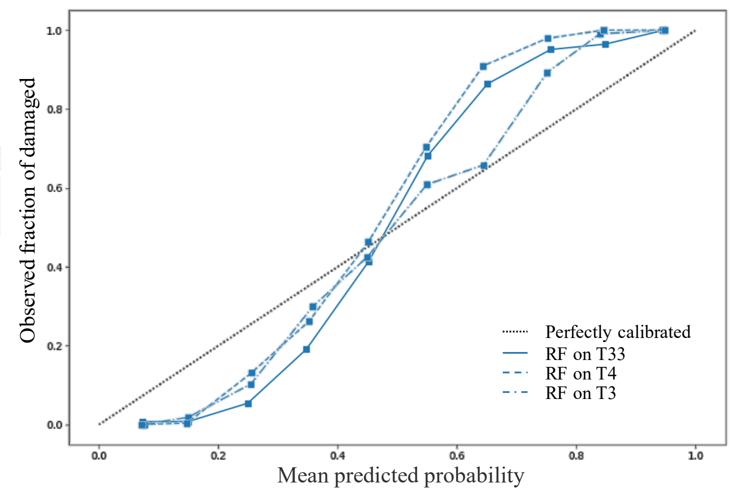
Sensor type	Sensor set up			
	S0	S1	S2	S3
SCADA	x	x	x	x
Accelerometer	x	x	x	
Inclinometer		x	x	x
Strain Gauge			x	

	Acronym	Loading conditions
D	D0	design
	D1	design + TI_U
	D2	design + TI_L
	D3	design + TI_U + TI_L
T	T33	-
	T1	TI_U
	T2	TI_L
	T3	TI_{MU}
	T4	TI_{ML}

- RF reliability curve RF below rated

	Dataset	Sensor	CV	T33			T1			T2			T3			T4		
			acc	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR	acc	TDR	FDR
BR	D1	S0	82%	85%	✓	✓				63%	✗	!	69%	!	✓	72%	!	!
	D2	S0	88%	91%	●	●	57%	!	✗				68%	!	●	80%	●	!
	D3	S0	67%	88%	●	●							73%	!	!	82%	!	✓
AR	D1	S0	68%	85%	!	!				63%								
	D2	S0	76%	91%	!	✓	57%	●	✗									
	D3	S0	60%	88%	!	✓												





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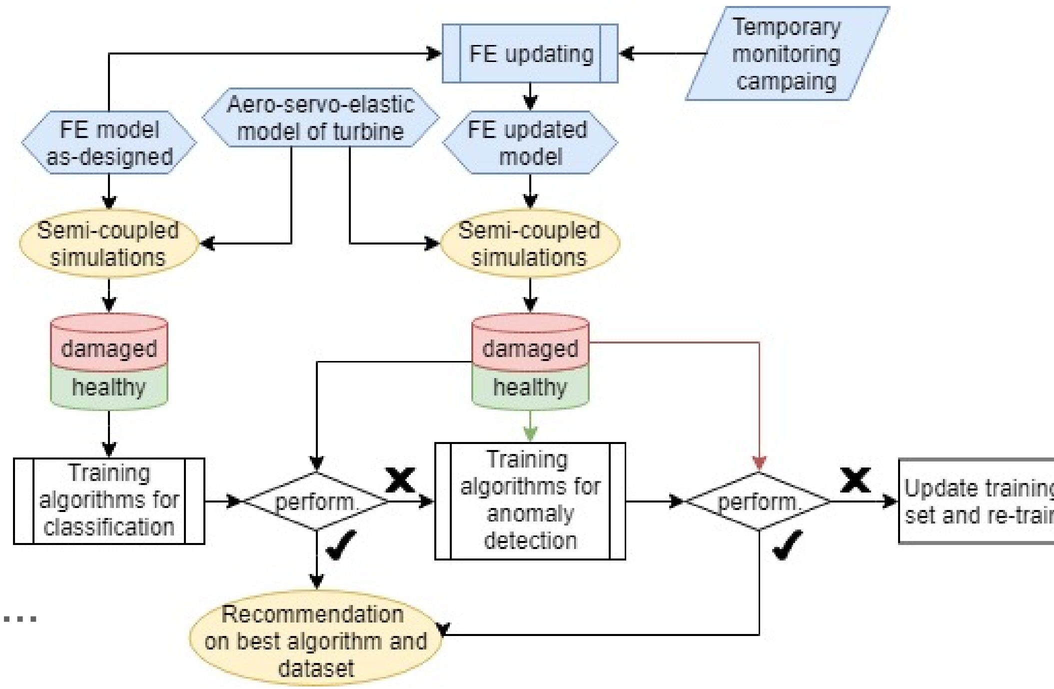
5.2. Future Work

$$\begin{tikzcd} \sum_{\text{as-design}} \arrow[r, "\Delta_1"] \arrow[rr, bend right, "\Delta_3 \sim \Delta_1"'] & \sum_{\text{FE-updated}} \arrow[r, "\Delta_2 \ll \Delta_1"] & \sum_{\text{real}} \end{tikzcd}$$

- **Applicability**
  - based on simulated data
  - Does detection algorithms accommodate model uncertainties?
  - If not, suggest a detection approach trained on healthy data only



- **repeat for other type/level of failure…**