Neural Networks for Offshore Wind Turbine Converter Failure Prognosis

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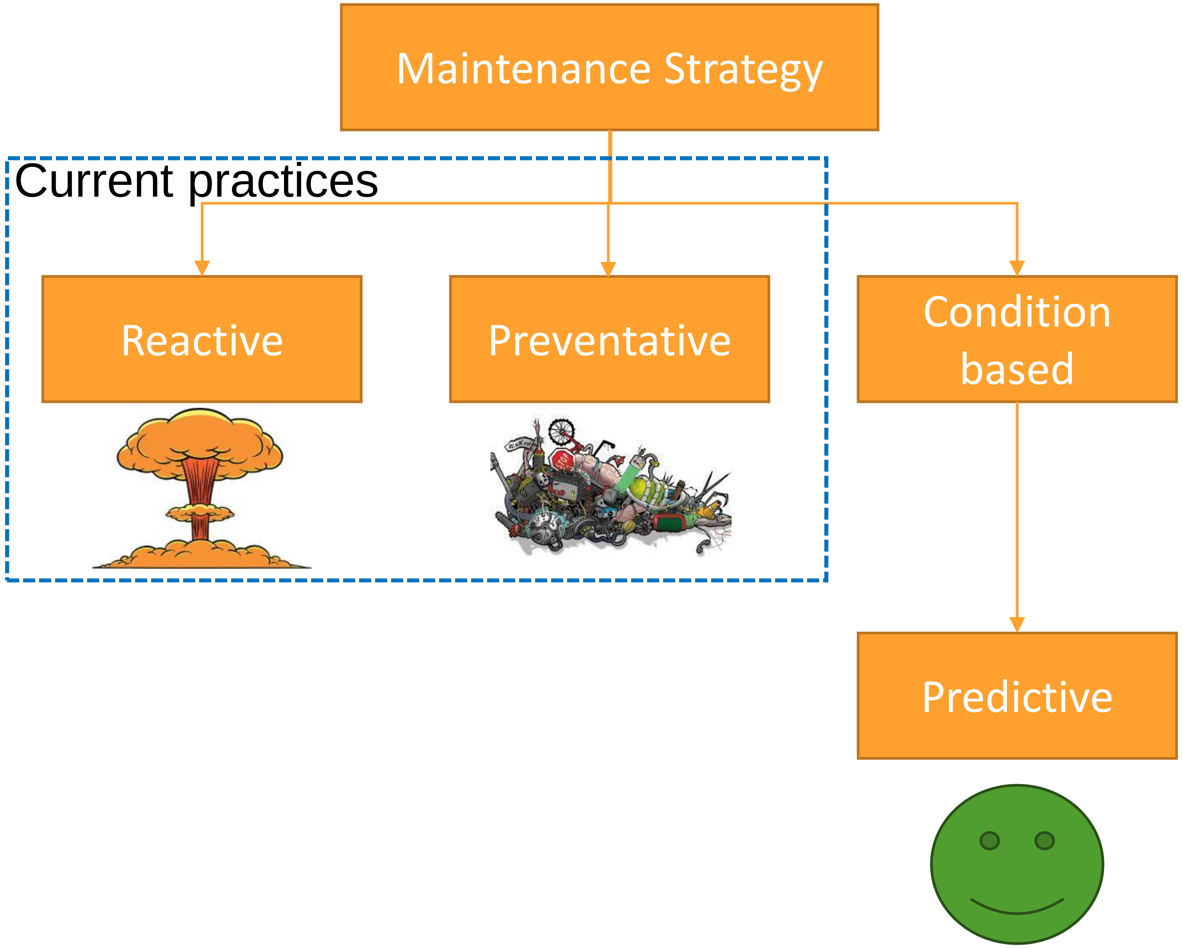
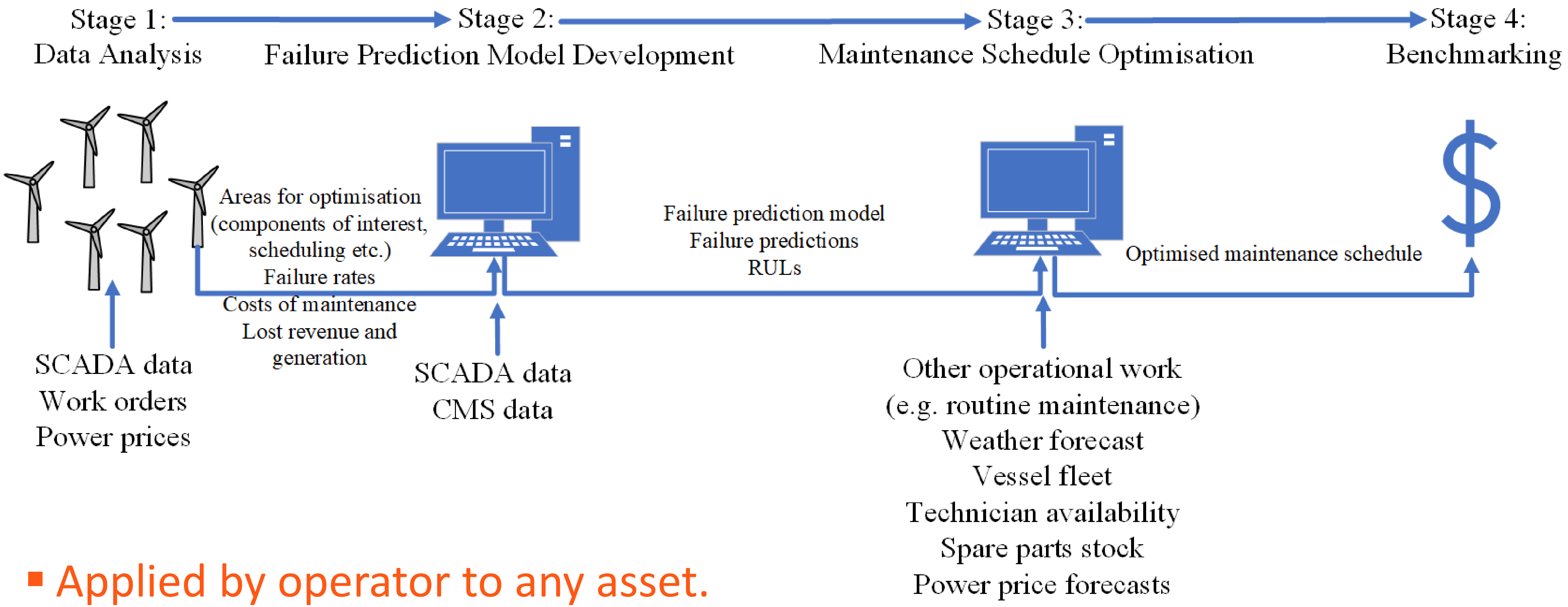
Outline

What is the problem?

- ~30% of lifetime costs of an OWF are O&M [1].
  - Opportunity for cost saving.
- Current maintenance practices are considered not optimal.
  - Reactive = catastrophic failure/large downtime.
  - Preventative = wasted component life.

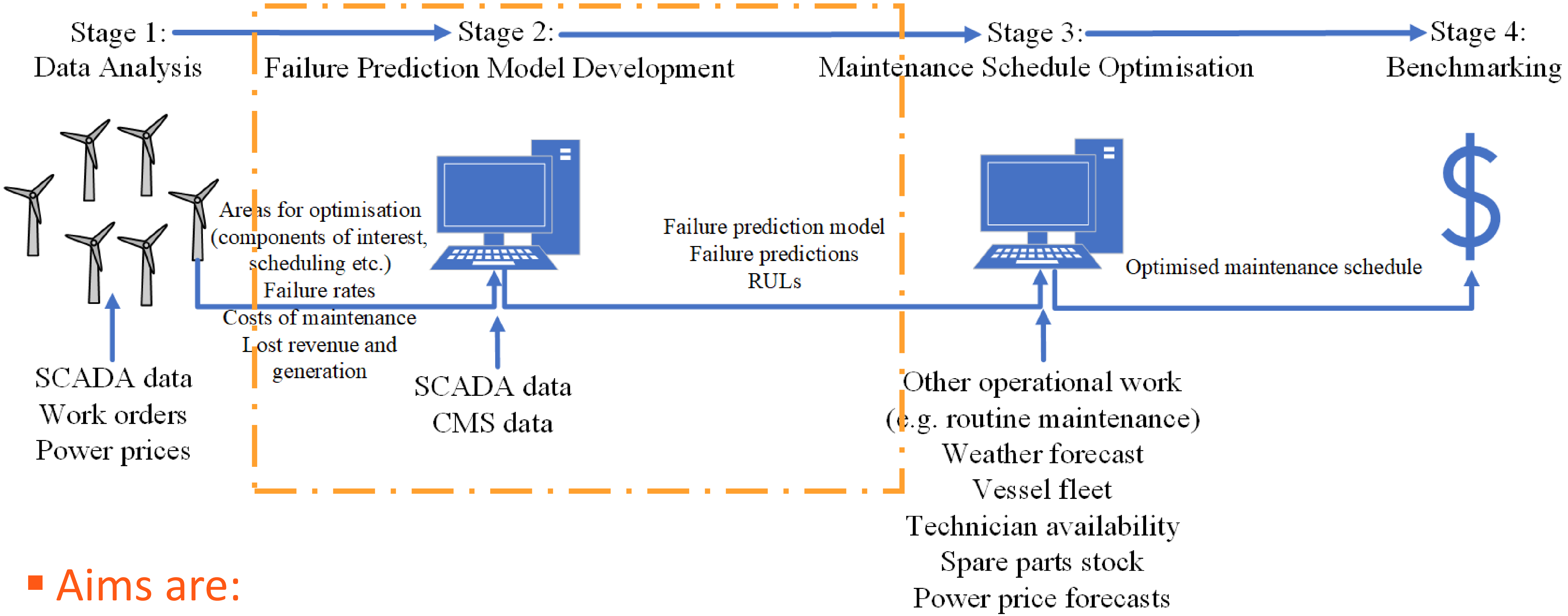


Four Stage Data Driven Framework



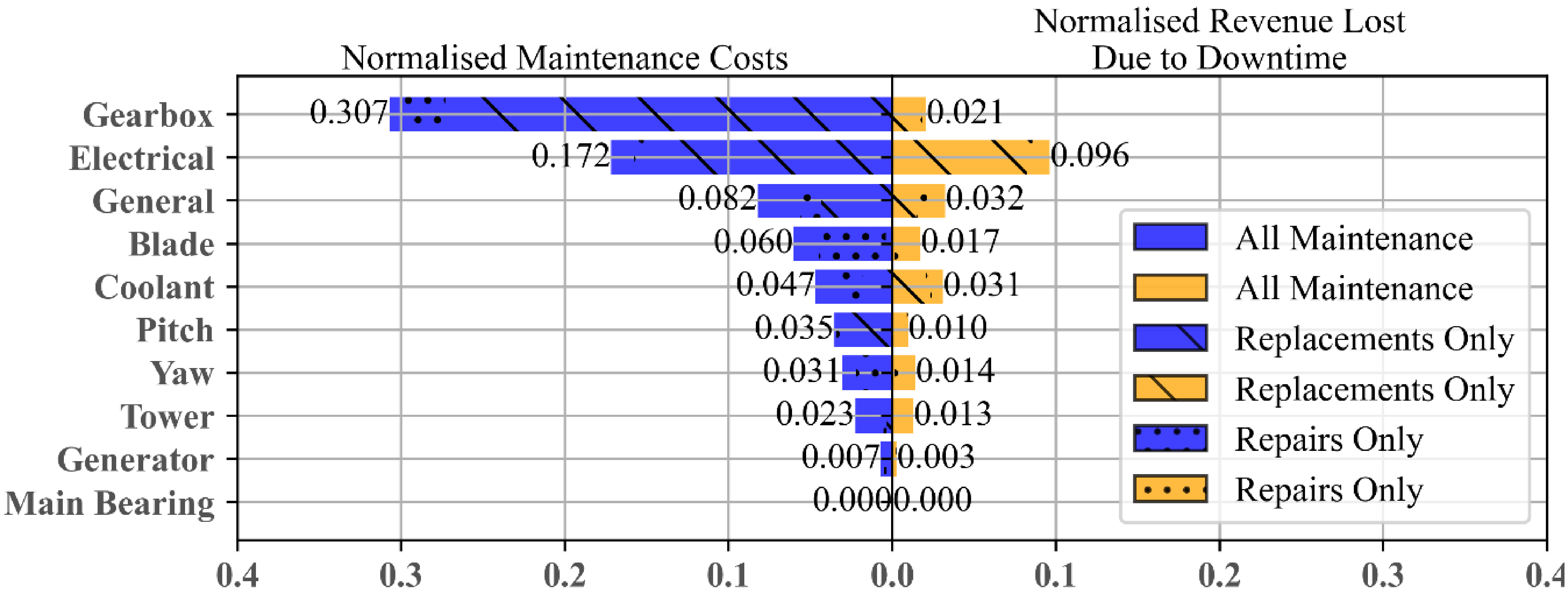
- Applied by operator to any asset.
- Step by step process to reduce maintenance costs.

Stage 2 – Failure Prediction Model Development



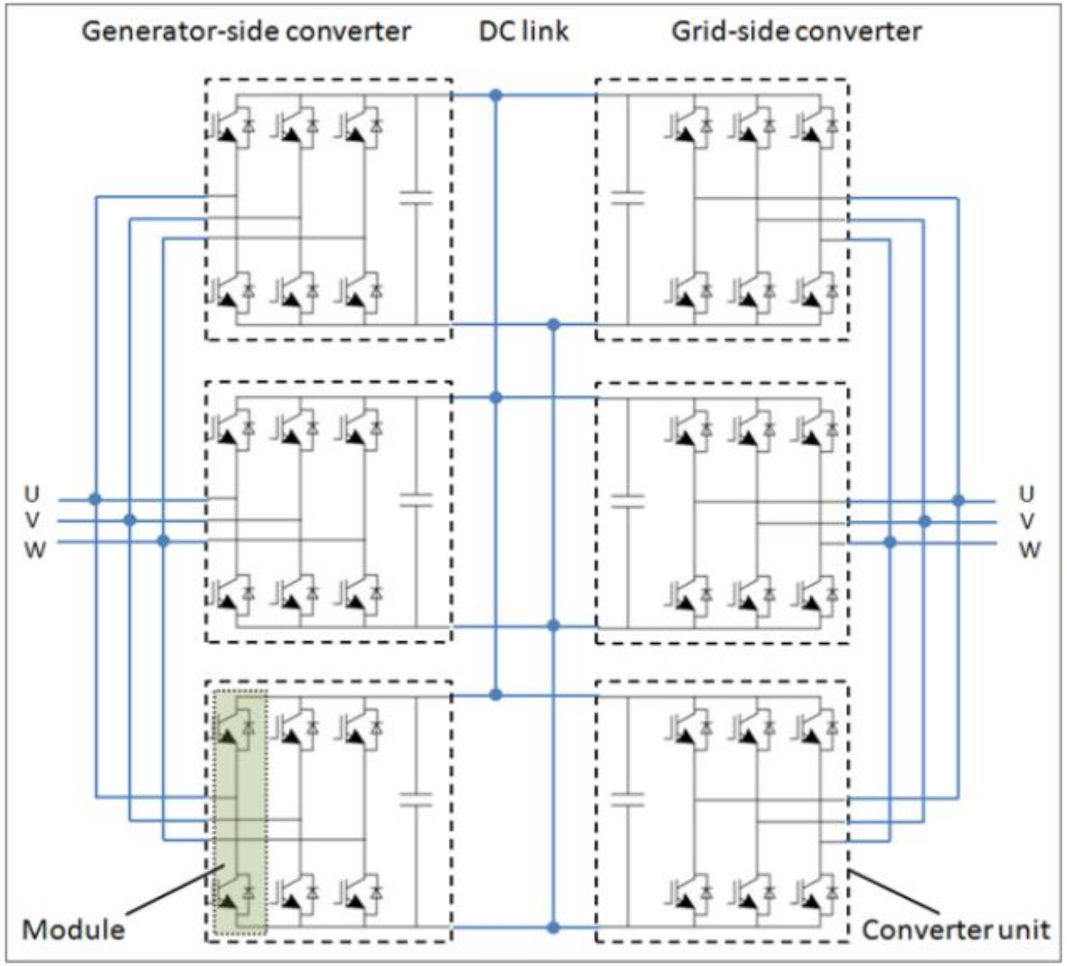
- Aims are:
  1. Reduce turbine downtimes by providing failure predictions,
  2. Eliminate unnecessary maintenance actions.

Why Power Converters?



Wind Turbine Power Converters

- Change variable frequency generated electricity to fixed frequency grid electricity.
- Back-to-back AC/DC/AC converter layout connected by a DC Link.
- Three units per side.



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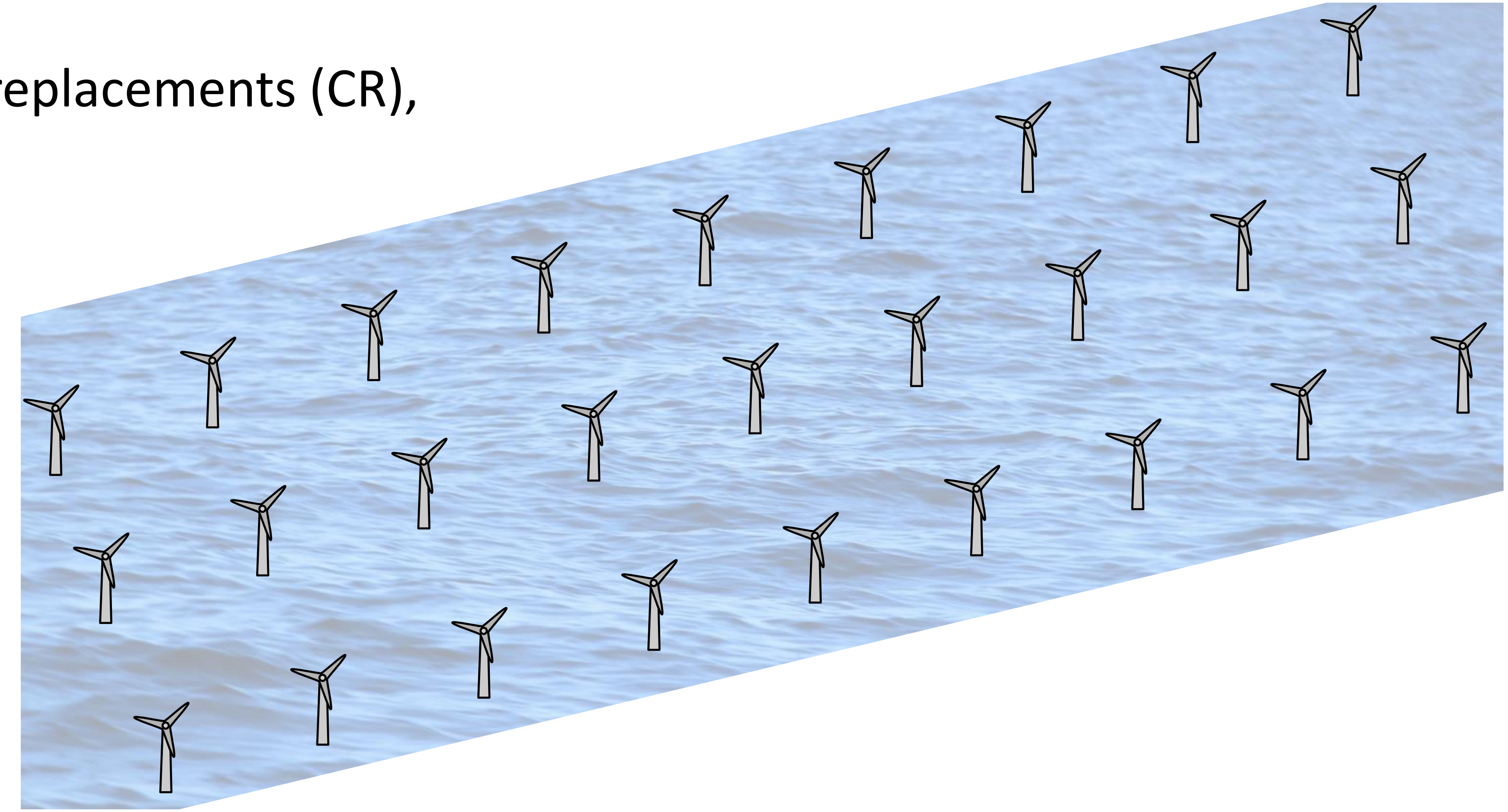
What data have we used?

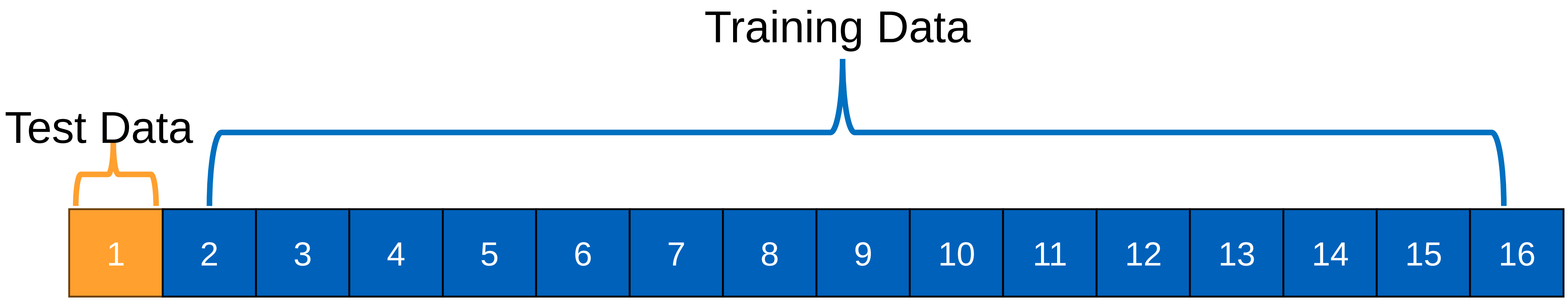
- 27 turbines offshore:
  - 2.3MW,
  - 16 corrective replacements (CR),
  - SCADA Data,
  - 4 years.



Problem set up

- Binary classification
  - Target variable is time to failure
  - Classify each datapoint
- Highly imbalanced
  - Resampled to a ratio of 5:1
- 8 model architectures
- 16 models trained per architecture
  - 1 replacement kept separate for testing

Problem set up



What data have we used?

Feature	Source	Sample Rate	Scaling	6-feature models	12- feature models
Active power	SCADA	10-min averages	Rated power	✓	✓
Wind speed	SCADA	10-min averages	Min-max	✓	✓
Converter coolant temperature	SCADA	10-min averages	Min-max	✓	✓
Inverter coolant pressure	SCADA	10-min averages	Min-max	✓	✓
Tower humidity	SCADA	10-min averages	Min-max	✓	✓
Cumulative energy converted	Engineered	10-min averages	Min-max	✓	✓
Current phase L1-L2 difference	Engineered	10-min averages	Min-max	×	✓
Current phase L1-L3 difference	Engineered	10-min averages	Min-max	×	✓
Current phase L2-L3 difference	Engineered	10-min averages	Min-max	×	✓
Voltage phase L1-L2 difference	Engineered	10-min averages	Min-max	×	✓
Voltage phase L1-L3 difference	Engineered	10-min averages	Min-max	×	✓
Voltage phase L2-L3 difference	Engineered	10-min averages	Min-max	×	✓

Pre-processing

1. Calculate cumulative energy conversion from installation to replacement
2. Remove datapoints for any overlapping instances of converter maintenance
3. Resample data to address class imbalance
4. Current and voltage difference features are engineered by subtracting one phase from the others. E.g. current L1 – L2 and current L1-L3.
5. Data are assigned a time to failure interval of longer than 8 weeks to failure or within 8 weeks.
6. Scale the features
7. The target variable is ordinal encoded.

Evaluation metrics

- Classic metrics
  - Precision and recall
- Doesn’t really evaluate the operational performance of a model
  - More interested in if we make a correct replacement decision and the cost impact of this
- Propose a new scoring function based on “expected cost of deployment”

		Predicted	
		More than 8 weeks to failure	Less than 8 weeks to failure
Actual	More than 8 weeks to failure	TN	Precision FP
	Less than 8 weeks to failure	Recall FN	TP

Expected Cost of Deployment

- What is the cost of utilising our model in deployment?
- Annual failure rate of x (per turbine per year)
- A successful detection rate of z (recall)
- A false positive rate of y (per turbine per year)
- A corrective maintenance cost of C_c and preventative maintenance cost of C_p
- Over the course of n years we get the following cost:

$$C = c_p(ny + nzx) + c_c nx(1 - z)$$

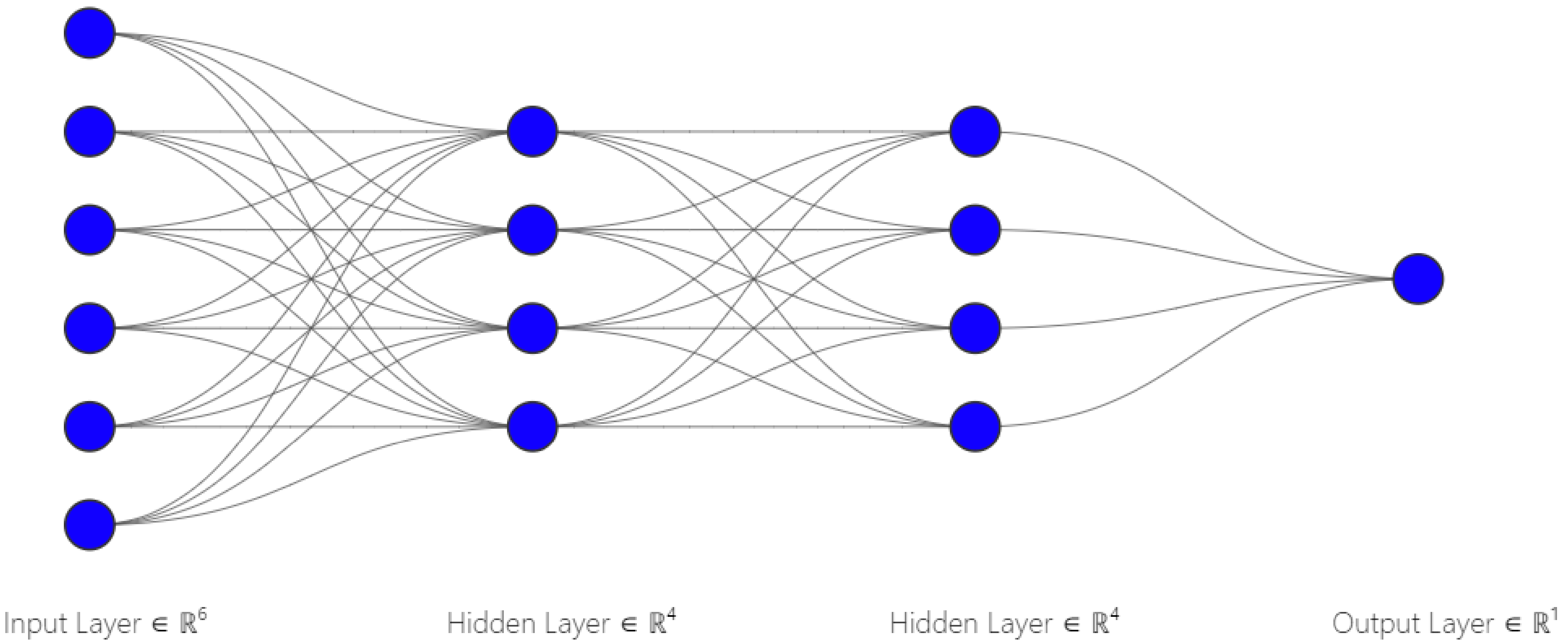
How to use the model outputs?

- We also need to decide how we can use the output of our models to decide on replacements
- 10 different thresholds:
  - 3,5,7,10,21,28 day consecutive thresholds
  - Weekly, 2,3,4-weekly modal predictions

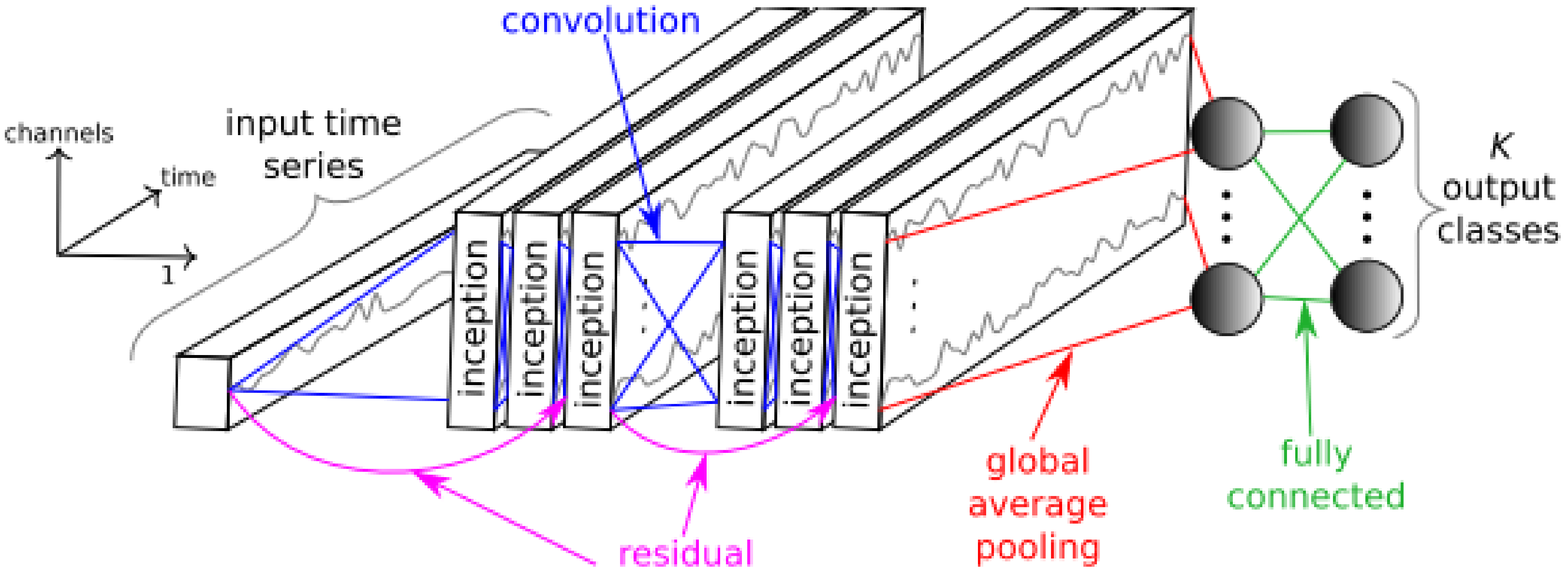
Model architectures

- 8 different architectures:
  1. Logistic Regression (LR) – 6 input features
  2. Decision Tree (DT) – 6 input features
  3. Random Forest (RF) – 6 input features
  4. XGBoost (XGB) – 6 input features
  5. ANN (ANN6) – 6 input features
  6. ANN (ANN12) – 12 input features
  7. InceptionTime network (IT6) – 6 input features
  8. InceptionTime network (IT12) – 12 input features

Model architectures



Model architectures



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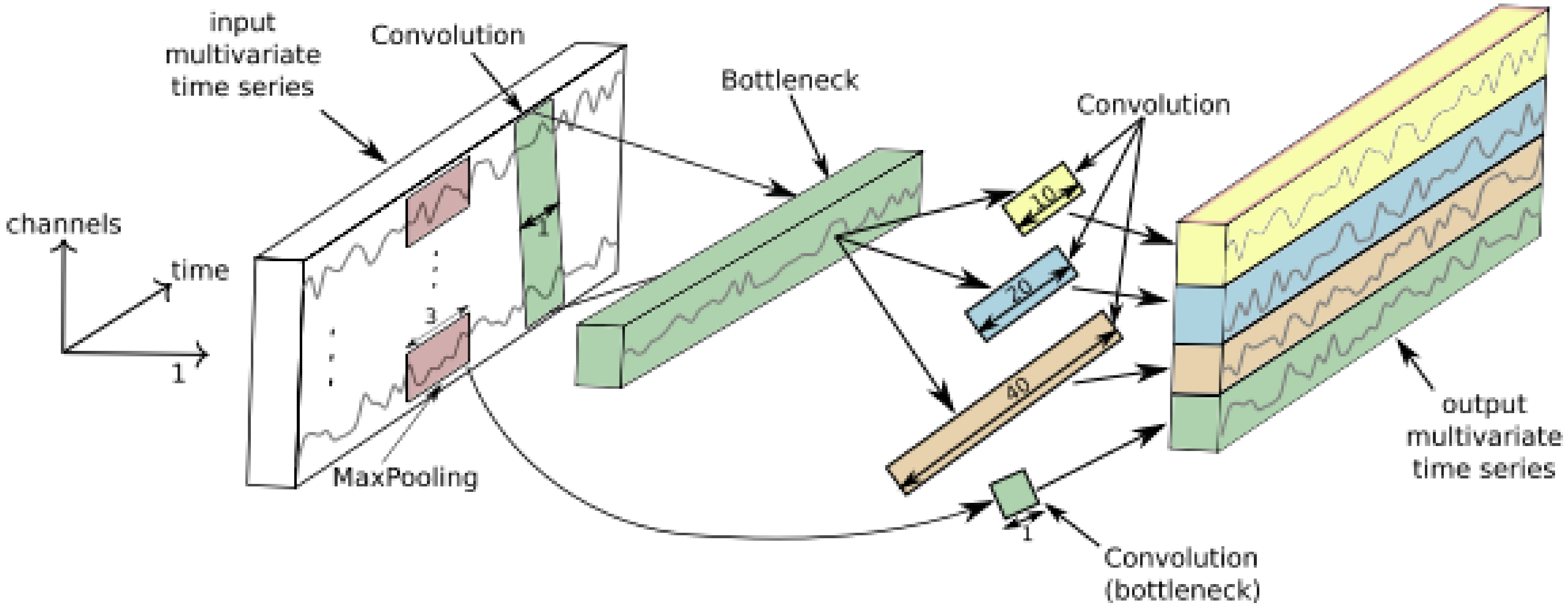
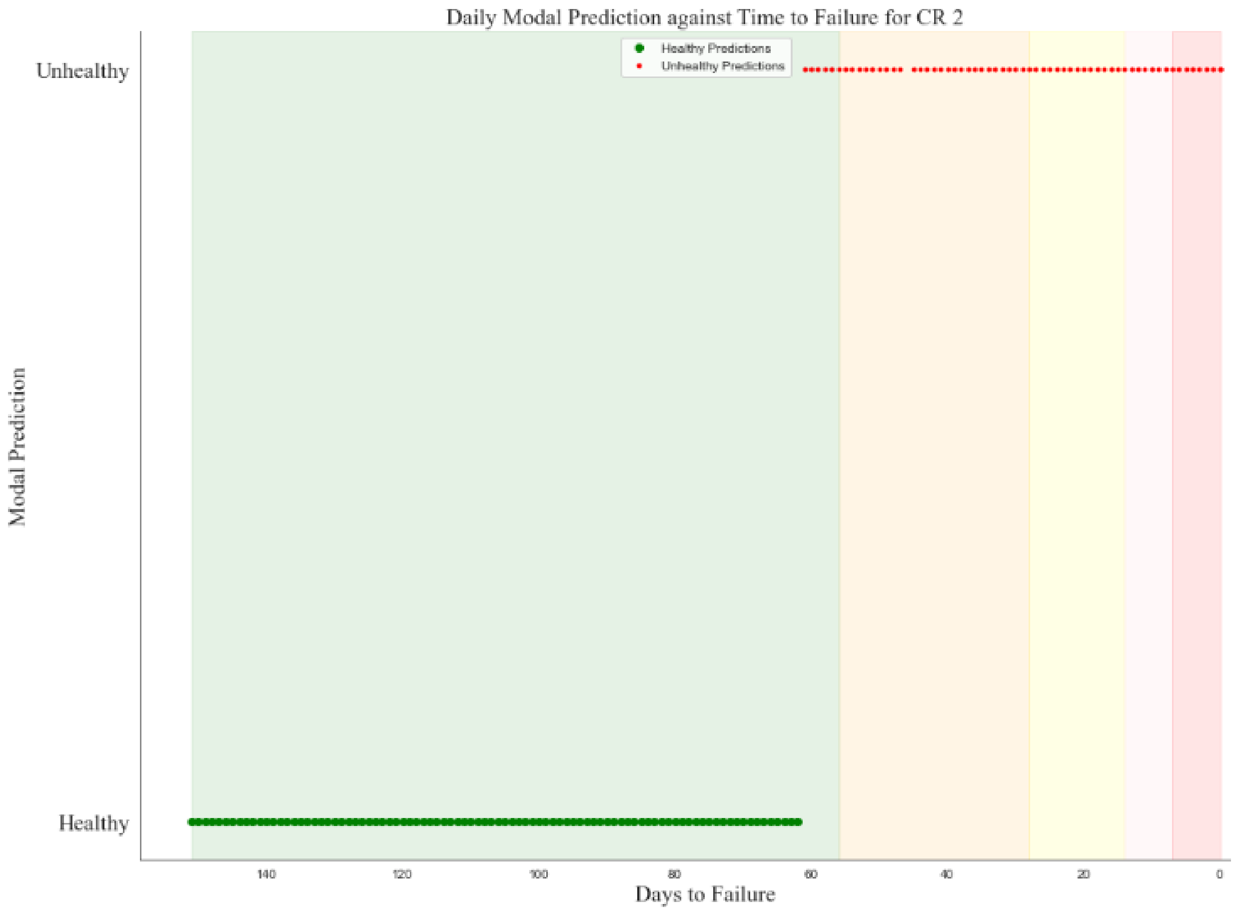
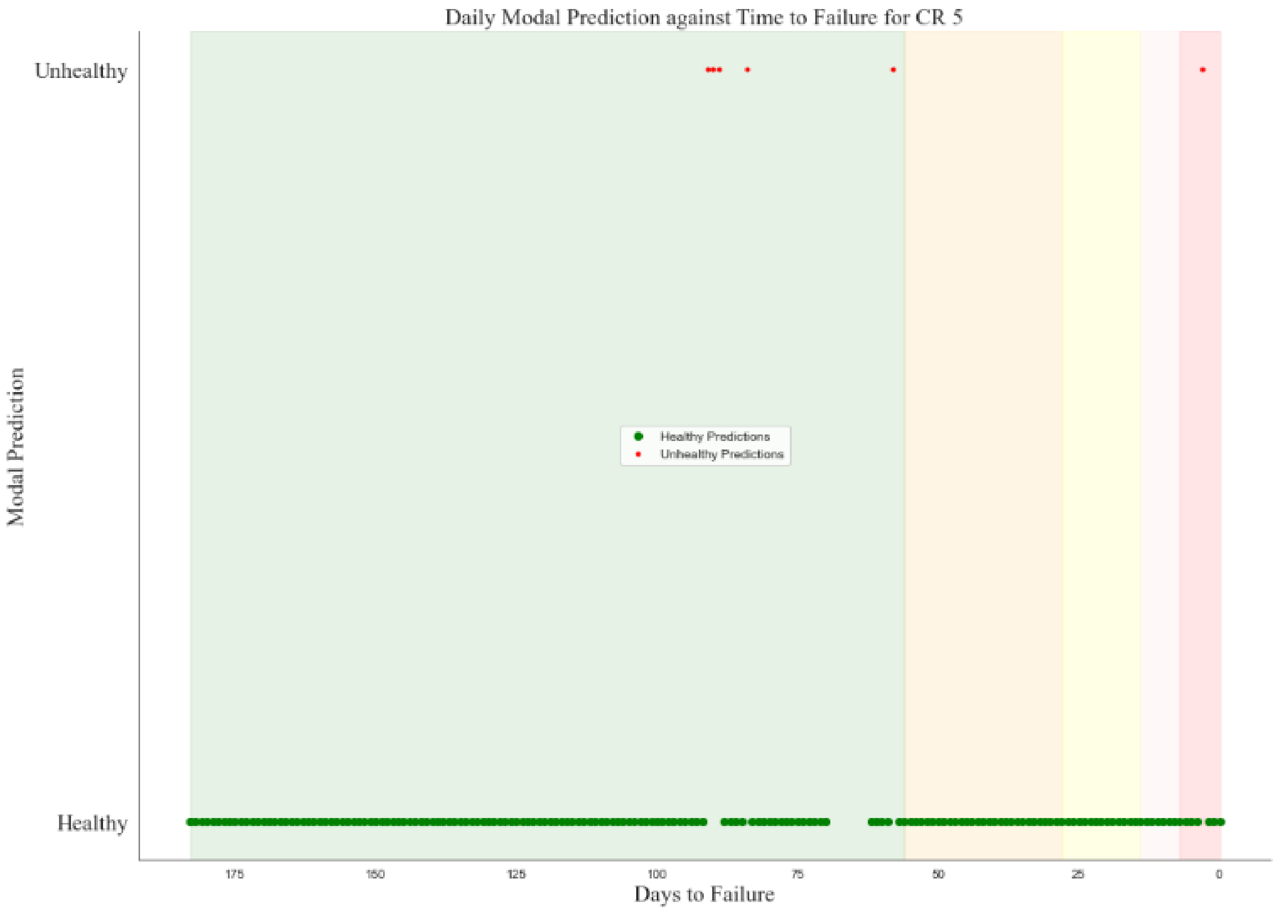


Test Results

Model	Average Recall (%)	Average Precision (%)
LR	0	0
DT	26	49
RF	51	24
XGB	56	29
ANN6	57	39
ANN12	24	34
IT6	14	100
IT12	15	100

Failure Predictions





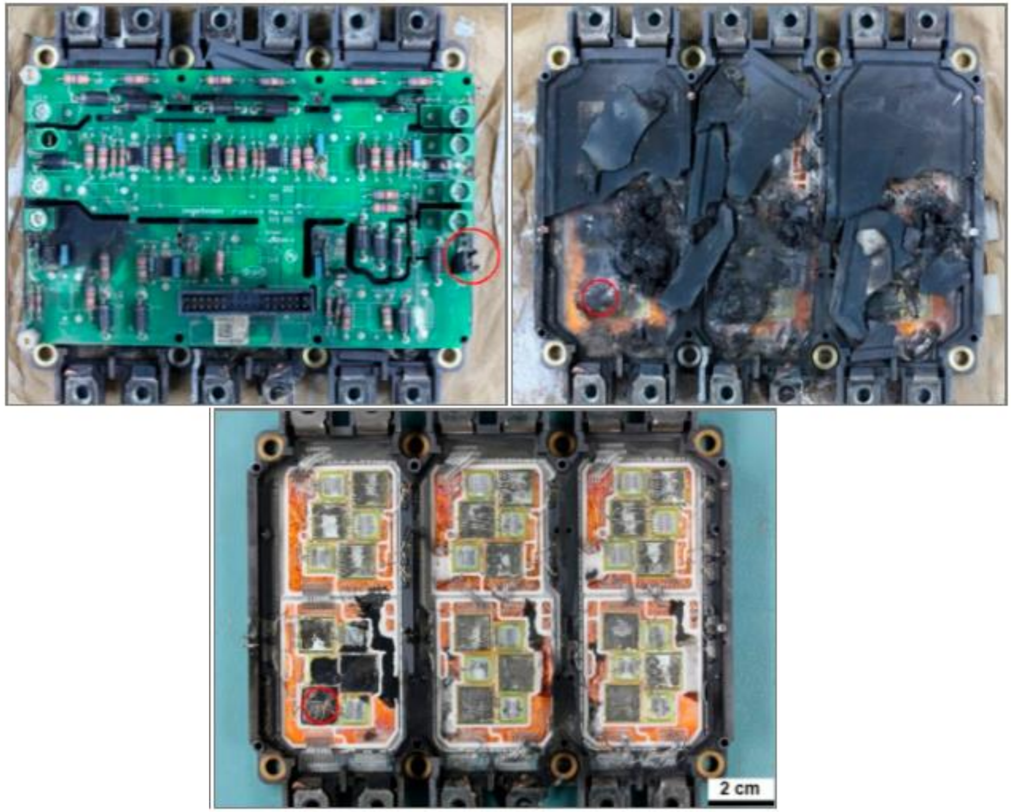
Performance in context of decision making

- Improved performance compared to just recall and precision

Decision Threshold	Model	Successful Failures Prevented	Missed Failures	False Positives	Total Cost	Detection Rate	False Positive Rate	Expected Cost of Deployment (n=15)
3-day	ANN6	8.00	8.00	0.00	40.00	0.50	0.00	**6.25**
3-day	ANN12	9.00	7.00	0.00	37.00	0.56	0.00	**5.78**
3-day	IT6	3.00	13.00	4.00	59.00	0.19	0.19	**11.45**
3-day	IT12	4.00	12.00	4.00	56.00	0.25	0.19	**10.98**
3-day	LR	0.00	16.00	0.00	64.00	0.00	0.00	**10.00**
3-day	DT	13.00	3.00	73.00	98.00	0.81	1.78	**30.58**
3-day	RF	12.00	4.00	73.00	101.00	0.75	1.77	**30.94**
3-day	XGB	13.00	3.00	77.00	102.00	0.81	1.82	**31.18**
Weekly modal	ANN6	8.00	8.00	0.00	40.00	0.50	0.00	**6.25**
Weekly modal	ANN12	8.00	8.00	0.00	40.00	0.50	0.00	**6.25**
Weekly modal	IT6	3.00	13.00	4.00	59.00	0.19	0.19	**11.45**
Weekly modal	IT12	3.00	13.00	4.00	59.00	0.19	0.19	**11.45**
Weekly modal	LR	0.00	16.00	0.00	64.00	0.00	0.00	**10.00**
Weekly modal	DT	13.00	3.00	64.00	89.00	0.81	1.63	**28.40**
Weekly modal	RF	12.00	4.00	59.00	87.00	0.75	1.54	**27.47**
Weekly modal	XGB	14.00	2.00	68.00	90.00	0.88	1.67	**28.53**

What might be causing the poor performance?

1. Poor model
2. Insufficient data
   - We don’t have enough data to capture all failure modes
3. Incorrect data
   - Not monitoring the right parameters
   - Sampling frequency too low



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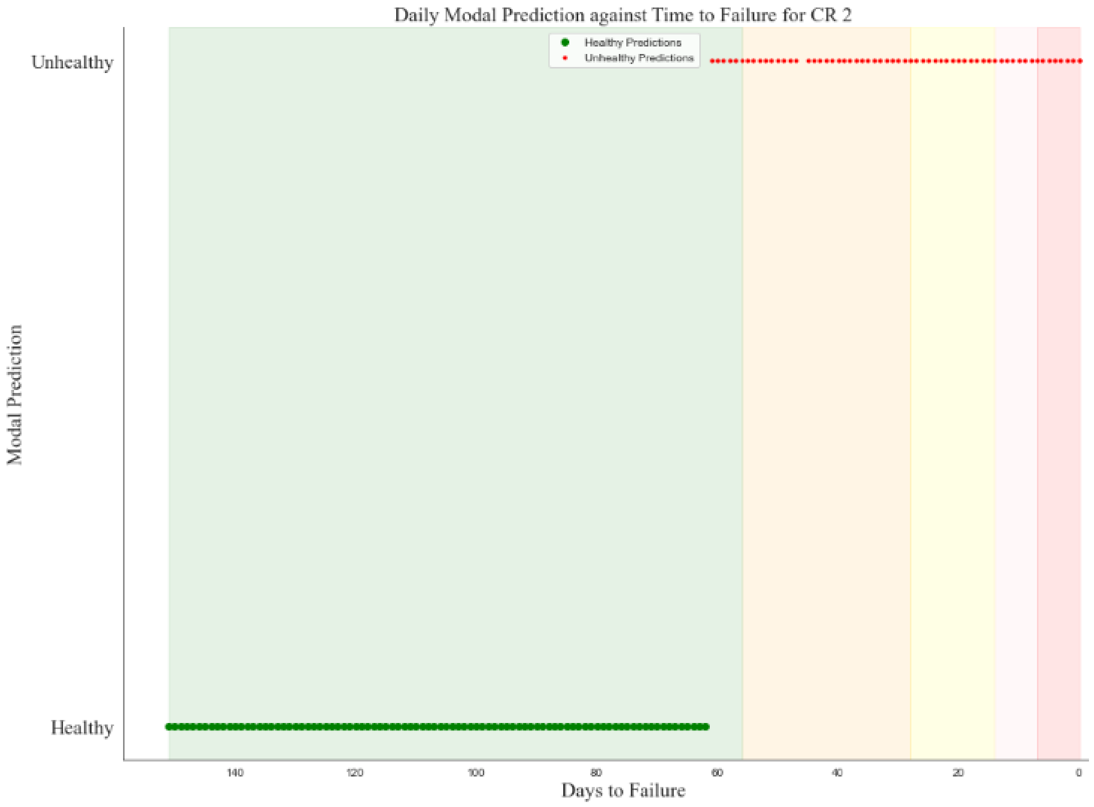
Wind Turbine Power Converter Failure Modes

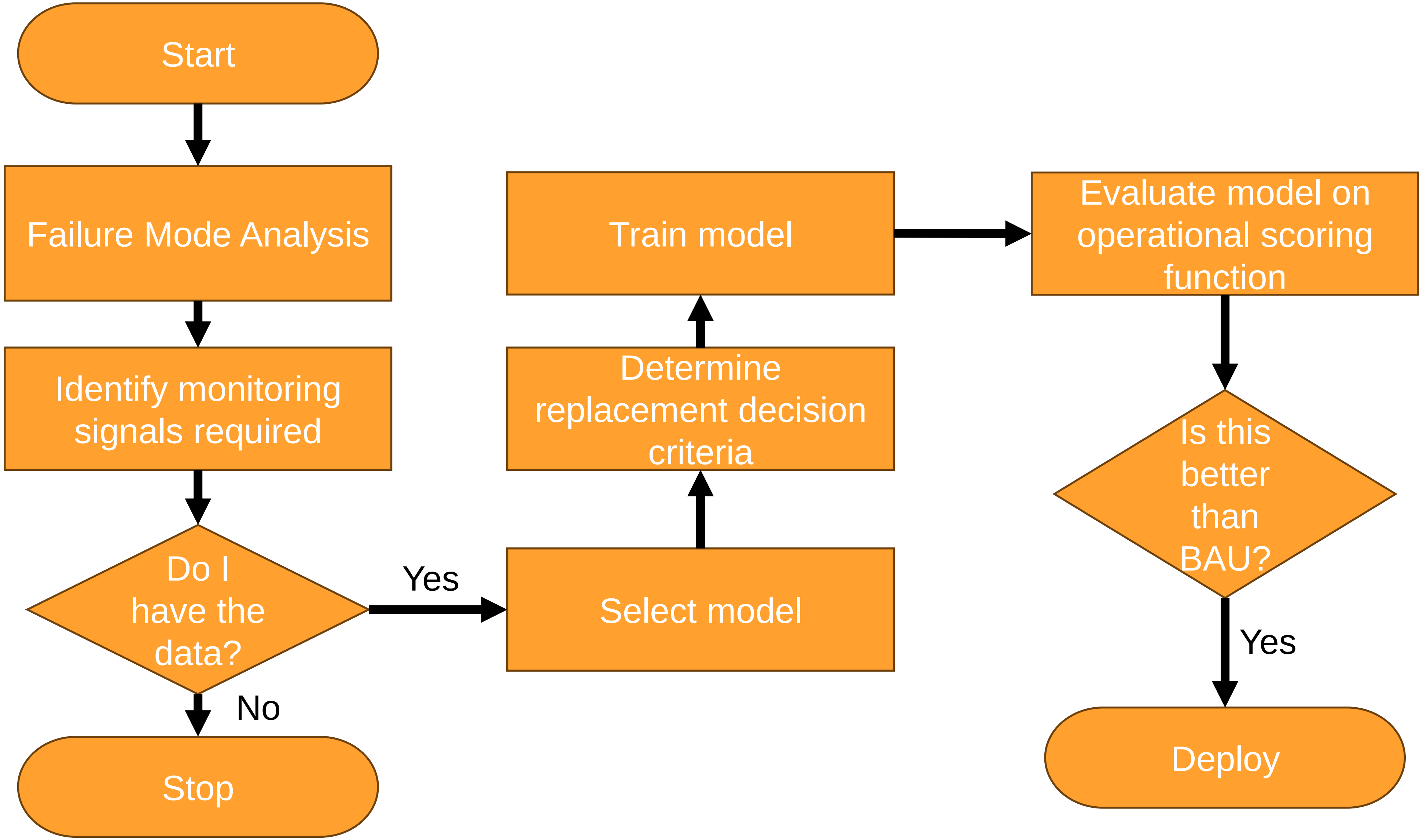
Failure Mode	Importance	Monitoring Signals	Influencing Factors
Bond-wire lift-off	**Low**	**$V_{CE,Sat.}$ R_{ON}**	**Temperature cycles**
Solder fatigue	Low	R_{th}, T_j, Tc, T_s	Temperature cycles
Degradation of thermal paste	Medium	R_{th}, T_j, Tc, T_s	Temperature cycles
Fretting corrosion	Low	$V_{CE,Sat.}$ R_{ON}, AE	Vibrations
Tin whiskers	Low	X-ray Inspections	Unknown
Driver board faults	**High**	**Inspections, V_{CE}, switch times, gate-voltages**	**Manufacturing defects, interference, humidity**
EOS	**High**	**Potentially gate voltages**	**Unknown**
ESD	Low	AE, decay of gate charge	Faulty discharge paths
Parasitic inductances	**High**	**Input and output currents to the converter and IGBTs**	**Improper converter design**
Contamination	**High**	**Inspections**	**Humidity, converter cabinet design**
Electrochemical migration	**High**	**Leakage currents**	**Humidity**
SEB	Low	N/A	Geographical location
Lightning strike	**High**	**N/A**	**Faulty lightning protection systems**
DC faults	Medium	C, ESR	Humidity

Learnings

1. We need to analyse our model performance/design our models for deployment
2. Operators don't have access in the SCADA to the right information to be able to predict power converter failures well
3. Performing a failure mode analysis before training can help with feature selection
    - And determine feasibility

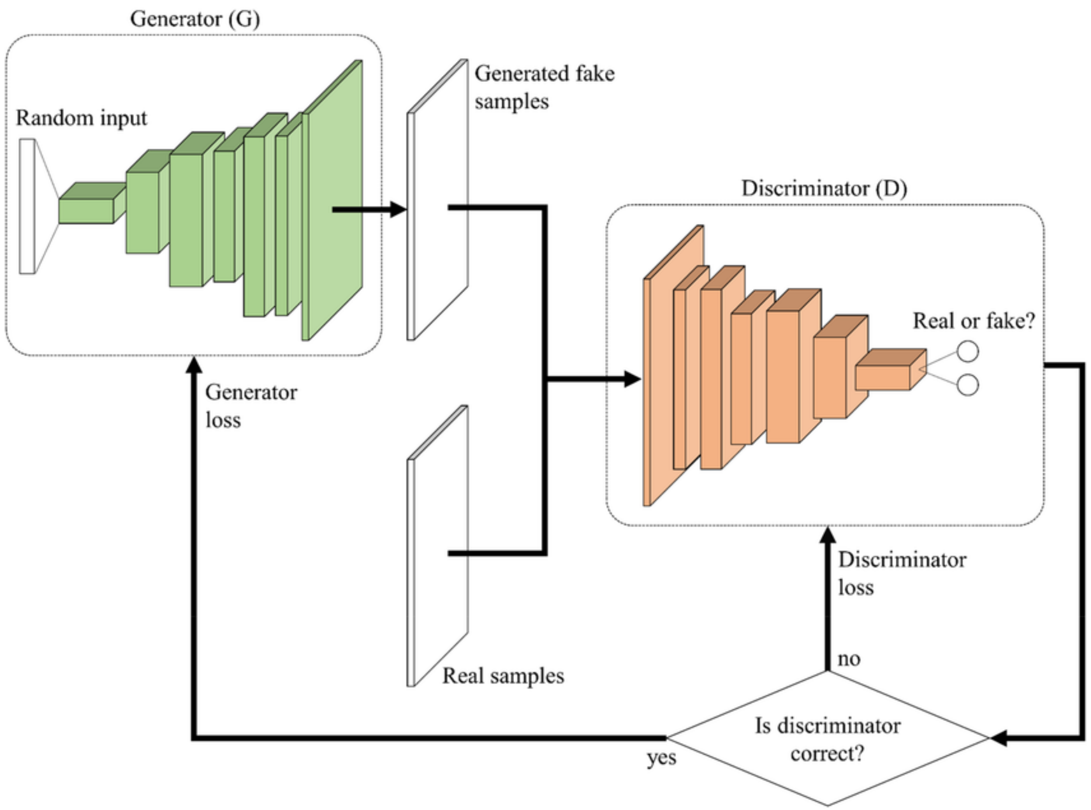


A general approach to designing failure prediction methods



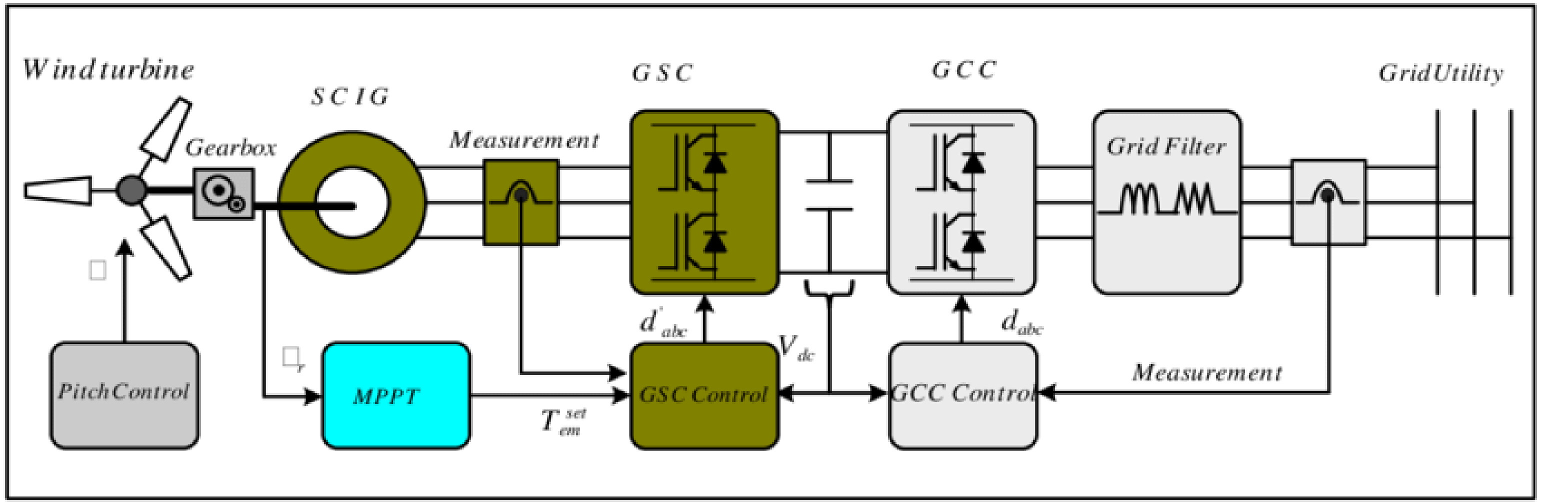
What can we do next?

- Try different models
- Collect better and more data
  - Understand the symptoms of various faults better
  - Collect high frequency data relating to these symptoms
  - Increase our examples of failure. Synthetic data or data of failures from other wind farms.



So what?

- Deep learning methods could be promising for converter failure predictions.
  - It is hard to create generalisable models.
- Improving the performance of models needs the right data to be collected.
- When designing the models we need to consider the maintenance decision making process.



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Thank you

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