P/O/E/T/S

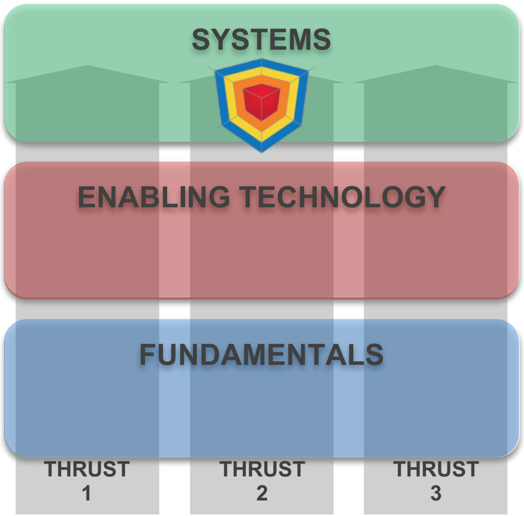
CENTER FOR POWER OPTIMIZATION OF ELECTRO-THERMAL SYSTEMS

Data-Driven Reliability Monitoring and Fault Diagnostics of High-Power Density Motors

PI: Debbie Senesky, Pingfeng Wang, Haran Kiruba

Optimizing Hall-effect Sensors for Motors

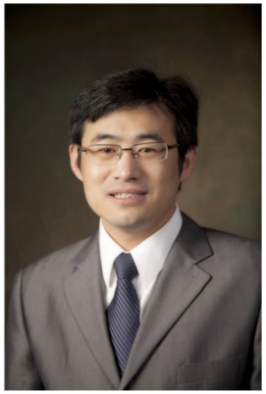
Develop Hall-effect sensor placements and machine learning algorithms to predict faults in electric motors



O1	Optimize Hall-effect Sensor Placement in Motor
O2	Digital Twin of Motor and Simulating Faults
O3	Detecting Fault in Motor System

Collaboration between Stanford and UIUC

Prof. Wang



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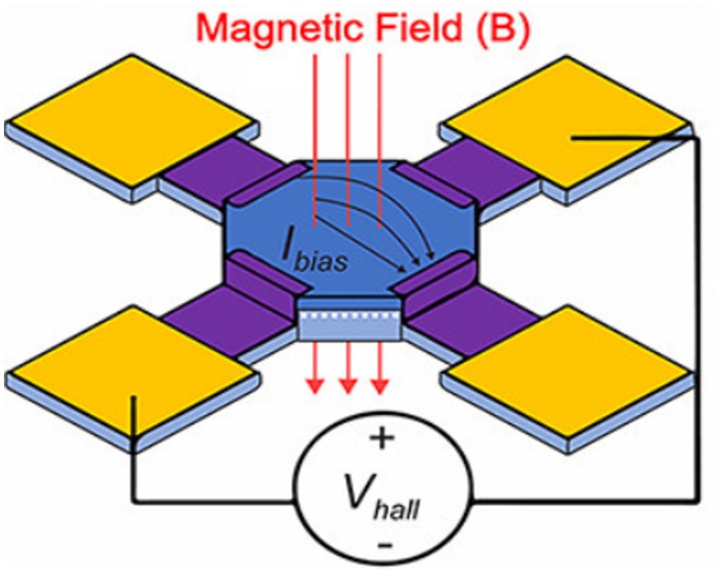
Industrial POC's: Timothy Krantz (NASA), Tim Deppen (PC Krause & Associates)

Motivation: Health of Motor Systems

Predictive Maintenance Market to Hit USD 111.34 Billion by 2030, at a CAGR of 26.2%

- Global News Wire

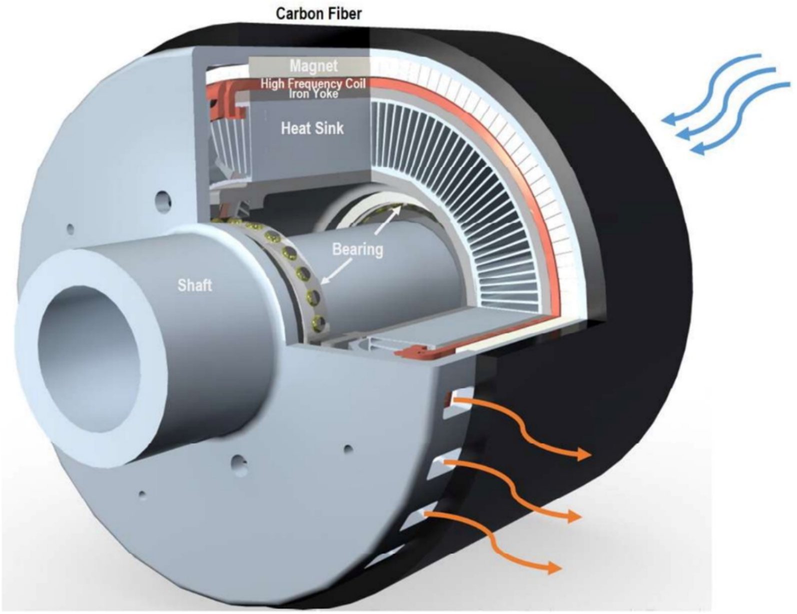


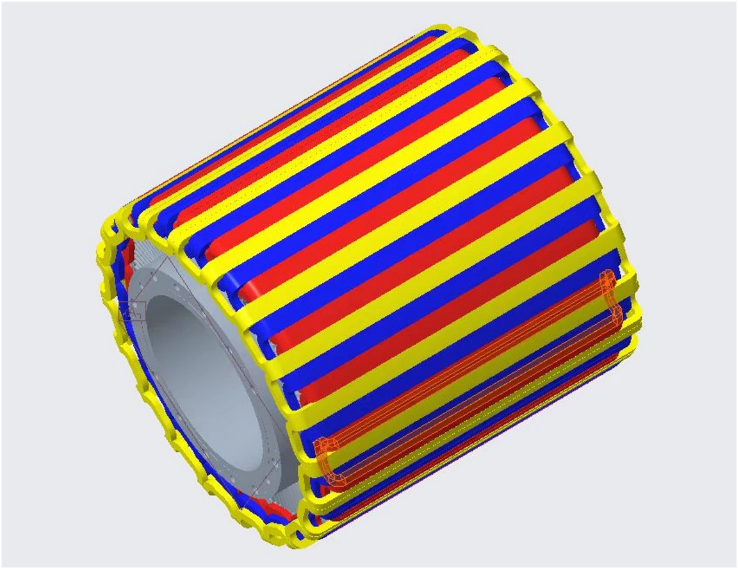
Hall-effect Sensors

- Non-invasive
- Measure magnetic field
- Low-footprint
- Low-cost
- Data rich (high frequency)

Motivation: Health of Motor Systems

1-MW, 15,000 rpm, radial-flux air-gap winding PMSM with an outer-rotor structure achieves 13~kW/kg specific power with a self-pumped air cooling system.



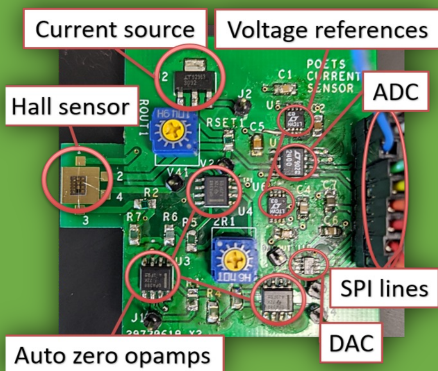


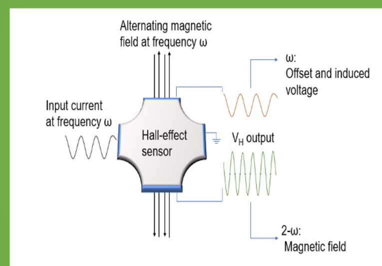
Air-gap winding

- Eliminate iron teeth
- Reduces active weight
- Mitigates the iron losses
- Require on force reaction, insulation and cooling.

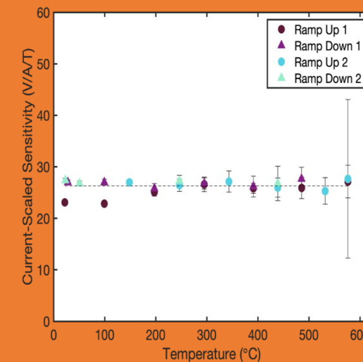
Recent Breakthrough in Hall-Effect Sensors

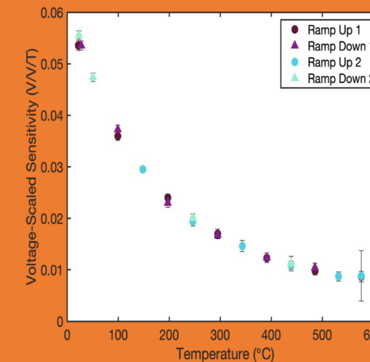
Circuits & Modalities



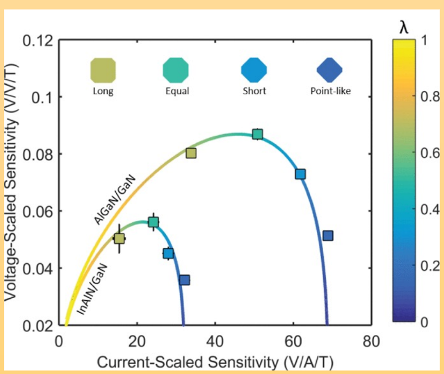


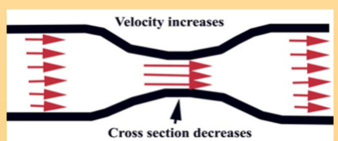
Temperature Range Extension

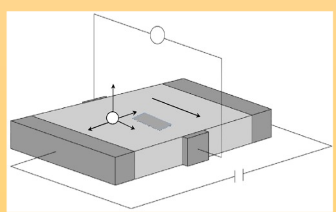




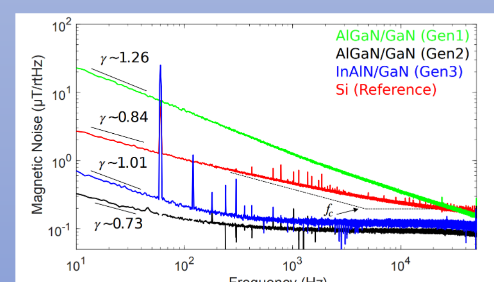
Sensitivity/Geometry Optimization

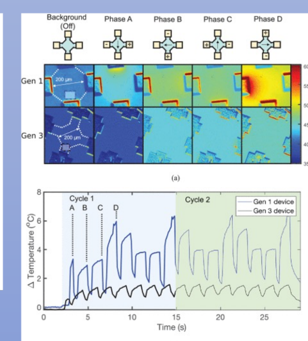






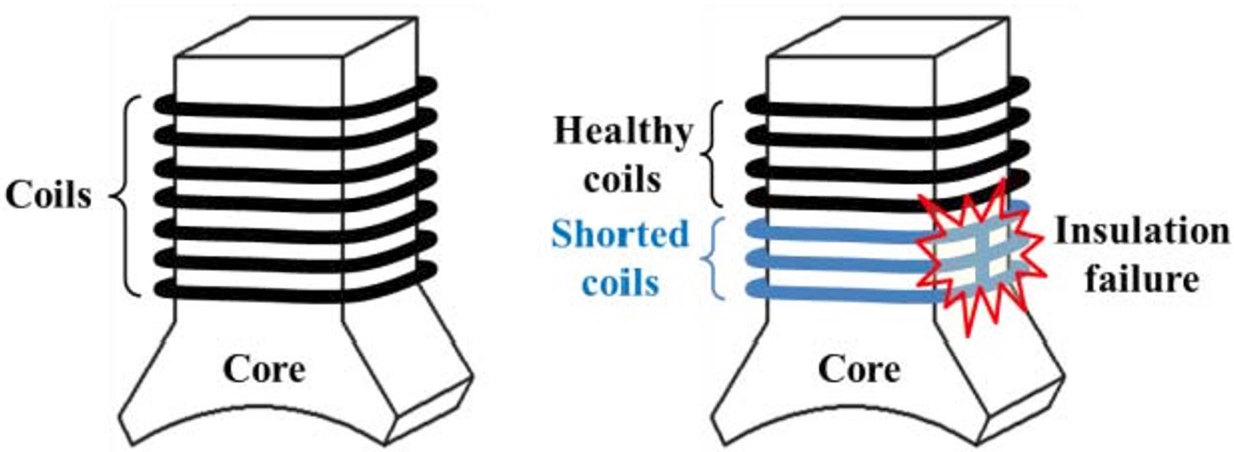
Noise Optimization





12 Papers, 4 Patents, 3 PhD thesis, 3 Labs, 1 Mission

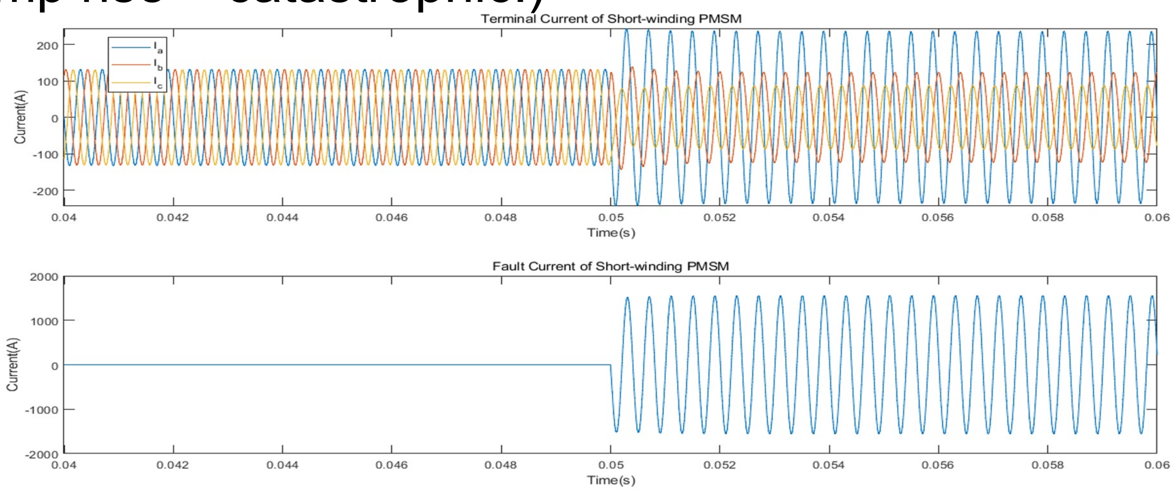
Starting Focus: Inter-turn/phase Winding Fault

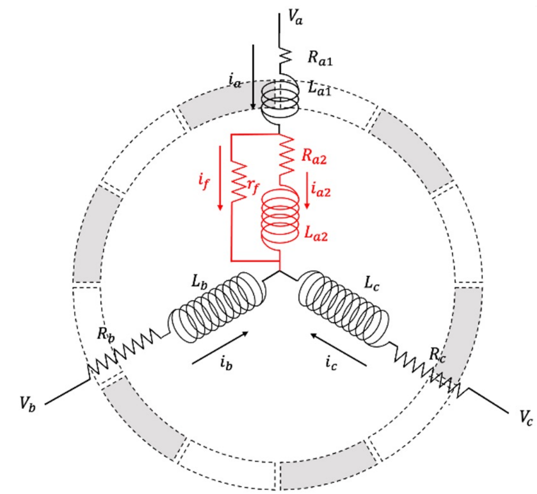


(a) Healthy state (b) Faulty state

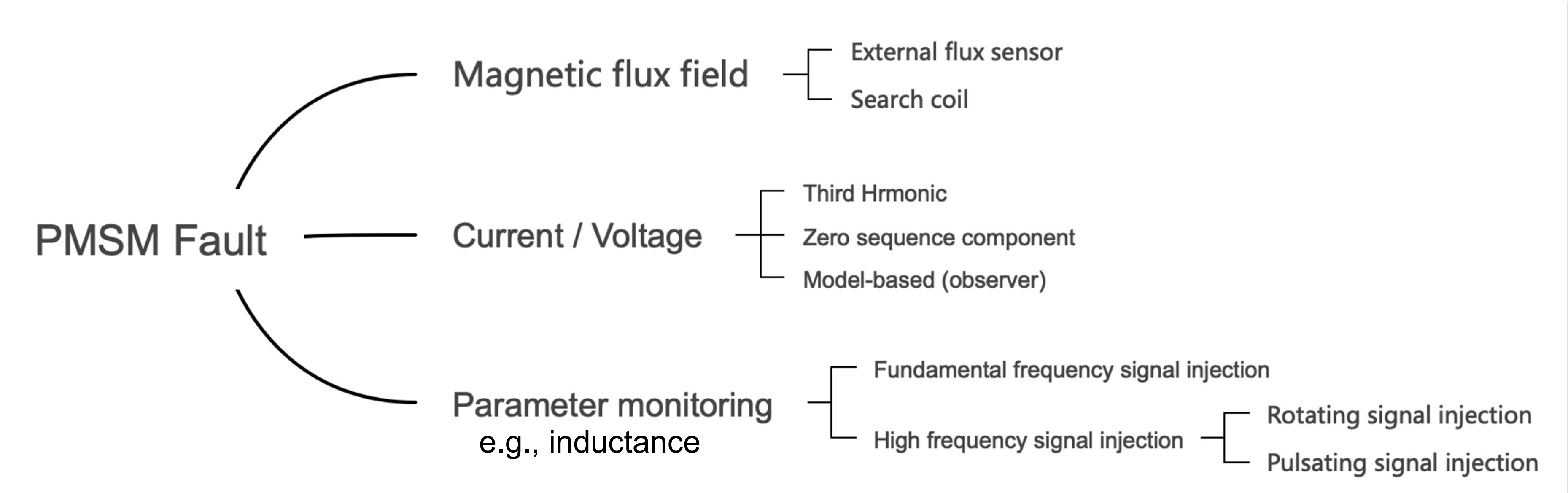
Occurs when insulation on the coil fails causing a short.

In 3-phase motor, shorting of coils causes unbalance current (e.g., 9000 Amp rise – catastrophic!)



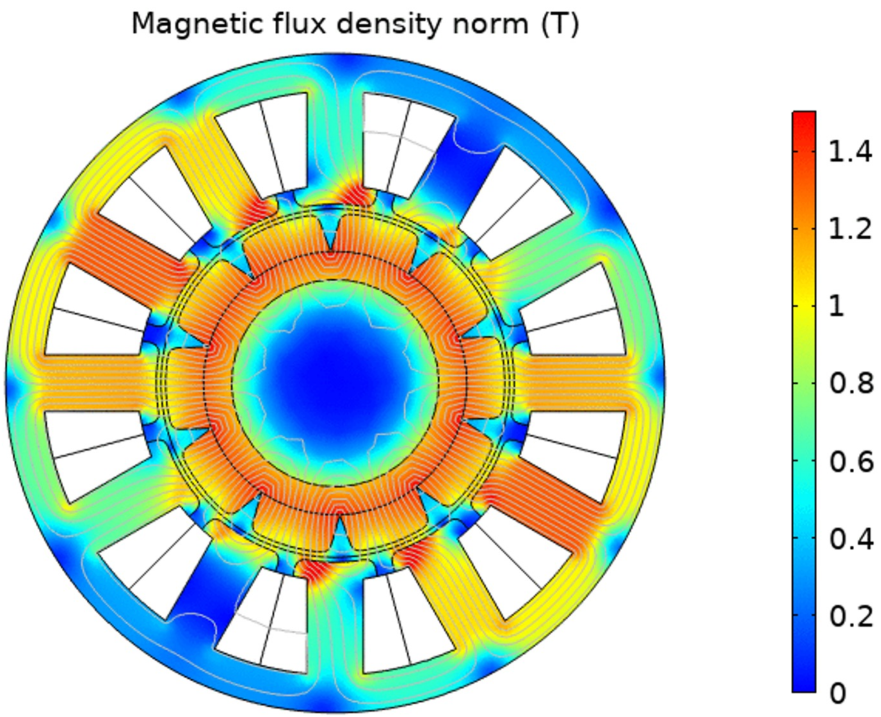


Existing Fault Detection Technologies

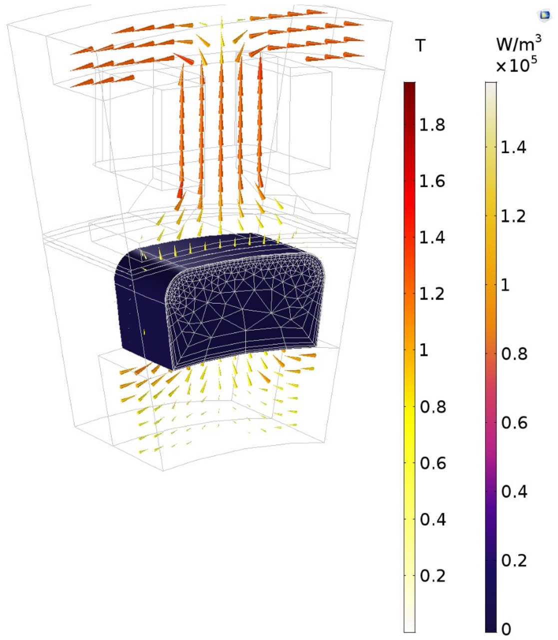


Cannot find the precise location of the fault with current methods

Digital Twin – FEA Modelling of Motor

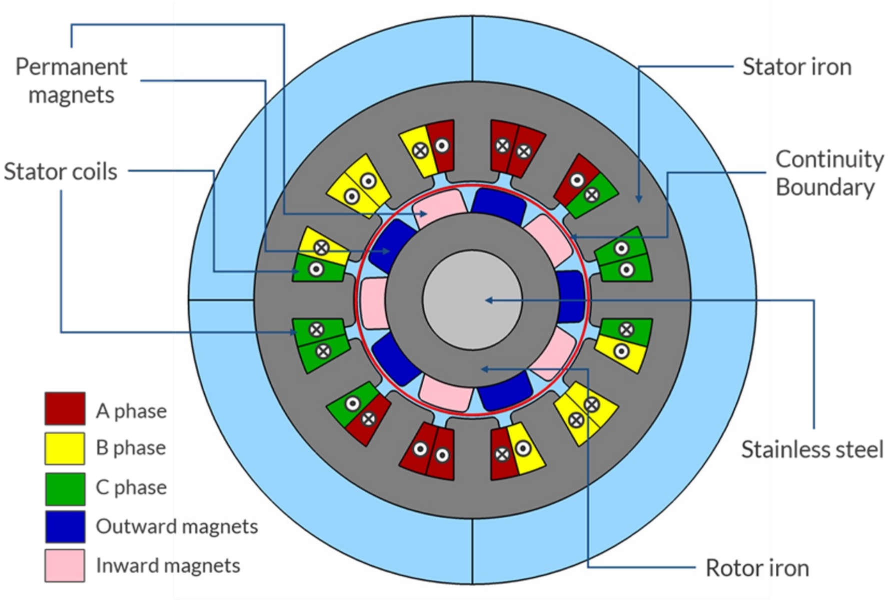


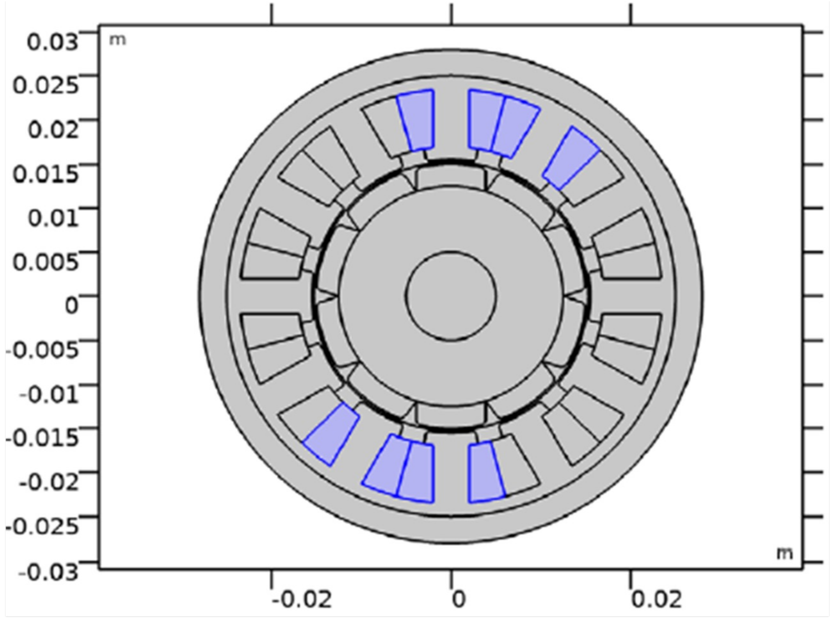
Magnetic Flux Density



Current Density, Magnet

Inter-fault Winding Fault introduced in FEA model





Insert fault by changing the coupling equivalent circuit of motor.

Dataset Description

7 fault categories

	Support	X_m	Y_m	Z_m	Magnetic_dens_normal
0	0.000000	0.155253	0.000135	0	-0.119832
1	0.000269	0.155253	0.000405	0	-0.128518
2	0.000539	0.155252	0.000674	0	-0.136584
3	0.000808	0.155251	0.000944	0	-0.143779
4	0.001078	0.155249	0.001213	0	-0.150019
...	...	...	...	...	...
176	0.041825	0.130546	0.041292	0	0.725355
177	0.042063	0.130474	0.041518	0	0.730311
178	0.042301	0.130402	0.041745	0	0.735012
179	0.042538	0.130329	0.041971	0	0.739453
180	0.042776	0.130256	0.042197	0	0.743640

5277960 rows × 15 columns

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Resistance	Rotor_angle	Fault_category	Placement
0.001	5.0	A_1coil_	outer
0.001	5.0	A_1coil_	outer
0.001	5.0	A_1coil_	outer
0.001	5.0	A_1coil_	outer
0.001	5.0	A_1coil_	outer
...	...	...	...
0.000	45.0	Healthy	airgap
0.000	45.0	Healthy	airgap
0.000	45.0	Healthy	airgap
0.000	45.0	Healthy	airgap
0.000	45.0	Healthy	airgap

3 possible areas for placement

Objective:

- *<u>Place sensors (any #) at the x,y coordinates within the 3 possible areas for optimal detectability of faults</u>*

Sensor output

Location of sensors (181 coordinates per placement) – 543 possible locations

17 levels of severity per fault (besides healthy)

Methodology for Sensor Placement

1.Define health states within the system

2.Sensor data acquisition – collect simulation training data for sensors

1.Perform health classification

- We use k-means distance clustering

2.Determine detectability measure

3.Perform optimization for sensor placement/design:

- Mixed integer nonlinear programming
- Reliability-based co-design optimization (RBDO)
- Genetic algorithm to search for optimal design

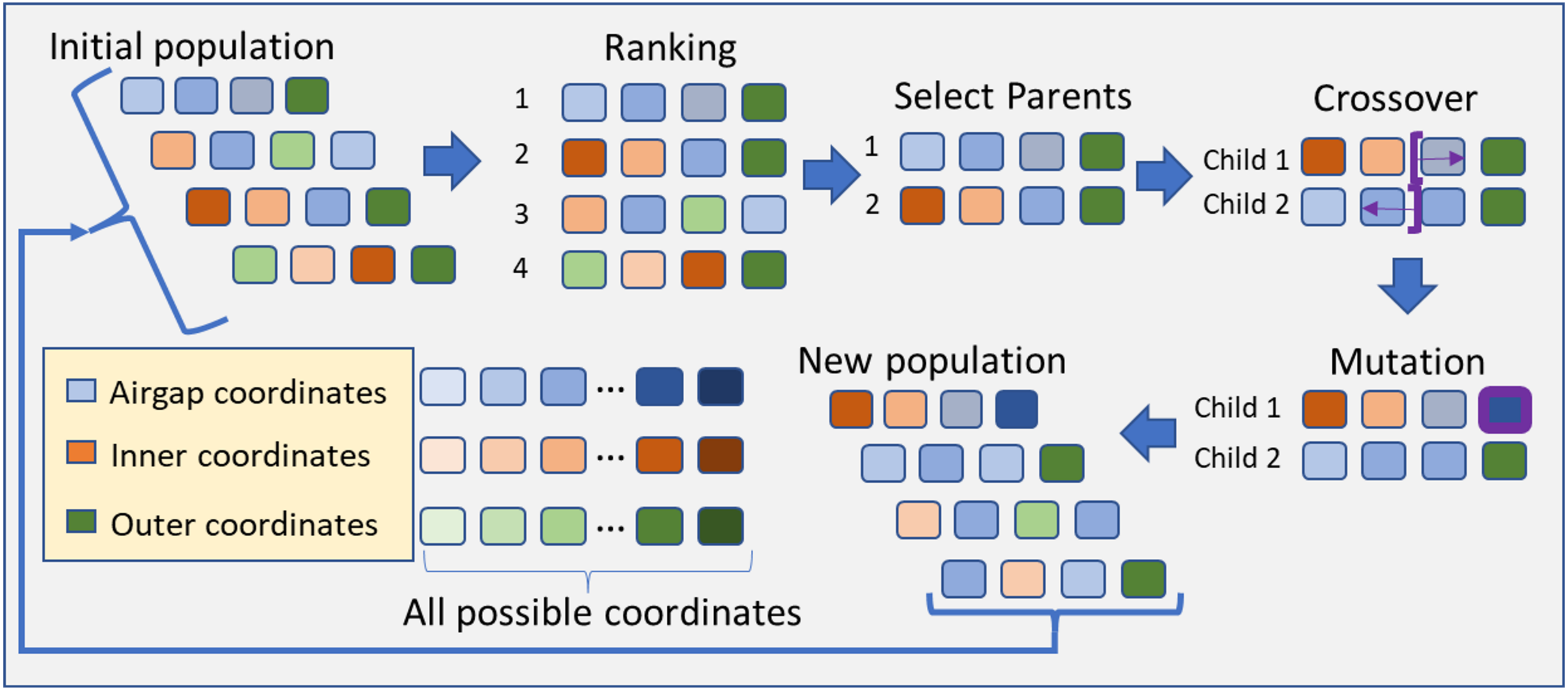
$$\mathrm{PoD} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1N_{HS}} \\ P_{21} & P_{22} & \cdots & P_{2N_{HS}} \\ \vdots & \vdots & \ddots & \vdots \\ P_{N_{HS}1} & P_{N_{HS}2} & \cdots & P_{N_{HS}N_{HS}} \end{bmatrix}$$

$$D_i = P_{ii} = \Pr(Detected\ as\ HS_i || opereted\ as\ HS_i)$$

$$P_{ij} = \Pr(Detected\ as\ HS_j | Operated\ as\ HS_i)$$

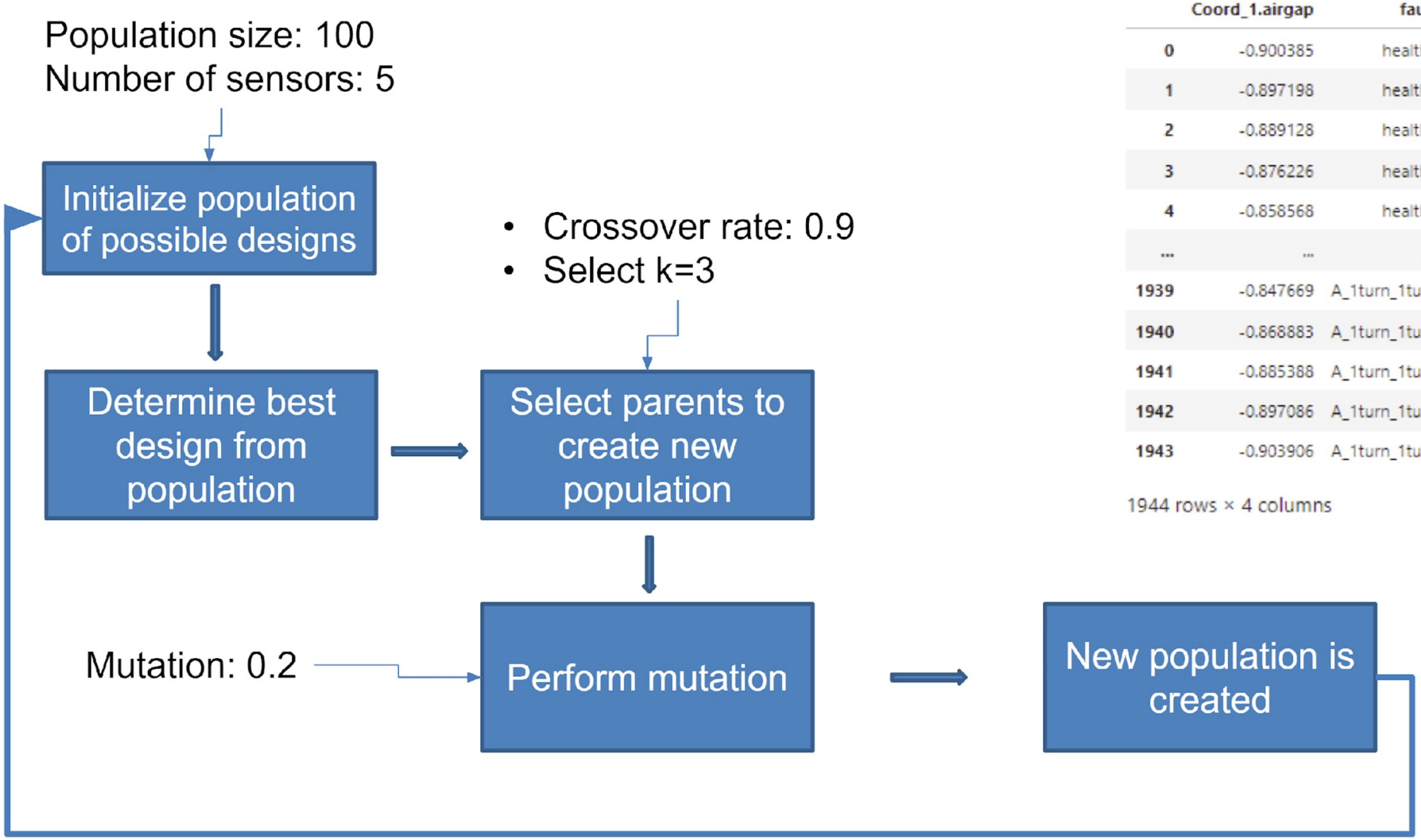
“A probabilistic detectability-based sensor network design method for system health monitoring and prognostics” – Wang et al 2015, Journal of Intelligent Material Systems

Genetic Algorithm for Sensor Optimization



Genetic algorithm for selecting the best sensor placements for detecting inter-turn winding fault

Genetic Algorithm Flow-Chart

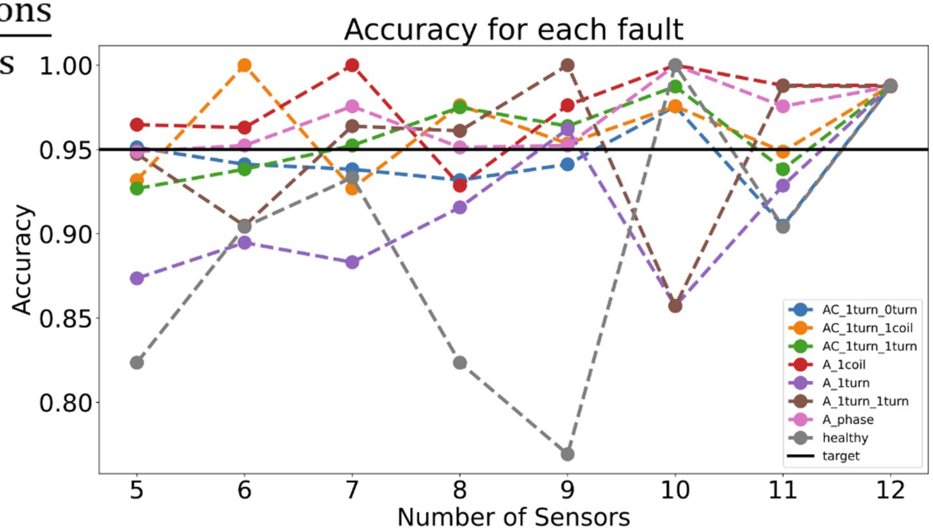


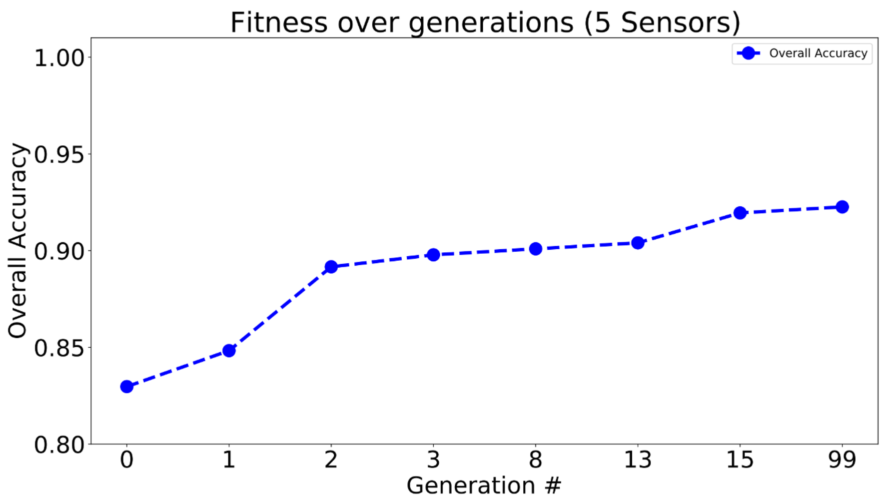
	Coord_1.airgap	fault	Coord_2.inner	Coord_3.outer
0	-0.900385	healthy	-0.000101	-0.172999
1	-0.897198	healthy	-0.000093	-0.183811
2	-0.889128	healthy	-0.000087	-0.125302
3	-0.876226	healthy	-0.000082	-0.044595
4	-0.858568	healthy	-0.000079	-0.006221
...	...	...	...	...
1939	-0.847669	A_1turn_1turn	-0.000080	-0.132537
1940	-0.868883	A_1turn_1turn	-0.000078	-0.055012
1941	-0.885388	A_1turn_1turn	-0.000077	-0.005094
1942	-0.897086	A_1turn_1turn	-0.000076	-0.025308
1943	-0.903906	A_1turn_1turn	-0.000076	-0.101226

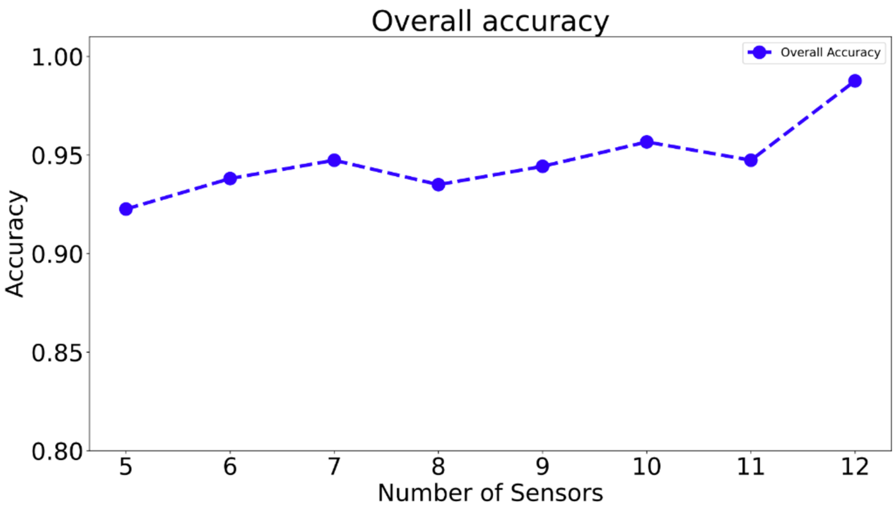
1944 rows × 4 columns

Evaluating Fault Type from Genetic Algorithm

- ***Precision:*** $\frac{\text{\# correct positive predictions}}{\text{total positive predictions}}$
- ***Recall:*** $\frac{\text{\# correct positive predictions}}{\text{total actual positives}}$
- ***F1-score:*** $\frac{2*(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})}$



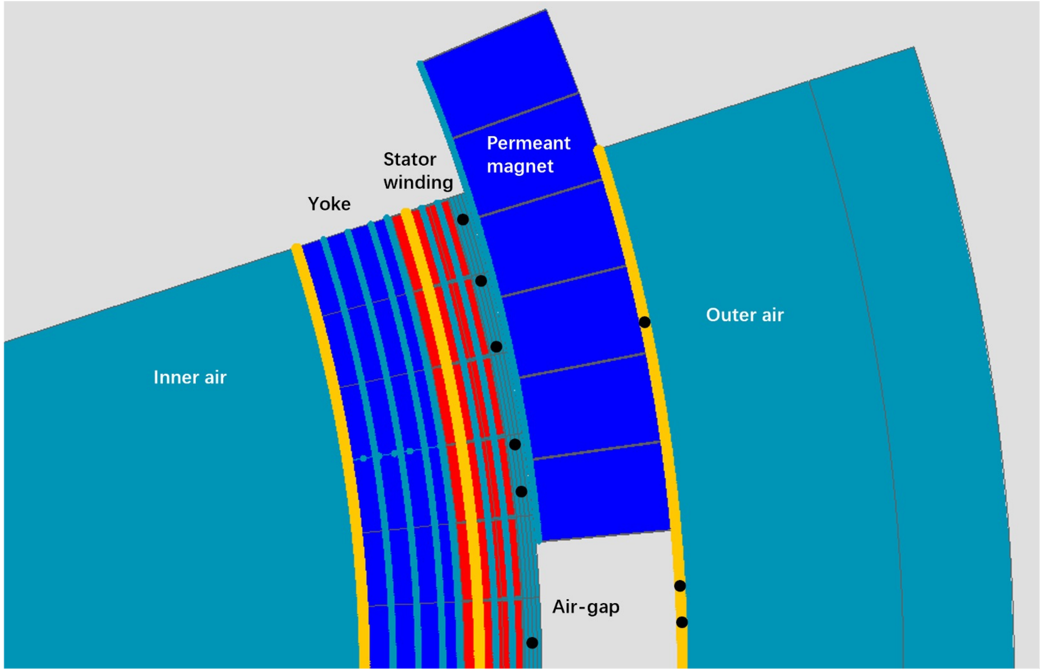




Optimal Locations – Results from GA

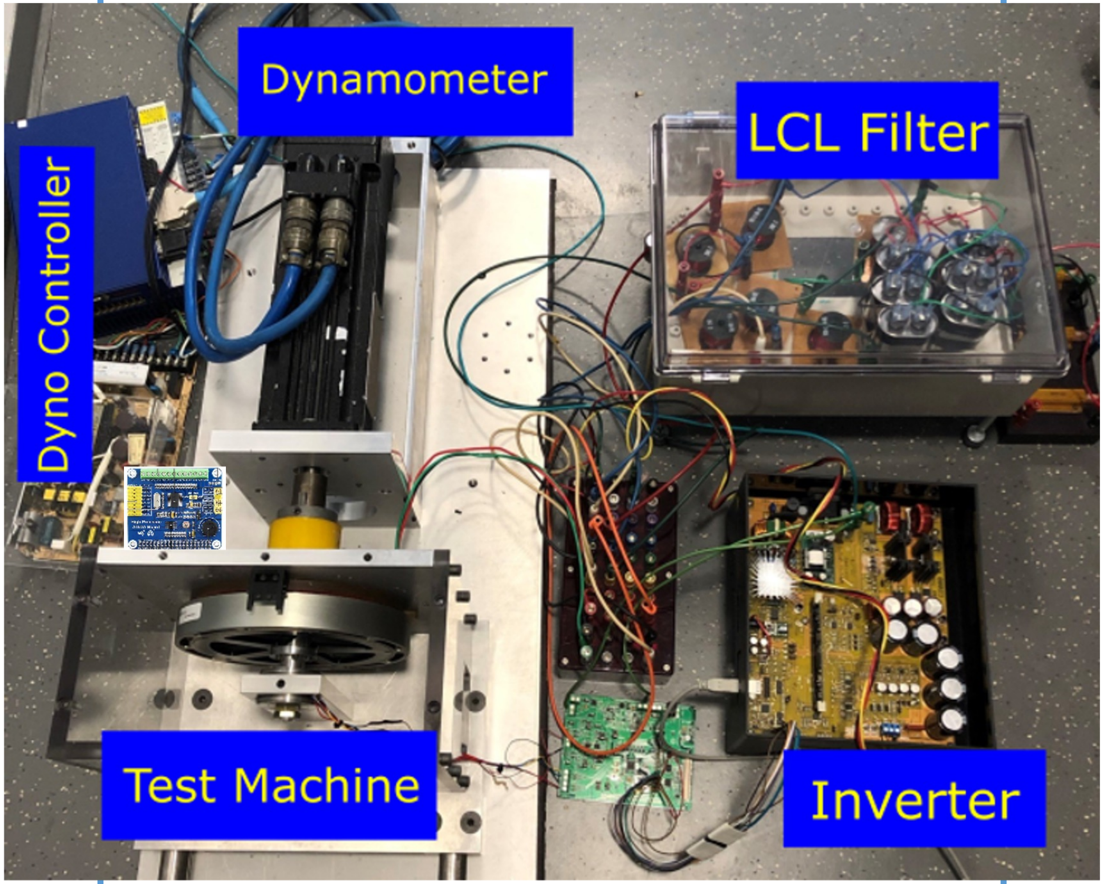
Optimal sensor location for evaluating faults

1. Because the intensity of the magnetic field at airgap than outside, so we prefer more sensors in the airgap.
2. Because the intensity of the inner air magnetic field is weak, so we do not need sensor inside of the motor
3. We recommend evenly distributed within air gap.



Next Steps: Test Bench at UIUC

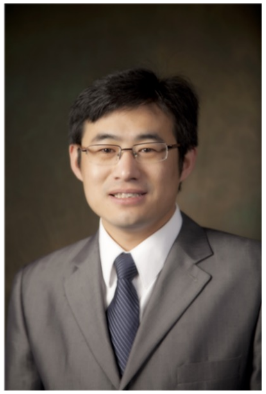
Electric Motor with Hall-Effect Sensor



Location: Prof. Kiruba Lab, UIUC

Thank you!

Prof. Wang



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