A Two-Stage Fault Detection and Classification for Electric Pitch Drives in Offshore Wind Farms using Support Vector Machine

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Contents

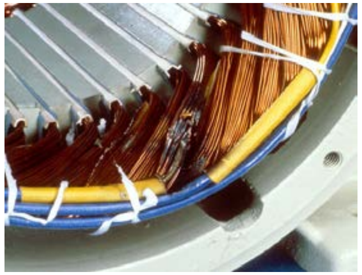
Introduction

- Offshore wind farms are growing larger and farther offshore.
- Maintenance costs are a major concern.
- A *farm-level maintenance strategy* is necessary to cut down maintenance costs.
- Requires increased scope of CBM.

Investigation: Are Pitch and Yaw drives suitable for CBM?

[1] *BVG Associates 2017, Oil and Gas seize the opportunity guides, Offshore Wind*

Faults in Induction motor drives



Common faults in pitch and yaw drives in offshore wind turbines[1]

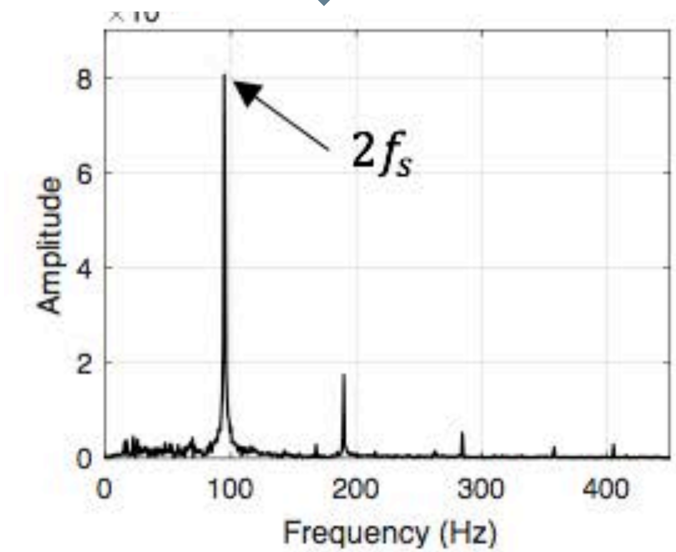
- Stator faults [STF] ~ 40%[2]
- Rotor faults [BRB] ~ 10%
- Bearing faults [BRG] ~ 35%

Variations in the electrical circuit or airgap magnetic field

Manifests as specific fault signature in Extended Parks Vector (EPVA)

$$i_P = |i_d + j i_q|$$

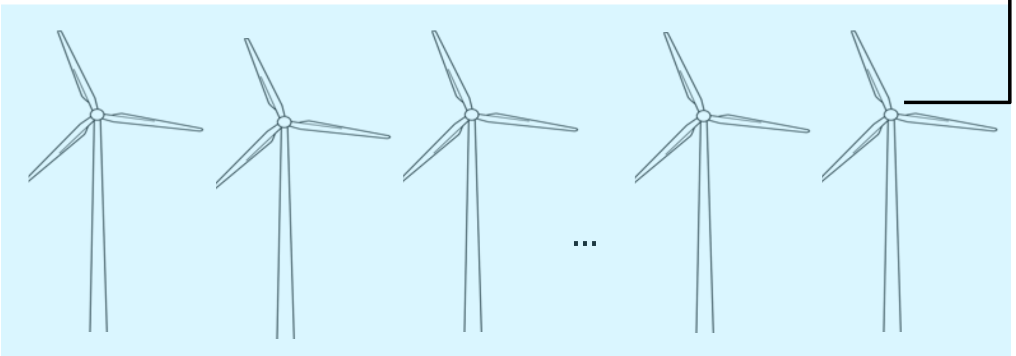
- $f_{STF} = 2f_s$
- $f_{BRB} = 2sf_s$
- $f_{BRG} = f_v, 2f_v, |2f_v - f_s|$



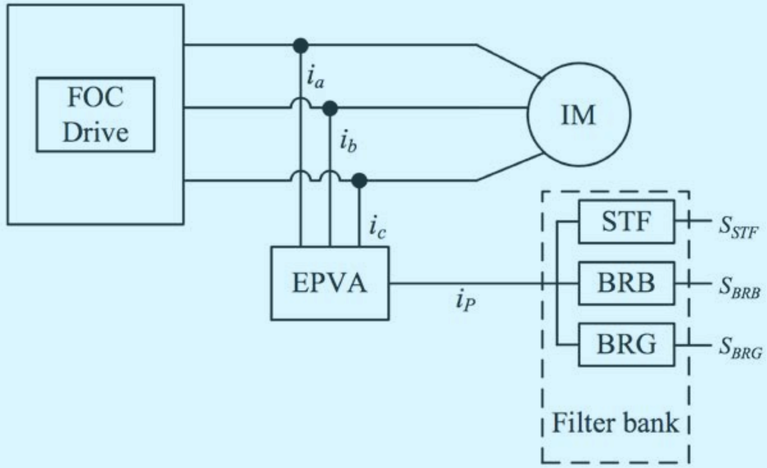
FFT of EPV in the case of Stator Fault

[1] *Yin et al., Fault analysis of Wind Turbines in China, RSER 2016*
[2] *Benbouzid et al., What stator current processing-based technique to use for induction motor rotor faults diagnosis? , IEEE Trans. Energy Conversion, 2003*

A 2-stage approach



Stage 1: Onboard Fault Detection



Faulty?

No

End

Yes

Stage 2: Farm-level Classifier

Advantages

- Easy to retrofit at the WT, only requires information from the drive.
- Less data transfer from turbines
- Benefit from farm-level knowledge
- Need not replicate computationally intensive tasks at WTs

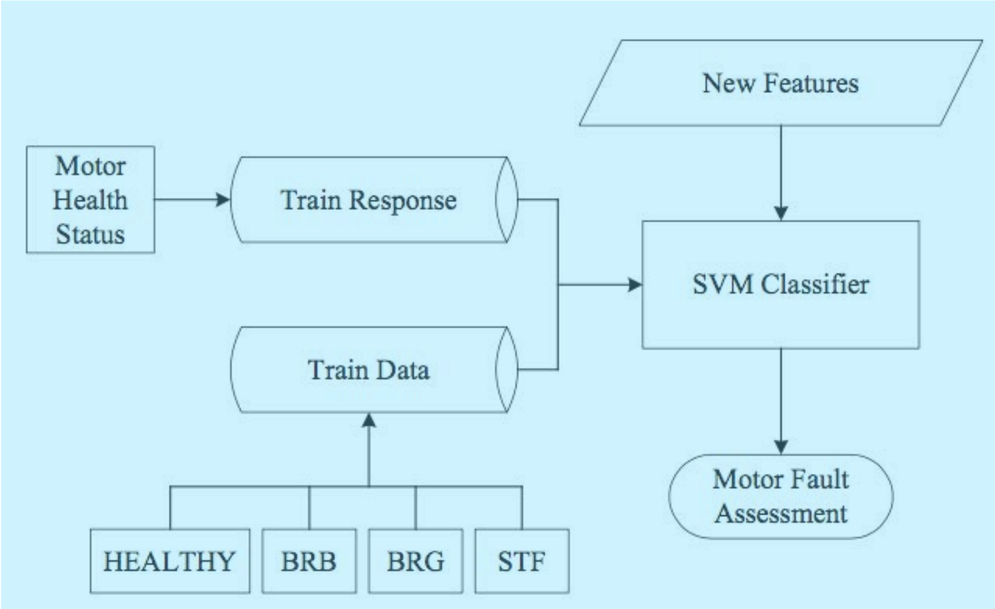
Support Vector Machine Classification

- SVM draws an optimum hyperplane in feature-space for classification.
- Classify faults accurately in variable loads and speeds
- *Look beyond the current signatures – time & frequency domain features*

Feature set: $[f_{STF}, f_{BRB}, f_{BRG}, F]$

$F =$

Time domain	Frequency domain
$t_1 = \sum_{n=1}^{N} x(n)/N$	$f_1 = \sum_{k=1}^{K} s(k)/K$
$t_2 = \sqrt{\sum_{n=1}^{N}(x_n - t_1)^2/N}$	$f_2 = \sum_{k=1}^{K}(s(k) - f_1)^2/K$
$t_3 = \sqrt{\sum_{n=1}^{N} x(n)^2/N}$	$f_3 = \sum_{k=1}^{K}(s(k) - f_1)^3/K$
$t_4 = max(\lvert x(n)\rvert)$	$f_4 = \sum_{k=1}^{K}(s(k) - f_1)^4/K$
$t_5 = \frac{\sum_{n=1}^{N}(x(n)-t_1)^3}{t_2^3(N-1)}$	$f_5 = \sum_{k=1}^{K} ks(k)/\sum_{k=1}^{K} s(k)$
$t_6 = \frac{\sum_{n=1}^{N}(x(n)-t_1)^4}{t_2^4(N-1)}$	$f_7 = \sqrt{\frac{\sum_{k=1}^{K}(k^2 s(k)}{\sum_{k=1}^{K} s(k)}}$
$t_8 = \frac{t_4}{(\frac{1}{N}\sum_{n=1}^{N}\sqrt{\lvert x(n)\rvert})^2}$	$f_8 = f_6/f_5$
	$f_9 = \frac{\sum_{k=1}^{K}(k-f_5)^3 s(k)}{K f_6^3}$
	$f_{10} = \frac{\sum_{k=1}^{K}(k-f_5)^4 s(k)}{K f_6^4}$
where $x(n)$ is signal time series $n = 1, 2, \ldots N$	where $s(k)$ is the frequency spectrum, $k = 1, 2, \ldots K$



Supervised Learning

Reliable fault classification → Improved maintenance planning

Wealth of farm-level analytics → better inventory planning and insights into RCA

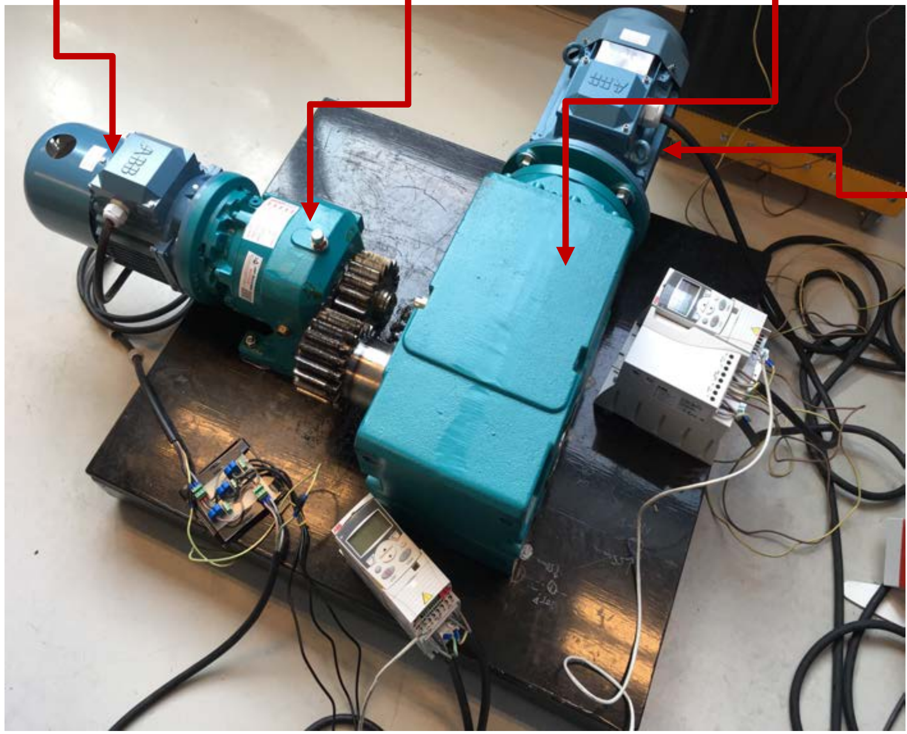
Experimental Results

Test motor
1.1kW 4-pole
3-phase IM

Test gearbox
2-stage
planetary
gearbox
(1:48)

Load gearbox

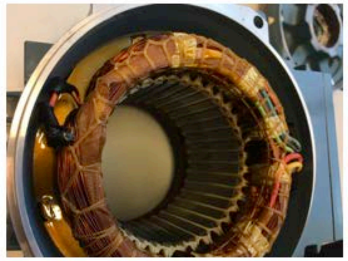
Load
Motor



~600 cases,4 scenarios in variable load and speed conditons:

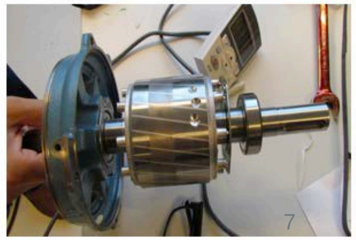
a. Healthy motor

b. Seeded stator turns fault



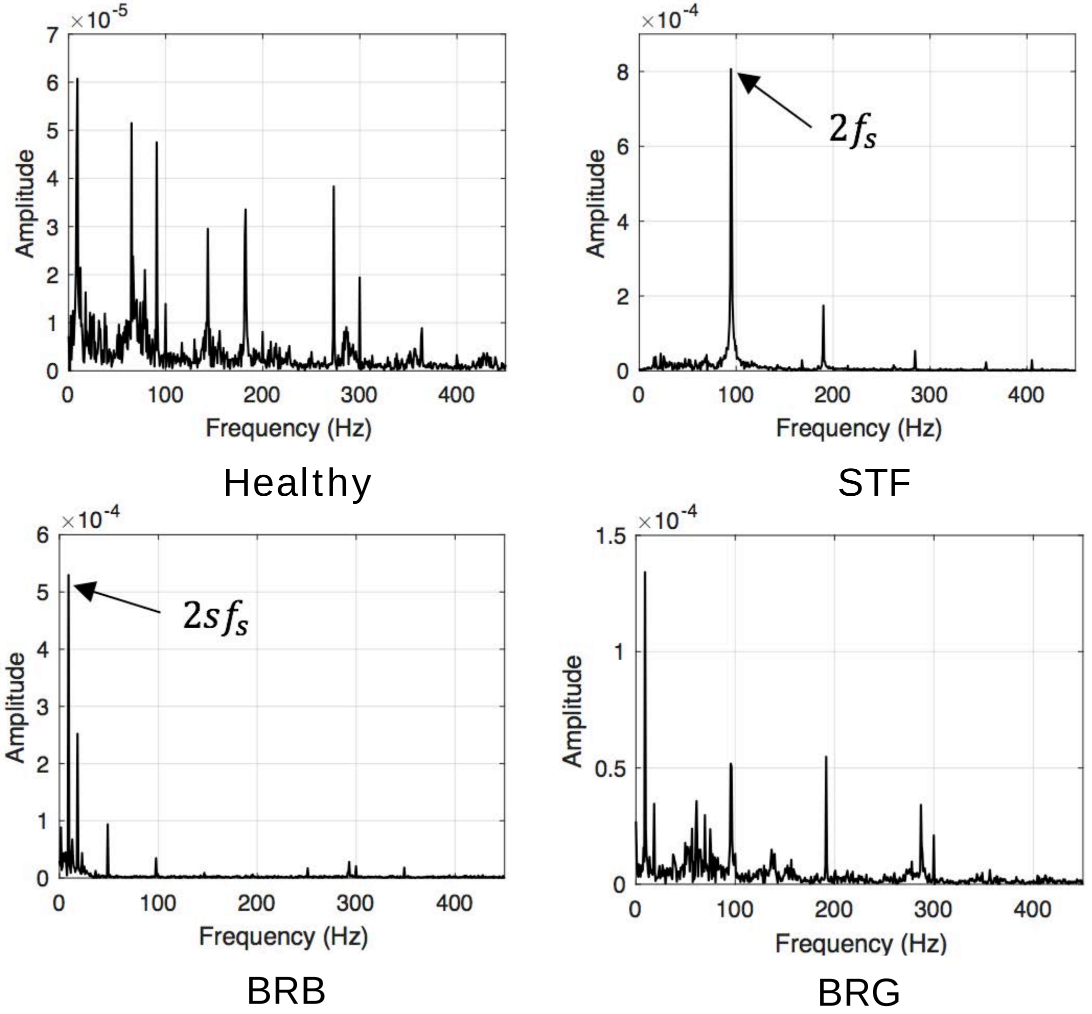
c. Seeded bearing fault

d. Seeded broken rotor bars fault

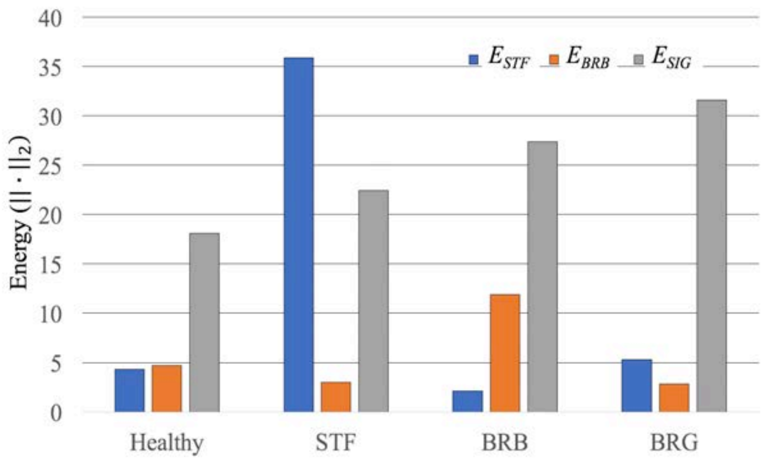


Experimental Results (contd.)

- Stage I – Thresholds for fault detection (WT level)



$$E_{SIG} = E_{i_p} - [E_{STF} + E_{BRB}]$$



Thresholds - band energy > 1.5 times the healthy.

[This may not be generalized. Needs to be calibrated for the motors and operation profiles]

Experimental Results (contd.)

- Stage II – SVM classification

About 50% data was used for training and remaining for classification

Output class \ Target class	Healthy	STF	BRB	BRG	TPR FNR
Healthy	48 19.8%	0 0.0%	0 0.0%	0 0.0%	100% 0.0%
STF	6 2.5%	59 24.3%	0 0.0%	1 0.4%	89.4% 10.6%
BRB	0 0.0%	0 0.0%	60 24.7%	0 0.0%	100% 0.0%
BRG	0 0.4%	2 0.8%	1 0.4%	66 27.2%	95.7% 4.3%
	88.9% 11.1%	96.7% 3.3%	98.4% 1.6%	98.5% 1.5%	95.9% 4.1%

Overall accuracy of 95.9%

Bearing faults were also correctly diagnosed

Conclusions

Pros:

- A procedure for leveraging farm-level knowledge for accurate fault classification.
- Provides insights into root cause analysis.
- A combination of physics-of-failure metrics and statistical features yields better results under variable load and variable speed conditions.
- The methodology can be extended to incorporate other WT subsystems.
- Reduction in amount of data to be transferred from each wind turbine.
- Retrofit-friendly.

Cons:

- Accurate thresholding may be a difficult task and may need to be fine-tuned over time.
- Requires data for learning progressively.
- Assumption: the wind farm consists of same type of equipment. What happens if you have different types of WTs in the same farm?
- ...

Thank you for your attention!

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