Domain Generalization for Fault Detection in Rotating Machinery: A Study

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Bio of Sagar Naik

Dr. Kshirasagar Naik received his B.Sc (Engg.) and M.Tech degrees from Sambalpur University, India, and the Indian Institute of Technology, Kharagpur, India, respectively. He received an M. Math degree in computer science from the University of Waterloo and a Ph.D. degree in electrical and computer engineering from Concordia University, Montreal. He worked as a software developer for three years in Wipro, Bangalore. Later, he worked as a faculty member at the University of Aizu in Japan and Carleton University in Canada. At present he is a Full Professor in the Department of Electrical and Computer Engineering at the University of Waterloo. He was a visiting Professor at the Research Institute of Electrical Communications at Tohoku University, Sendai, Japan, during May-November 2003.

His research interests include anomaly detection in cyber-physical systems, energy efficiency of mobile devices, energy harvesting IoT (Internet of Things) devices for sustainable monitoring of physical systems, vehicular communication protocols, forest fire modeling and analysis, and artificial intelligence and machine learning techniques.

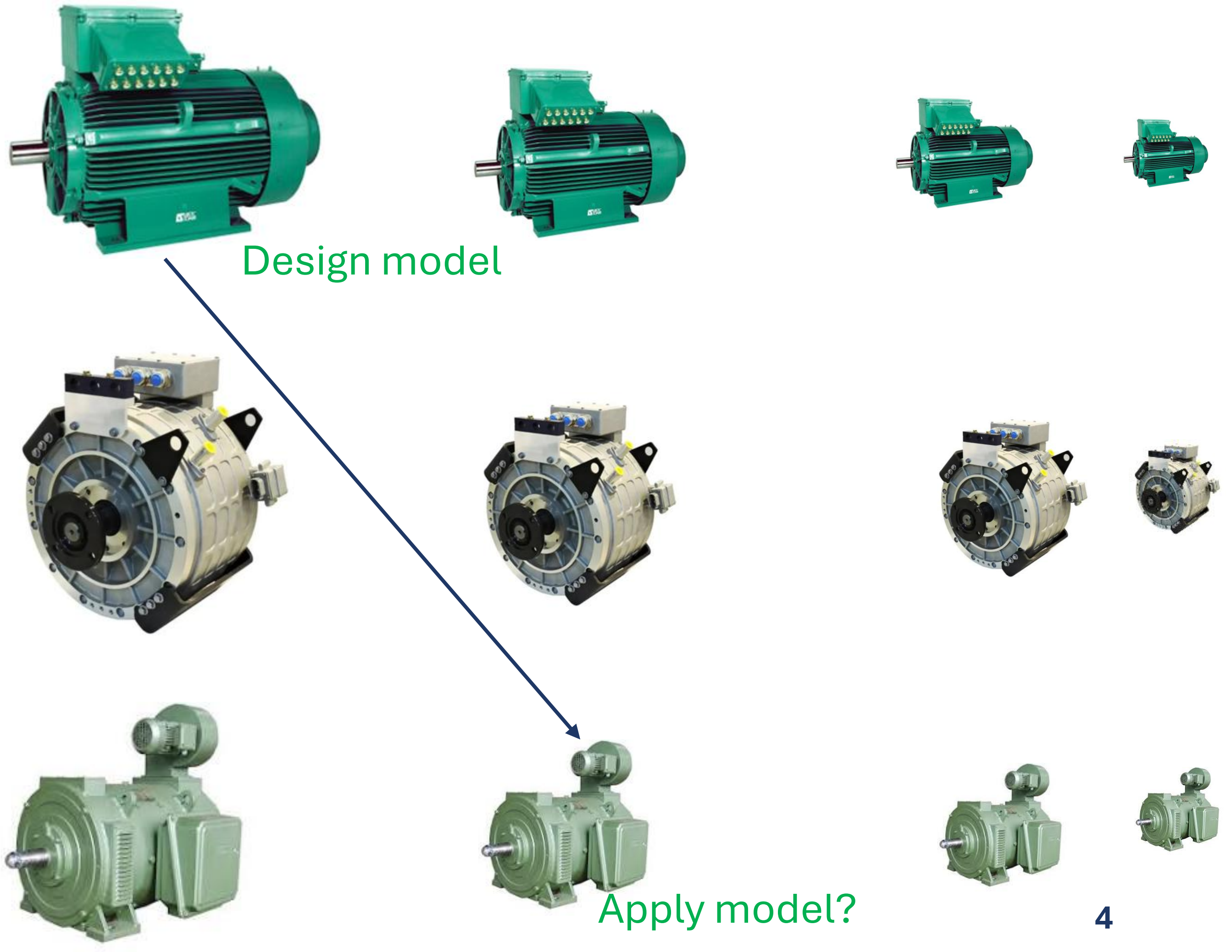
He has served on the editorial boards of many journals, including: *Journal of Peer-to-Peer Networking and Applications*, *International Journal of Parallel, Emergent and Distributed Systems*, *Journal of Circuits, Systems, and Computers,* and *IEEE Transactions on Parallel and Distributed Systems*. He was a co-guest editor of four special issues of *IEEE Journal on Selected Areas in Communications* and *IEEE Transactions on Cloud Computing*. He is a co-author of two widely used textbooks, namely, *Software Testing and Quality Assurance: Theory and Practice* (Wiley, 2008) and *Software Evolution and Maintenance: A Practitioner's Approach* (Wiley, 2014).

Organization

- Motivation
- Prognostics and Health Management (PHM) of Rotating Machinery
- Two systems/ datasets
- Experiment design to test domain generalization + results
- Challenges in domain adaptation/generalization
- Future work

Many electric motors of similar types

- **High level view:** all those motors are doing similar works.
- Can a PHM system designed for motor M1 be **adapted** for M2?
- In other words: Can **knowledge be transferred** from M1 to M2?

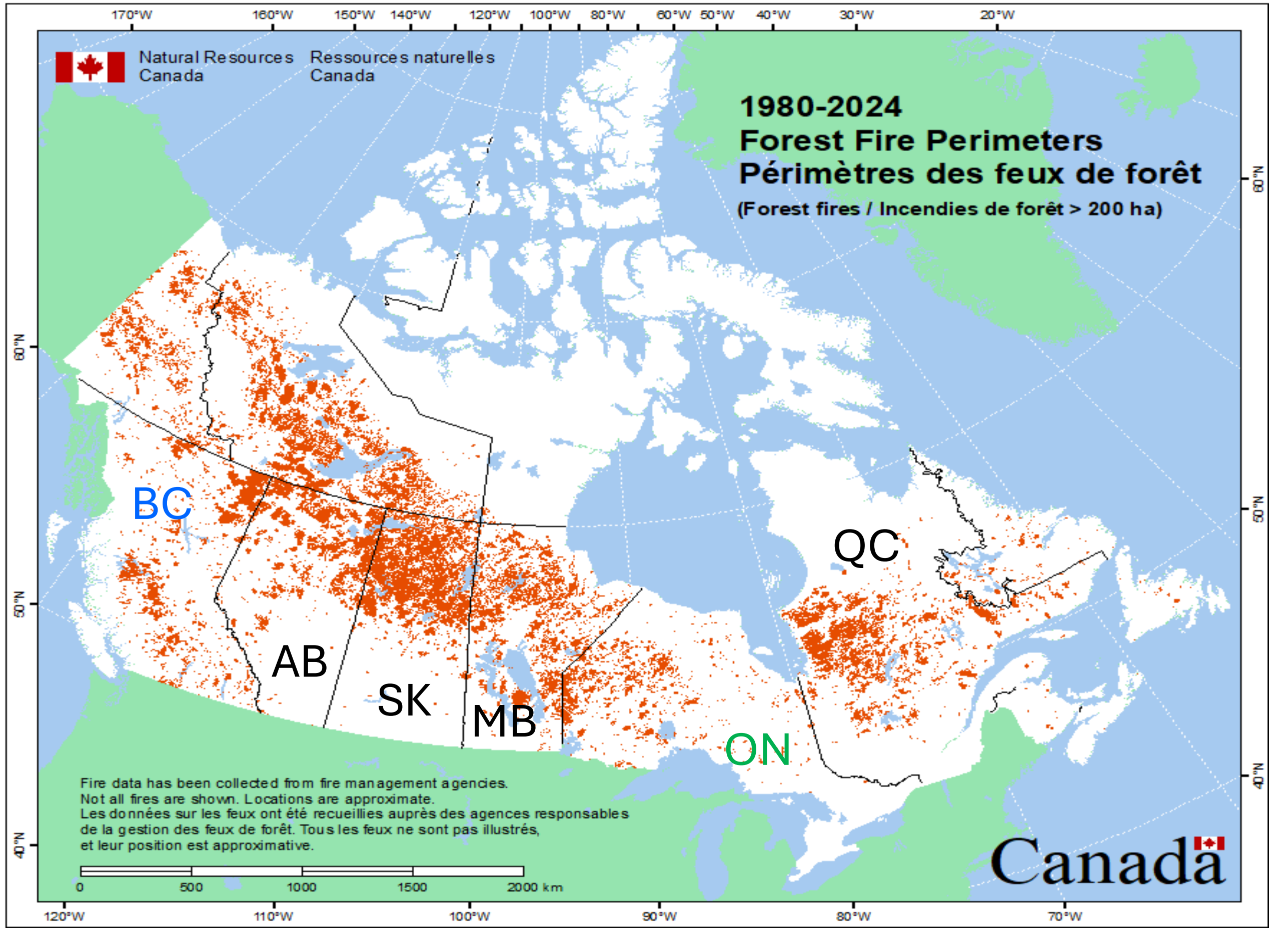


Another example: forest fires in Canada

Can a forest fire (FF) model (prediction, spread) developed using BC data be reliably applied in ON?

Can FF models be adapted within the same province, country, …?

Advantage: Model reuse/ adaptation can save cost.



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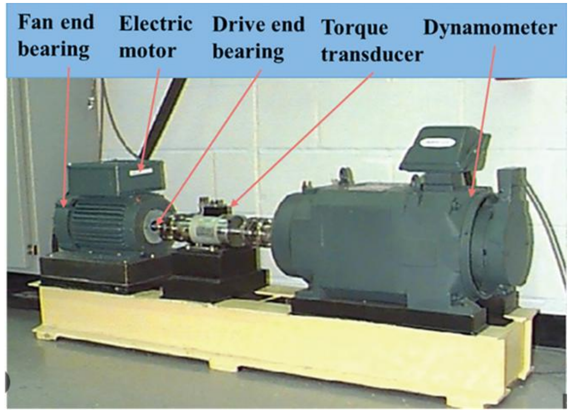
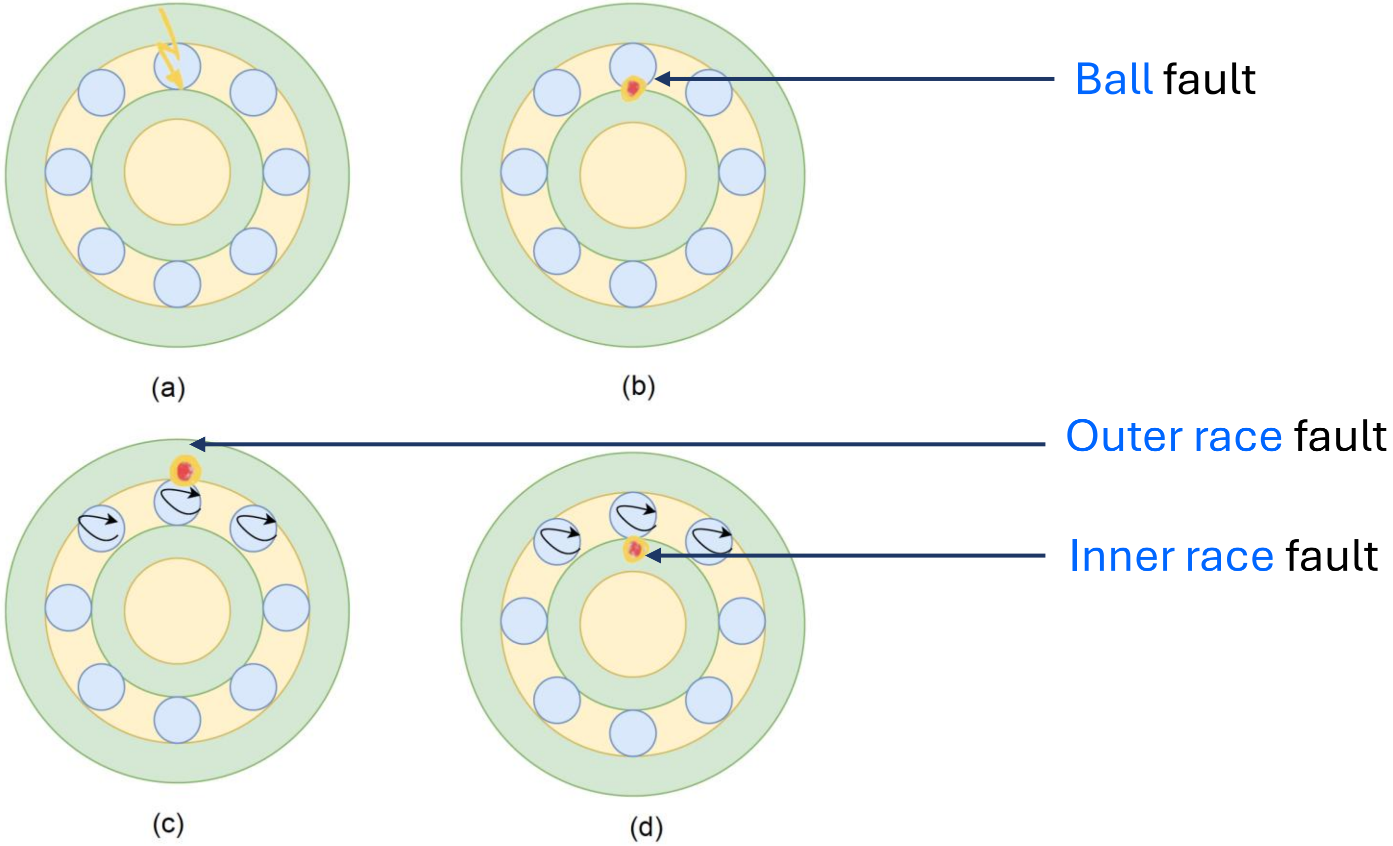
Prognostics and Health Management (PHM) of Rotating Machinery

- **Rotating machinery** (Ex. motors) serve as the backbone of modern industrial infrastructure.
- **Continuous operations** under varying loads make the system susceptible to **mechanical degradations**:
  - shaft **misalignment**
  - rolling element bearing **failures**



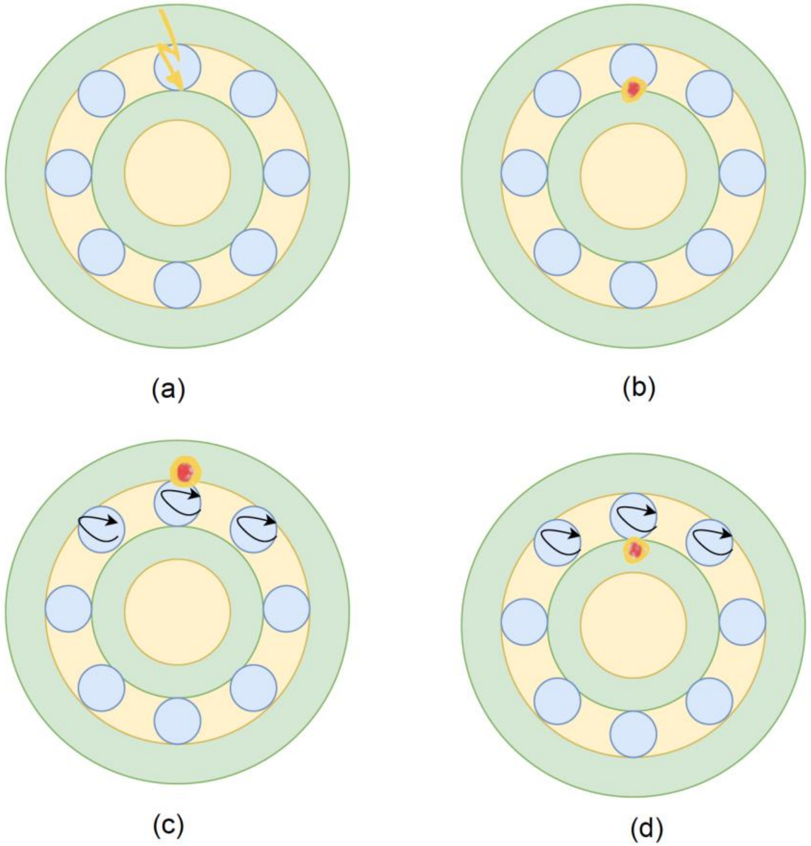
- Those faults can escalate into **catastrophic system failure**: safety issues and economic losses.
- **(Motivation)** There is a need for PHM frameworks for early detection and accurate diagnosis of faults to facilitate condition-based maintenance.

Fault Types



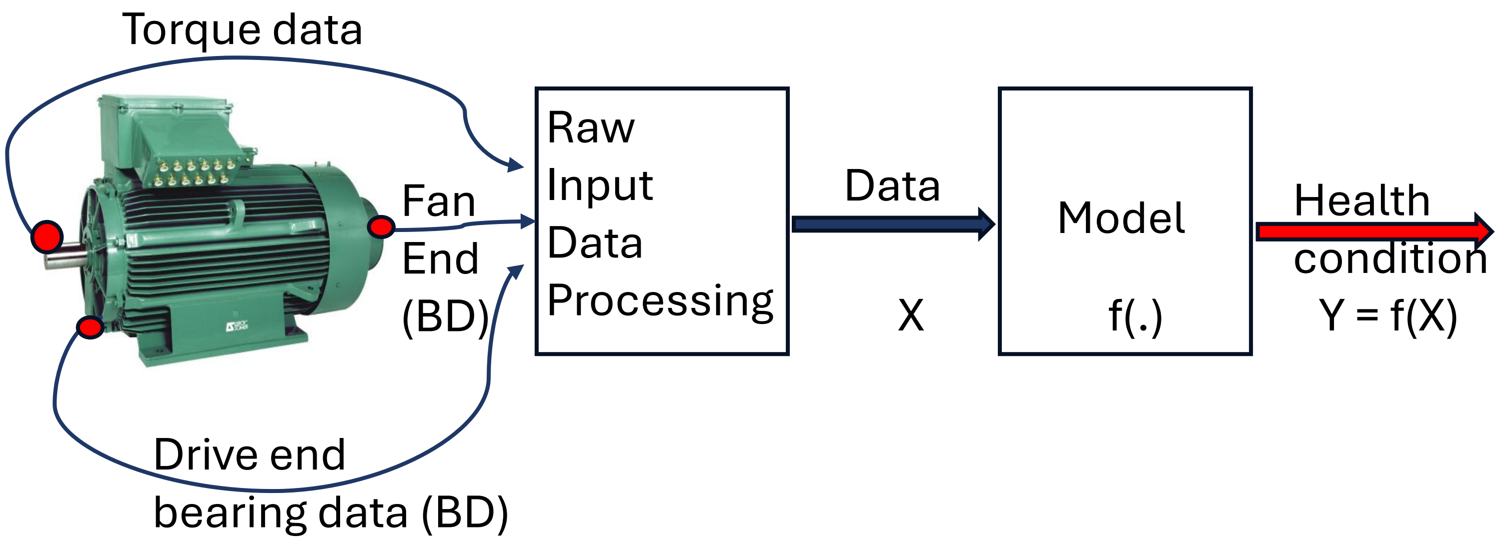
Fault Types and Intensity

Fault Type	Fault Diameter (Unit: inches) (Severity of faults)
Ball Fault (Fig. b) Ball Fault (Fig. b) Ball Fault (Fig. b)	0.007 0.014 0.021
Inner Race Fault (Fig. d) Inner Race Fault (Fig. d) Inner Race Fault (Fig. d)	0.007 0.014 0.021
Outer Race Fault (Fig. c) Outer Race Fault (Fig. c) Outer Race Fault (Fig. c)	0.007 0.014 0.021
Normal (Fault-free)	0.0



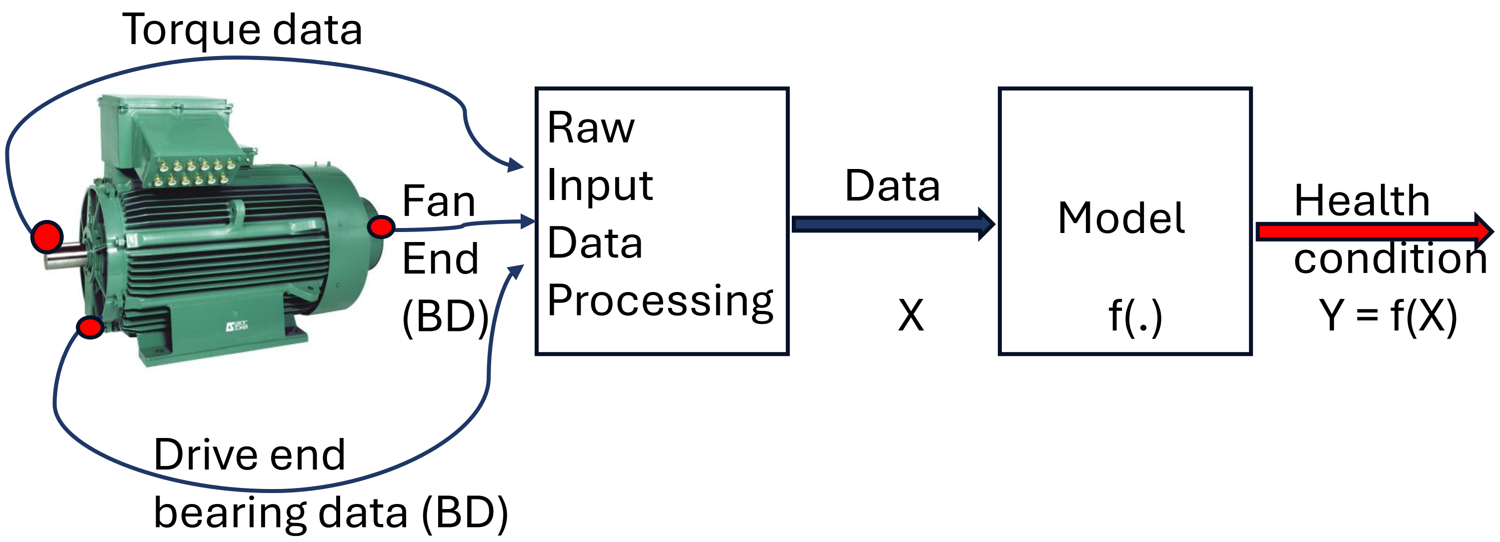
Prognostics and Health Management (PHM) of Rotating Machinery

- **A simple PHM system: training, validation, and testing have not been shown.**



Prognostics and Health Management (PHM) of Rotating Machinery

- **Identify two key concepts**
  - Domain (*D*)
  - Task (*T*)



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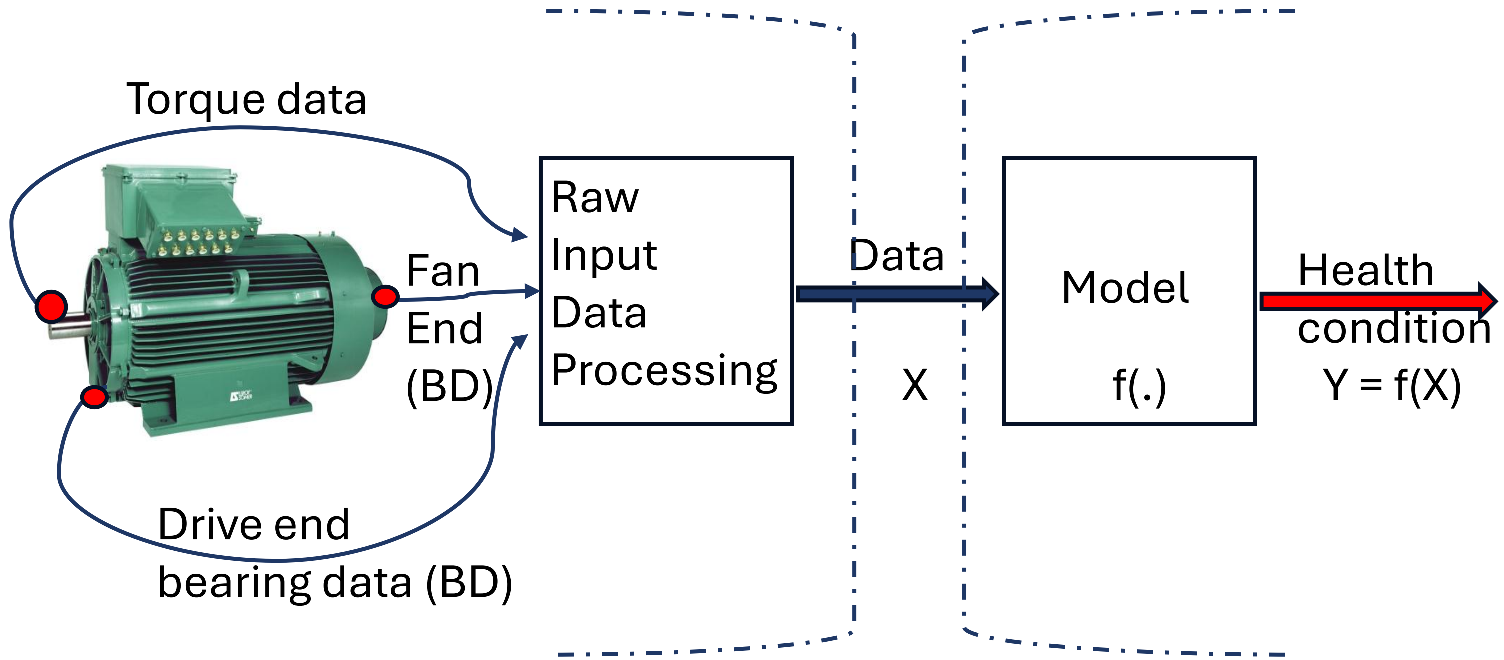

Domain *D* = {χ, P(X)}

χ is the feature space of the system

$X = \{x_1, \ldots x_n\} \in \chi$

P(X) is a marginal probability distribution

Task $T = \{\mathcal{Y}, f(.)\}$

$\mathcal{Y}$ is the label space

f(.) is an objective predictive function;

f(X) = P(Y|X)

Too many systems of “similar” types

- High level view: all those motors are doing similar works.
- Can a PHM system designed for motor M1 be adapted for M2?
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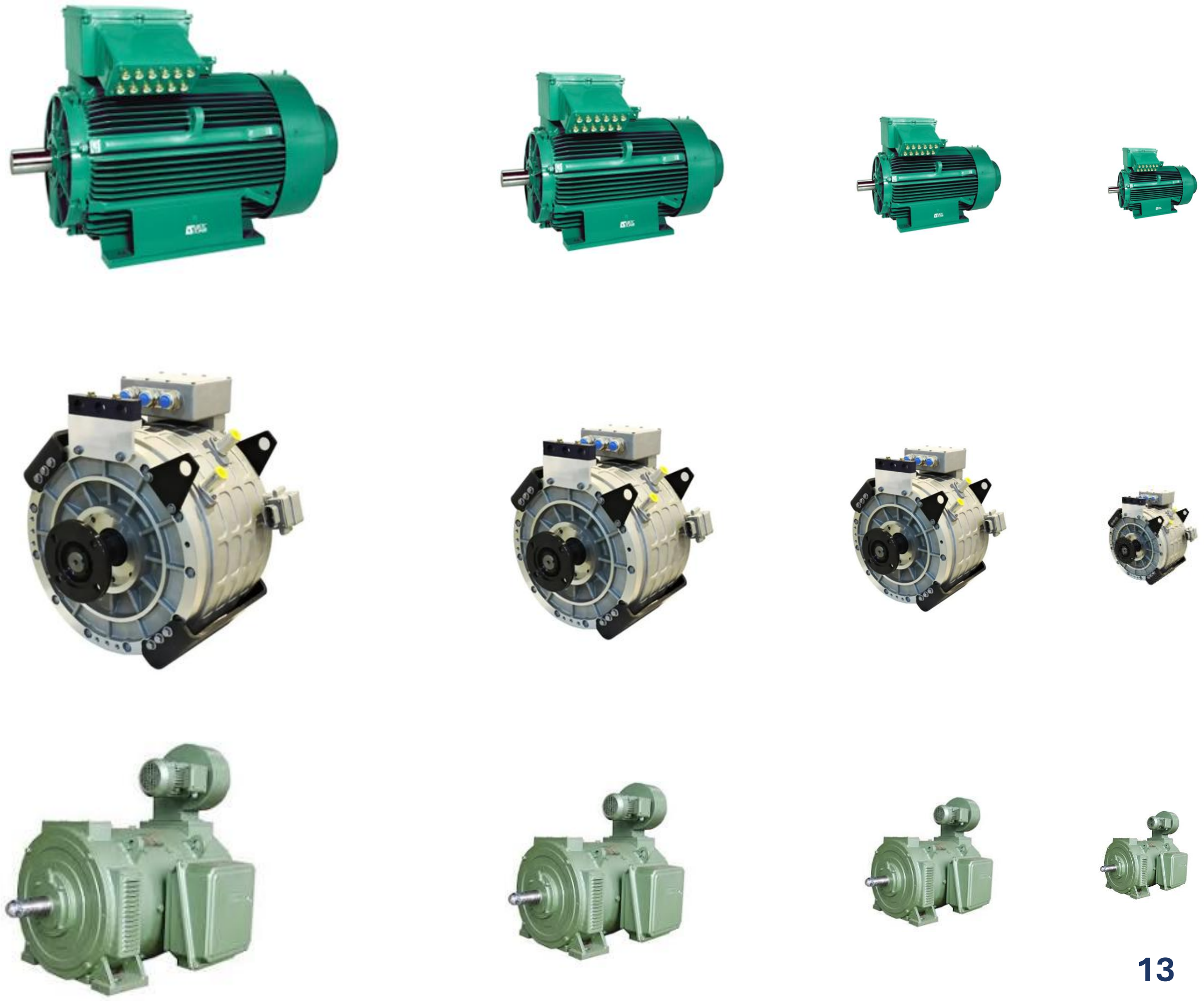

Problem Definition: Transfer Learning

- Given a
  - source domain $D_s = \{\chi_s, P(X_s)\}$ associated with a source task $T_s = \{\mathcal{Y}_s, f_s(.)\}$ and a target domain $D_t = \{\chi_t, P(X_t)\}$ associated with a target task $T_t = \{\mathcal{Y}_t, f_t(.)\}$

the goal of transfer learning is to leverage the knowledge learned from (D_s, T_s) to assist the learning of the target predictive function $f_t(.)$ to minimize the error on D_t, where $D_s \neq D_t$ or $T_s \neq T_t$.

- $D_s \neq D_t$ suggests that either $\chi_s \neq \chi_t$ or $P(X_s) \neq P(X_t)$.
- $T_s \neq T_t$ suggests that either $\mathcal{Y}_s \neq \mathcal{Y}_t$ or $f_s(.) \neq f_t(.)$.

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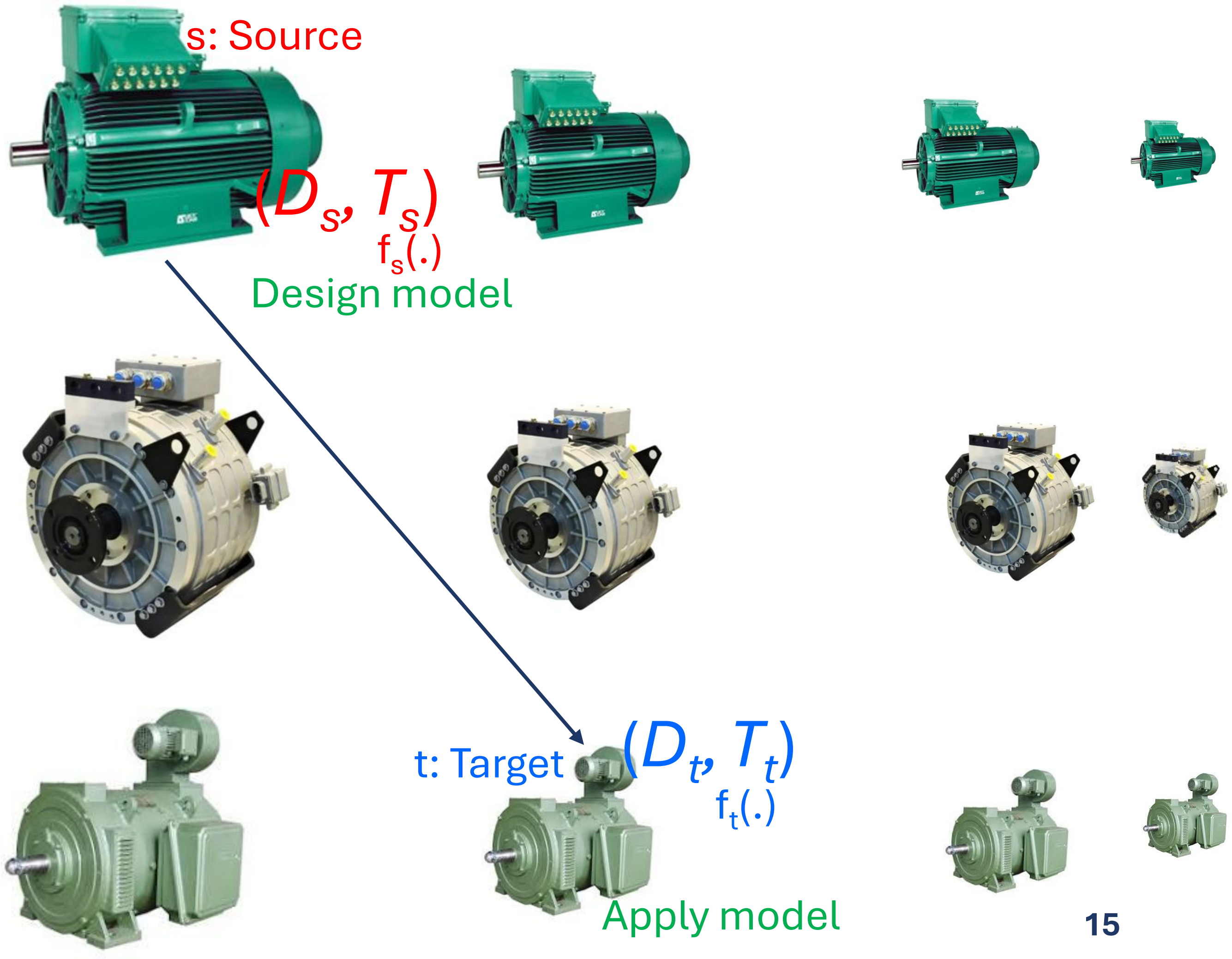

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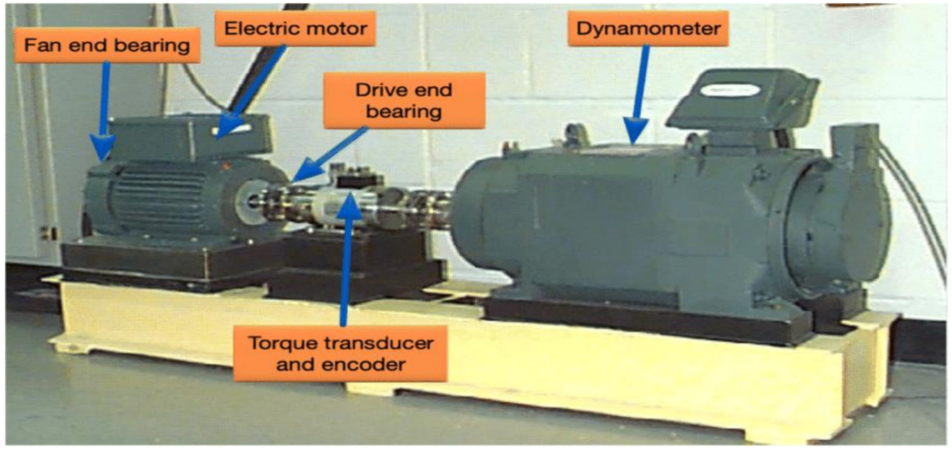
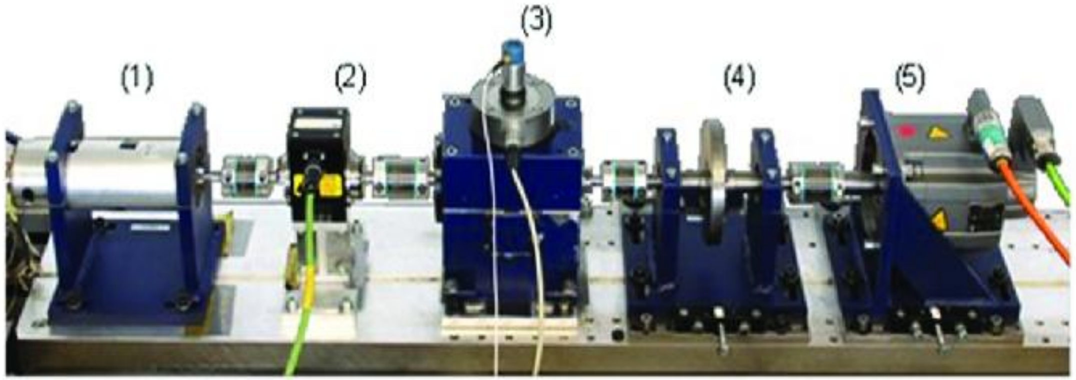
Two systems and two data sets

- Case Western Res U. (CWRU) Dataset: D1
  - **Faults:** seeded in drive end bearing
  - **Fault diameters:** 0.007", 0.014", 0.021" (0.18-0.54 mm)
  - **Fault classes (9)** : Ball, inner race, outer race (x 3)
  - **Data sampling rates:** 12 K, 48 K Samples/Sec
  - **Load conditions:** 0, 1, 2, 3 HP

- Paderborn Univ. (PU) Dataset: D2
  - **Faults:** induced in test module bearing
  - **Fault diameters:** 1-2 mm, 0.25 mm
  - **Fault classes (2):** inner race, outer race
  - **Data sampling rates:** 64 K
  - **Load conditions:** 900 RPM rotational speed, 0.7 NM Torque, 1000 N radian force (0.088 HP)





(1)An electric motor, (2) a torque-measurement shaft, (3) a rolling bearing 652 test module, (4) a flywheel, and (5) a load motor.

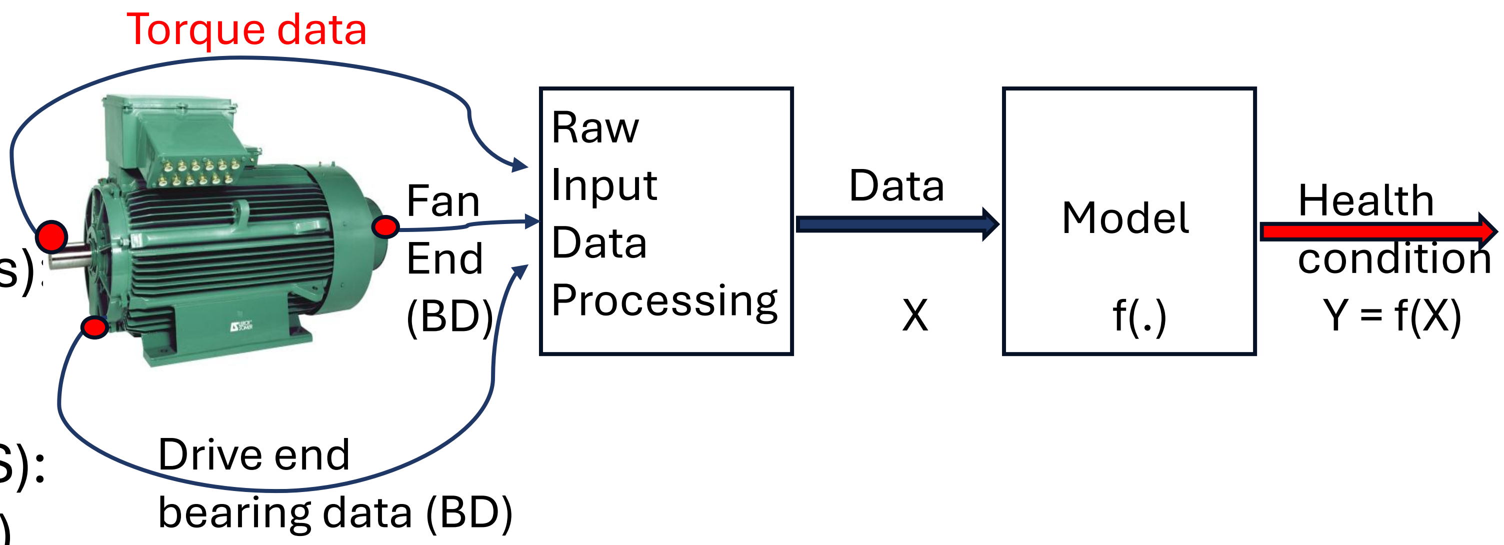
Even simple cases are challenging …

- Notation: DxFyCz

  - Dx: Different Machines (motors): D1, D2

  - Fy: Sampling Frequencies (SPS): (F1 = **12 K**, F2 = **48 K**, F3 = **64 K**)

  - Cz: Load Conditions: (C1 = **2 HP**, C2 = **0 HP**, C3 = **1 HP**, C4 = **3 HP**)



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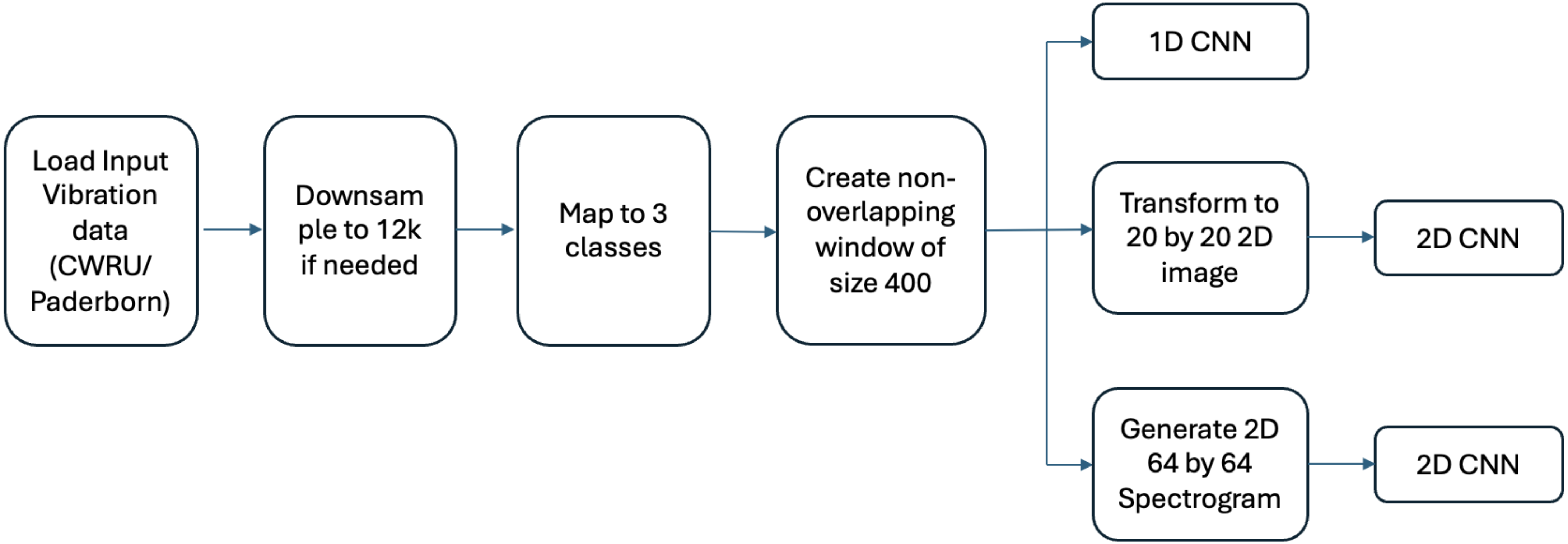
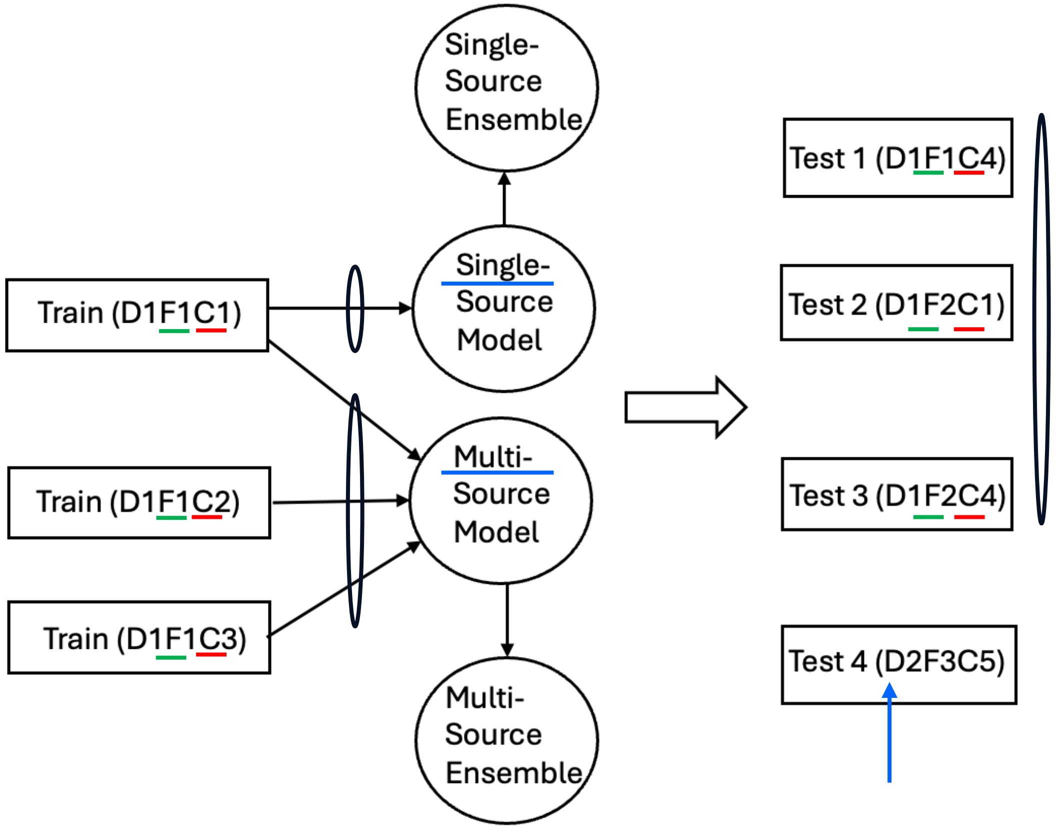
Flowchart of experimental pipeline



Schematic of exp. design for domain generalization



- Notation: DxFyCz (revisited)
  - Dx: Different motors: D1 (CWRU), D2 (PU)
  - Fy: Sampling Frequencies (Samples per Sec): (F1 = **12K**, F2 = **48 K**, F3 = **64 K**)
  - Cz: Load Condition: (C1 = **2 HP**, C2 = **0 HP**, C3 = **1 HP**, C4 = **3 HP**, C5 = **0.09** HP)

Training Data **2 Types of Models** 4 Types of Tests

Results: Single-source Training

Accuracy (for 3 types of modeling)

Test Scenario	1D CNN	2D CNN (Time Series)	2D CNN (Spectrogram)
Test 1	99.35	99.23	98.18
Test 2	80.53	83.28	81.12
Test 3	75.01	78.63	79.77
Test 4	33.33	33.39	15.67

F1-Score (for 3 types of modeling)

Test Scenario	1D CNN	2D (Time Series)	2D (Spectrogram)
Test 1	99.35	99.23	98.19
Test 2	79.79	82.74	80.76
Test 3	73.53	78.13	79.25
Test 4	16.67	16.80	09.82

High level meanings of the 4 tests

Test 1: Unseen Load (D1F1C4)
Test 2: Frequency Shift (D1F2C1)
Test 3: Freq. + Load Shift (D1F2C4)
Test 4: Cross-Machine (D2F3C5)

(F1 = **12K**, F2 = **48 K**, F3 = **64 K**)
(C1 = **2 HP**, C2 = **0 HP**, C3 = **1 HP**, C4 = **3 HP**, C5 = 0.09 HP (PU))

Results: Multi-source Training

Accuracy (for 3 types of modeling)

Test Scenario	1D CNN	2D CNN (Time Series)	2D CNN (Spectrogram)
Test 1	99.34	99.34	97.15
Test 2	78.03	80.63	82.47
Test 3	73.79	75.74	80.07
Test 4	33.33	33.56	11.89

F1-Score (for 3 types of modeling)

Test Scenario	1D CNN	2D (Time Series)	2D (Spectrogram)
Test 1	99.34	99.35	97.14
Test 2	76.87	80.29	81.79
Test 3	72.25	75.44	79.38
Test 4	16.67	17.13	07.71

High level meanings of the 4 tests

Test 1: Unseen Load (D1F1C4)
Test 2: Frequency Shift (D1F2C1)
Test 3: Freq. + Load Shift (D1F2C4)
Test 4: Cross-Machine (D2F3C5)

(Same system) Cross-load generalization accuracy [CWRU, Sampling feq.: 12 K]

Train load	Test 0 HP	Test 1 HP	Test 2 HP	Test 3 HP
0 HP	99.93	87.89	87.98	72.84
1 HP	88.31	99.93	99.51	92.08
2 HP	83.87	91.56	99.93	88.36
3 HP	75.07	78.89	79.50	99.91

Cross-domain generalization from CWRU Paderborn; All sampling rates: 12 K

CWRU: Train load	Paderborn: Testing Accuracy (Torque 0.7 NM, 1500 RPM: 0.147 HP)	Paderborn: Testing Accuracy (Torque 0.1 NM, 1500 RPM: 0.021 HP)
0 HP	39.58	33.33
1 HP	33.26	33.33
2 HP	24.34	21.94
3 HP	33.26	33.89

Power in Watts = Torque x Rotation (radians/sec); HP = Watts/746

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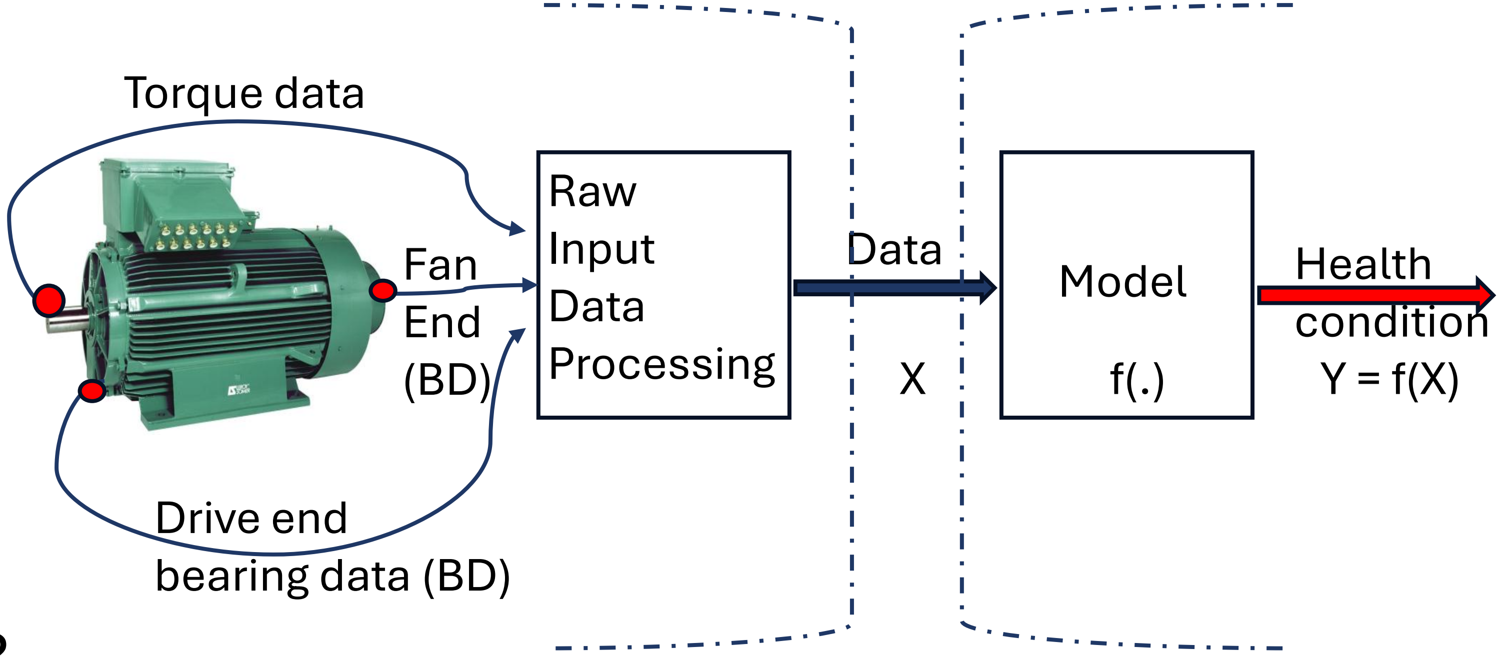
Challenges in domain adaptation

- Changes in operating conditions cause changes in test results even for the **same** domain (system).
- Are the definitions of Domain and Task **correct** and **complete**?
- Should we apply the notion of **equality** or **similarity** in comparing domains and tasks?
- While interpreting test results, should we have an **understanding** of the **similarity** between the two systems?



Domain $D = \{\chi, P(X)\}$

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Future Work

- Revisit and finetune: **Domain** $D = \{\chi, P(X)\}$
- Investigate the concept of domain similarity/ difference.
- Visualize the concept of domain similarity/difference.
- Track the changes in internal features in a domain as training and testing happen through multiples stages of model generation.
- Goal: Know when domain adaptation is feasible.

Thank you!

Selected References

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