



**POLITECNICO**  
MILANO 1863



# Intelligent Fault Diagnosis of Rotary Machinery

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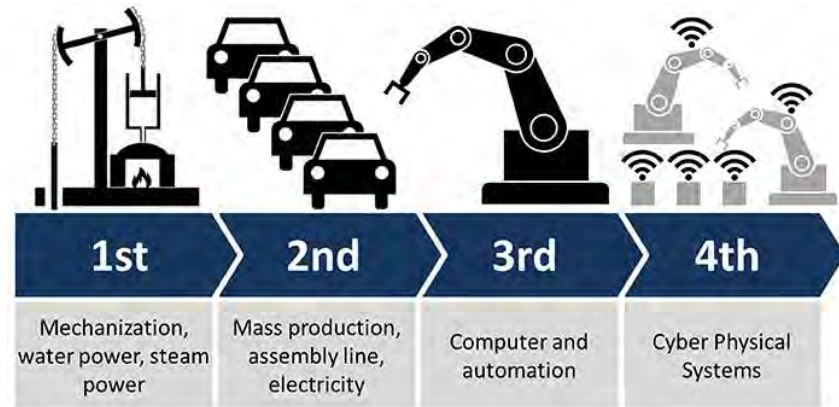
# Headlines

- ❑ Introduction to Faults
- ❑ Bearing Fault Diagnosis & Classification
  - Model-based Fault Analysis
  - Intelligent Filter-based Fault Analysis
  - Residual wide-kernel deep convolutional autoencoder

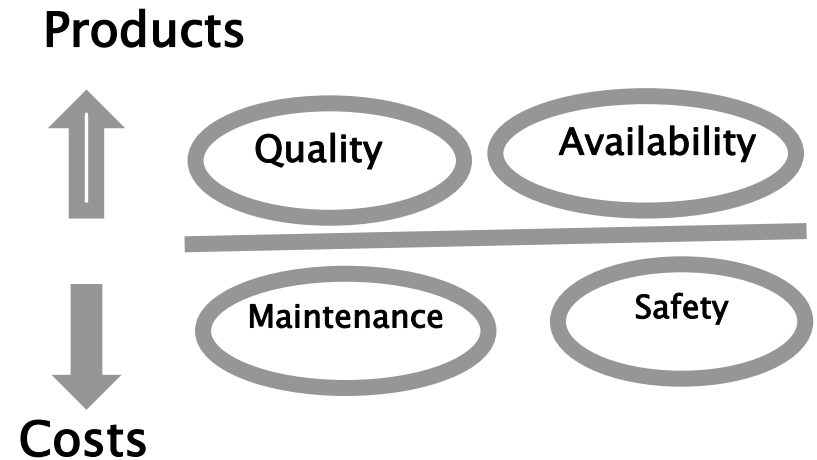
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# Revolutions in Industry

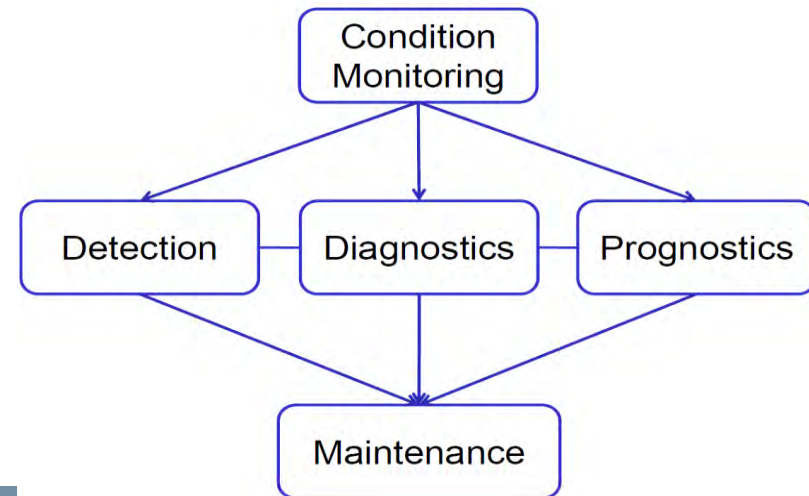


@ Roser, C. (2015). Industry 4.0 Wikipedia



Automation & Decision Support Tools help the plant meet Products & Costs targets by...

- ❑ Optimize Reliability Group's Time / Effort
- ❑ Capture Plant Knowledge
- ❑ Reduce O&M Costs by Managing Reliability



# Health Management System

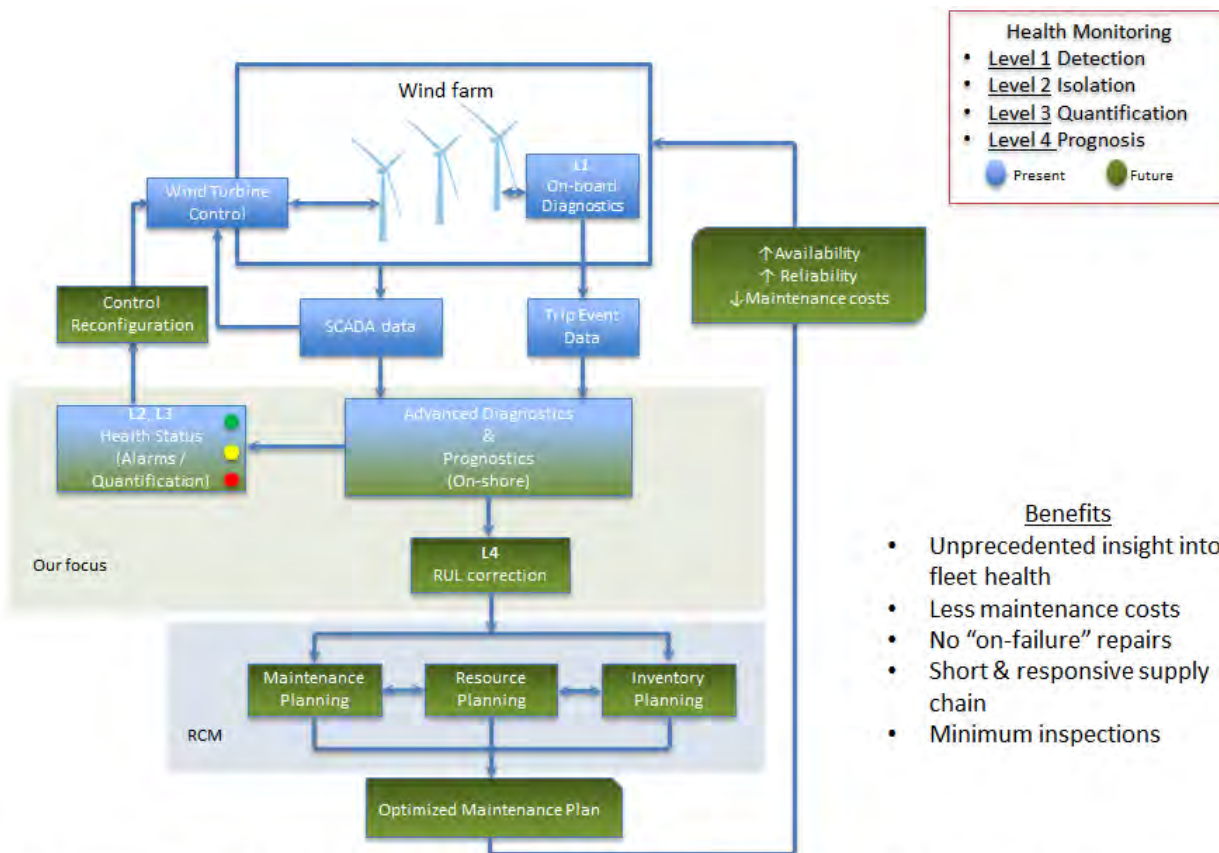
Health Management helps in:

- **Incipient failure detection** – detecting failures even before they substantially effect the performance
- **Prevention of fault progression** – eradicating fault conditions before secondary faults develop
- **Prediction of progression from fault to failure** – accurate prognosis for remaining useful life
- **Efficient maintenance planning** – economize on maintenance efforts, ensure best availability
- **Feedback to control laws** – Modify control laws based on the current health condition to extend life while obtaining the best possible performance.

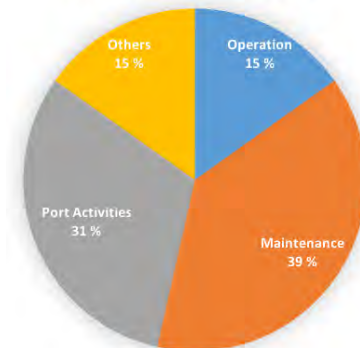
Overall System Health for increased RAM (Reliability and Maintainability) and minimized O&M (Operation and Maintenance) costs

# Health Management for Wind farms

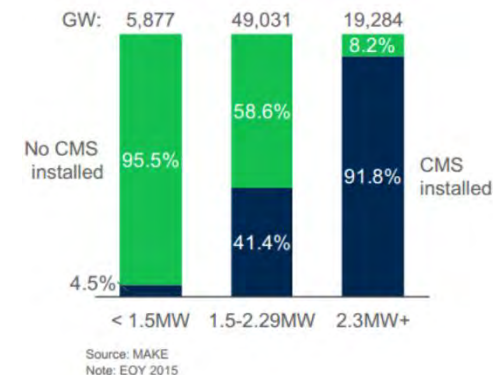
## Towards Farm-level Health Management



O&M Costs: Offshore Wind Farms



Penetration of CMS – US market



### Benefits

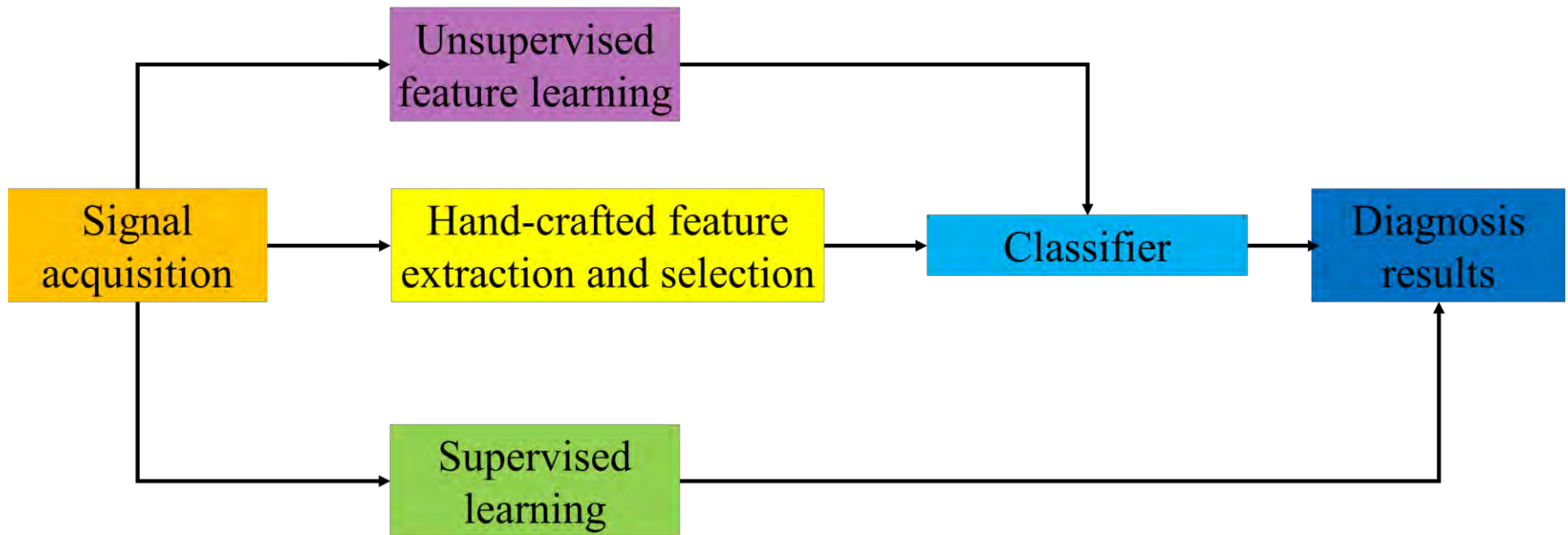
- Unprecedented insight into fleet health
- Less maintenance costs
- No "on-failure" repairs
- Short & responsive supply chain
- Minimum inspections

Health Management – capability to make intelligent, informed, appropriate decisions about maintenance and logistics actions based on diagnostics/prognostics information, available resources and operational demand. – Definition, JSF Program

# Intelligent-based methods

## General intelligent fault diagnosis framework

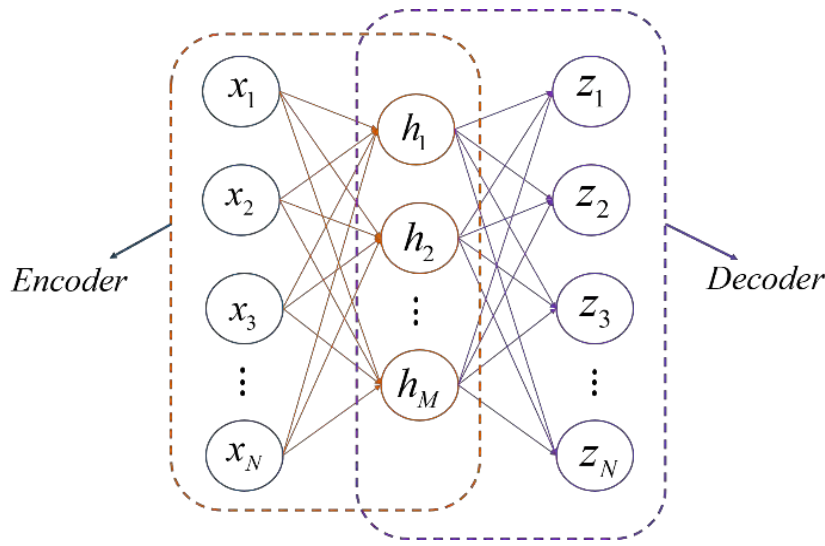
- Unsupervised learning
- Supervised learning
- Reinforcement learning



Three general intelligent fault diagnosis frameworks (Sensors, 2017)

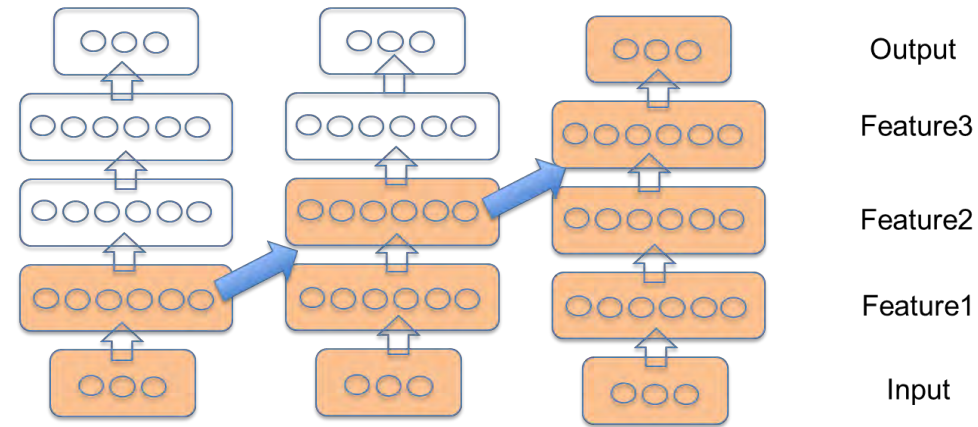
# Intelligent-based methods

## Unsupervised learning: Auto-encoder



The structure of standard Auto-encoder  
(Knowledge-Based Systems, 2020)

Advantages: Computation speed  
Disadvantages: High-dimensional signal



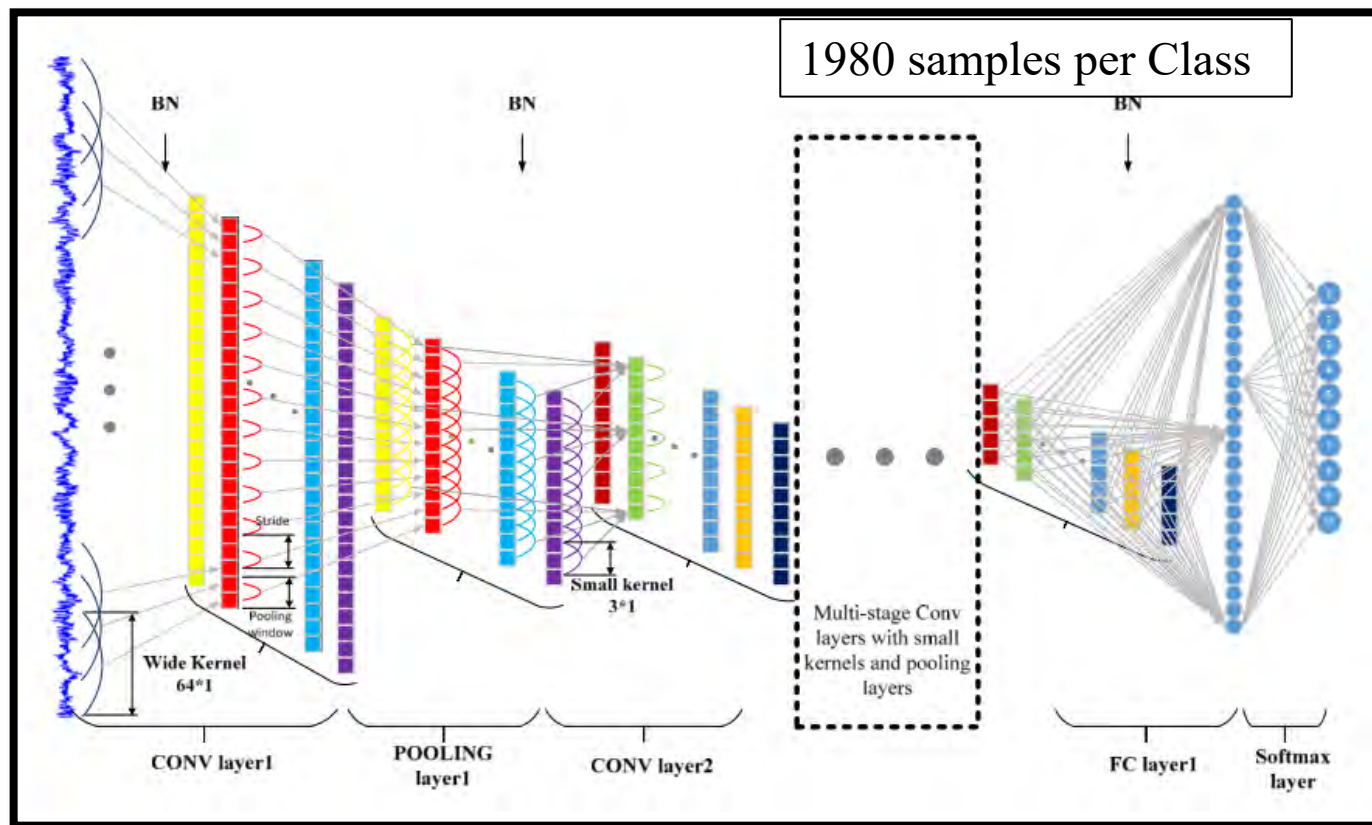
The training process of Stacked Auto-encoder  
(MSSP, 2018)

Advantages: Training efficiency  
Disadvantages: High-dimensional signal



# Intelligent-based methods

## Supervised learning: Convolutional Neural Networks



Architecture of the WKDCNN model (Sensors, 2017).

Wide-kernel deep convolutional neural networks

Advantages:

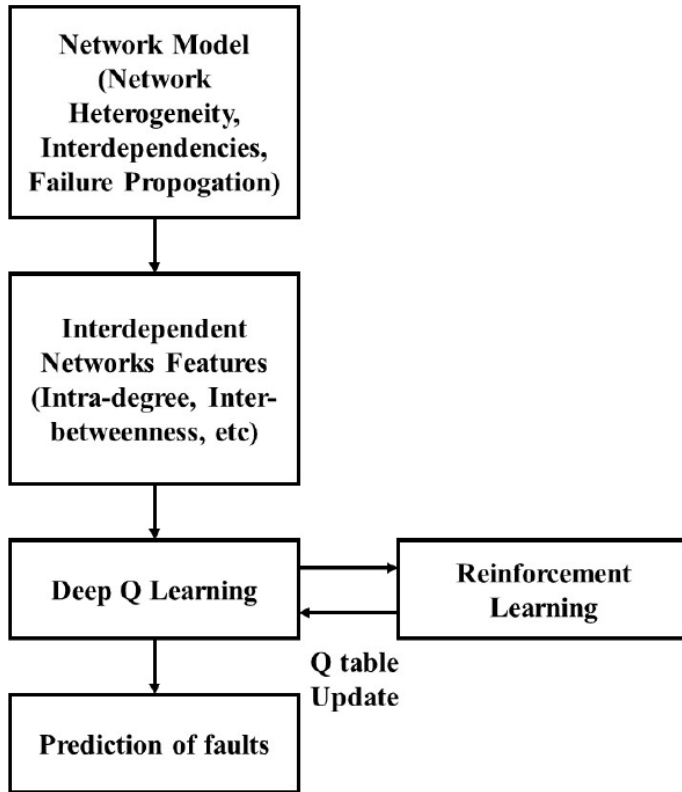
- Without signal processing

Disadvantages:

- General accuracy
- Need 1980 samples per Class

# Intelligent-based methods

## Reinforcement learning



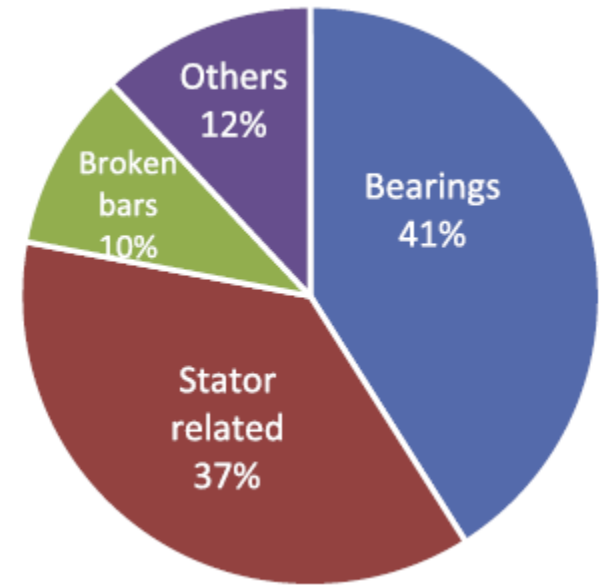
- Deep Q Network with reinforcement learning is applied to adaptively learn the system with reinforcement learning method to select the optimal action in a continuous interaction of a stochastic environment.
- Feature extraction techniques are applied for effective analysis of the network model to detect the fault.

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# Bearing Fault Diagnosis

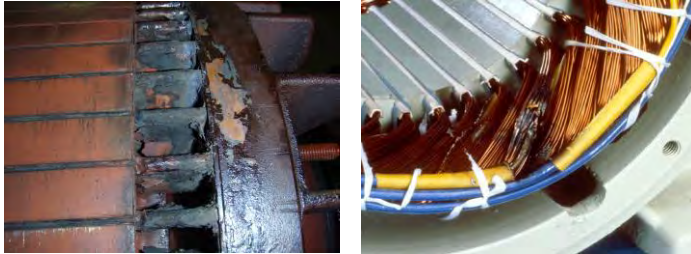
- ❑ Bearing faults - a majority of faults in electrical machines, or drive trains.
- ❑ **System reliability**: detect bearing faults and repair or replace the faulted bearings.
- ❑ Existing methods to monitor bearing faults - vibration monitoring and current-based techniques: cost vs advanced technique.
- ❑ The bearing fault detection and troubleshooting in the early stages will decrease the cost of unwanted shutdown.



Pie chart of induction motor failures percentage.

# Motor current signature analysis

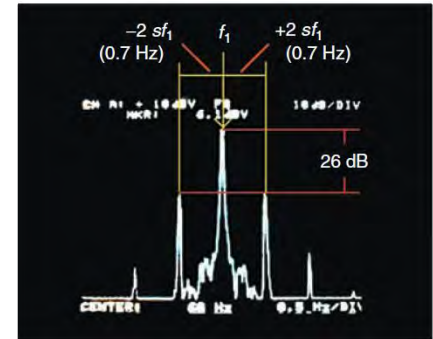
## Electrical faults



## Mechanical faults

Variations in electric circuit/airgap magnetic field

Manifest as periodic disturbances in supply current



- Bearing fault  $f_v \approx 0.6nf_r, 0.4nf_r, f_{brg} = f_s \pm mf_v$
- Stator winding fault  $f_{st} = f_s \left[ \frac{n}{p} (1-s) \pm k \right]$
- Air gap eccentricity  $f_{age} = f_s \left[ (R \pm n_d) \left( \frac{1-s}{p} \right) \pm n_{ws} \right]$
- Broken rotor bar  $f_{brb} = f_s (1 \pm 2s)$

# Fault models

Detailed induction motor modeling based on modified winding function theory (MWFTh)

$$\{V_s\}_{(3 \times 1)} = [R_s]_{(3 \times 3)} \{i_s\}_{(3 \times 1)} + \frac{d}{dt} ([L_s]_{(3 \times 3)} \{i_s\}_{(3 \times 1)} + [L_{sr}]_{3 \times N_r} \{i_r\}_{N_r \times 1})$$

$$\{0\}_{(N_r \times 1)} = [R_r]_{(N_r \times N_r)} \{i_r\}_{(N_r \times 1)} + \frac{d}{dt} ([L_r]_{(N_r \times N_r)} \{i_r\}_{(N_r \times 1)} + [L_{rs}]_{N_r \times 3} \{i_s\}_{3 \times 1})$$

The inductances are calculated considering the modified airgap function, due to faults.

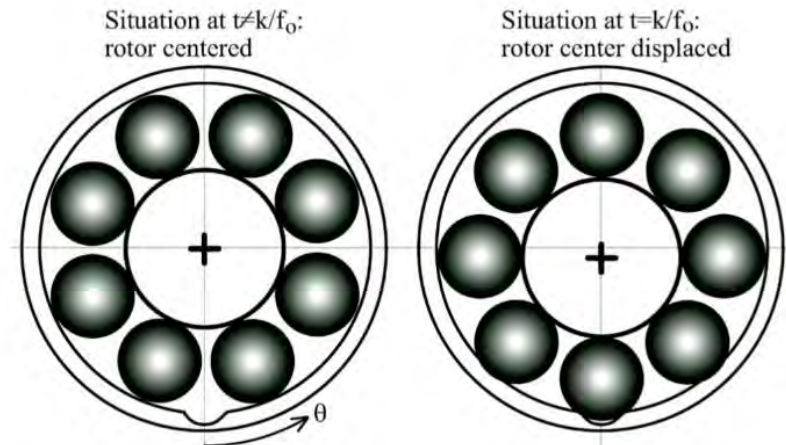
$$L_{AB} = \mu_0 r l \int_0^{2\pi} M_A(\phi, \theta) n_B(\phi, \theta) g^{-1}(\phi, \theta) d\phi$$

**Air gap eccentricity**

$$g(\phi, \theta) = g_0(1 - \delta \cos(\phi - \theta))$$

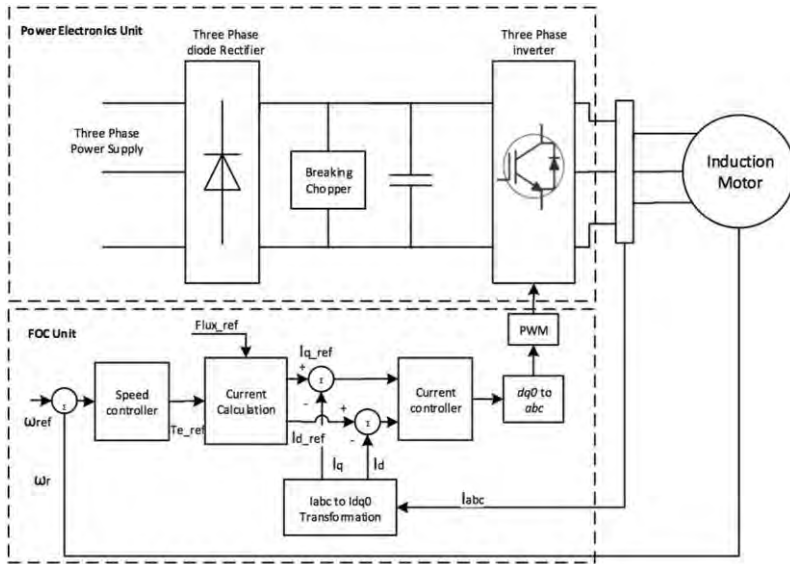
**Bearing fault (BRG)**

$$g(\phi, \theta, t) = g_0 \left[ 1 - e_0 \cos(\phi) \sum_{k=-\infty}^{+\infty} \delta \left( t - \frac{k}{f_c} \right) \right]$$

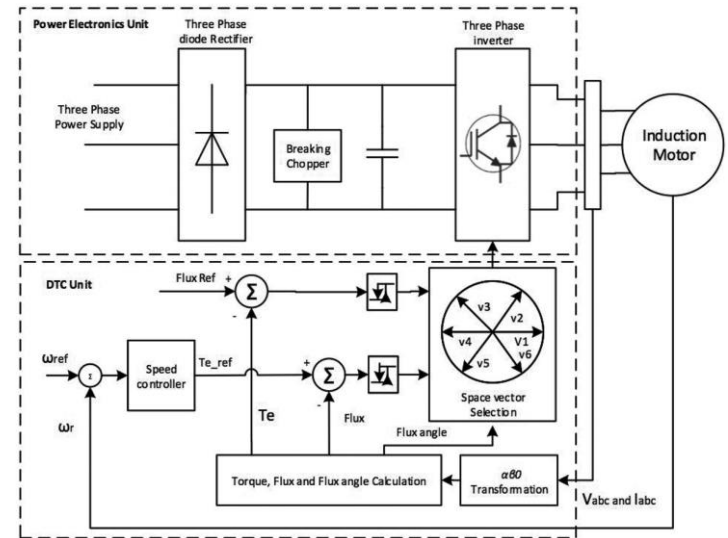




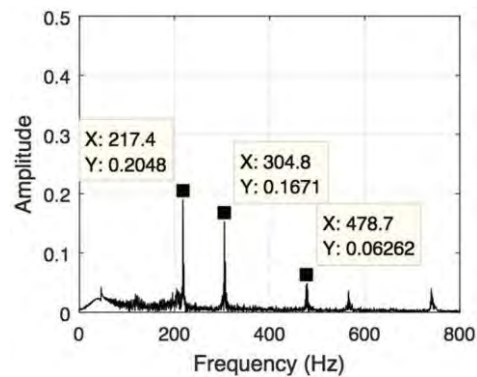
# Laboratory set-up for motor diagnostics



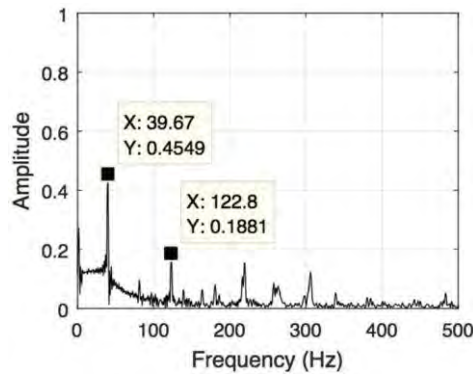
Field-oriented control system.



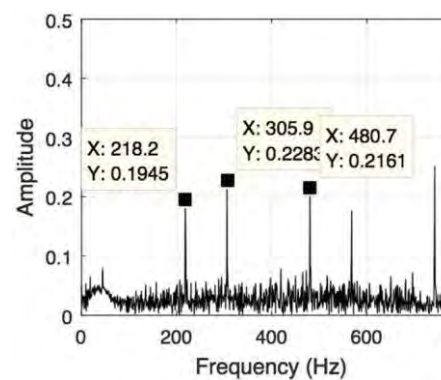
Direct torque control system.



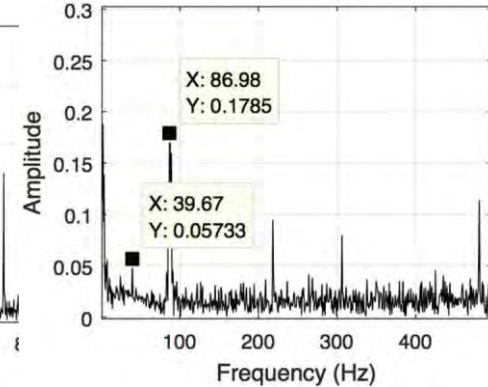
Current spectrum of a healthy motor with FOC



Fault frequencies at  $f_{AGE1}$  with FOC.



Current spectrum of a healthy motor with DTC.

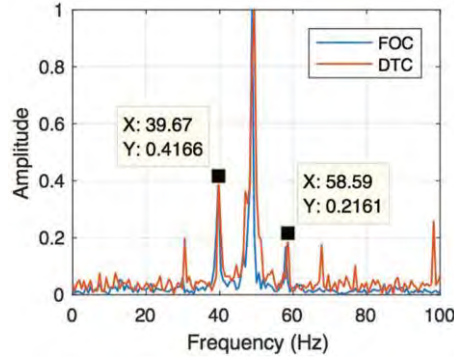


Fault frequencies at  $f_{AGE1}$  with DTC.

# Laboratory set-up for motor diagnostics



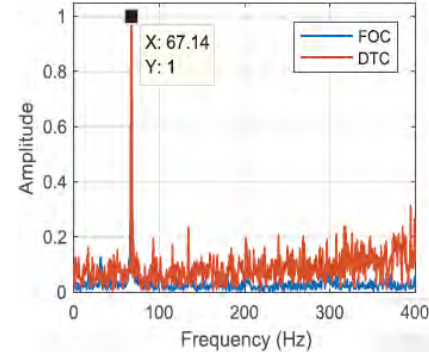
(a) broken rotor bars



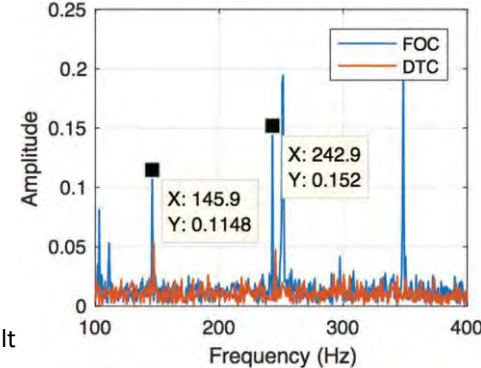
Single-line current spectrum with BRB fault at 1420 r/min



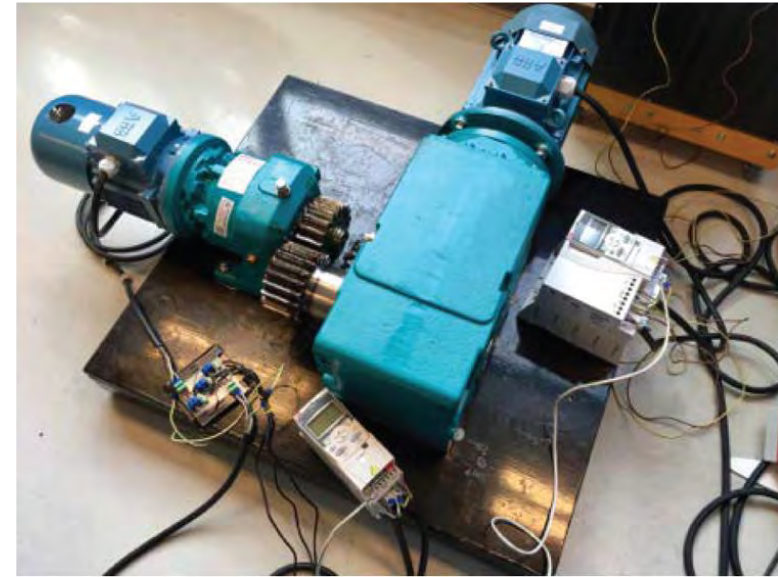
(b) stator-turn fault



$i_b$  current spectrum with STF at 1420 r/min.



(c) bearing outer race fault



Fault frequencies in closed-loop operation of the test motor in the laboratory set-up.

Control	Speed (r/min)	$f_{BRB}$ (Hz)	$f_{BRG}$ (Hz)
FOC	1000	27.5, 29.8	85.6, 94.4
		32.8, 41.5	145.6, 154.4
FOC	1420	36, 41	121.8, 133.8
		56.5, 61.2	207, 219
DTC	1000	28.03, 31.5	84.9, 95.1
		31.6, 42.1	144.9, 155.1
DTC	1420	25.1, 31.4	121.4, 134.2
		39.5, 59.6	206.6, 219.4

FOC: field-oriented control; DTC: direct torque control.



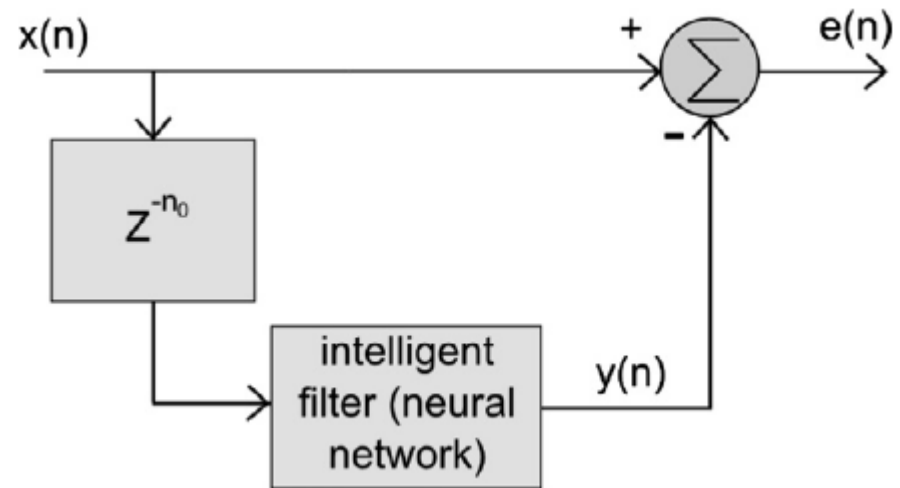
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# Bearing Fault Diagnosis & Classification

- ❖ Design of a removing non-bearing fault component (RNFC) filter based on neural networks.

Intelligent RNFC filter design



$e(n)$ : Faulty part of the vibration signal.

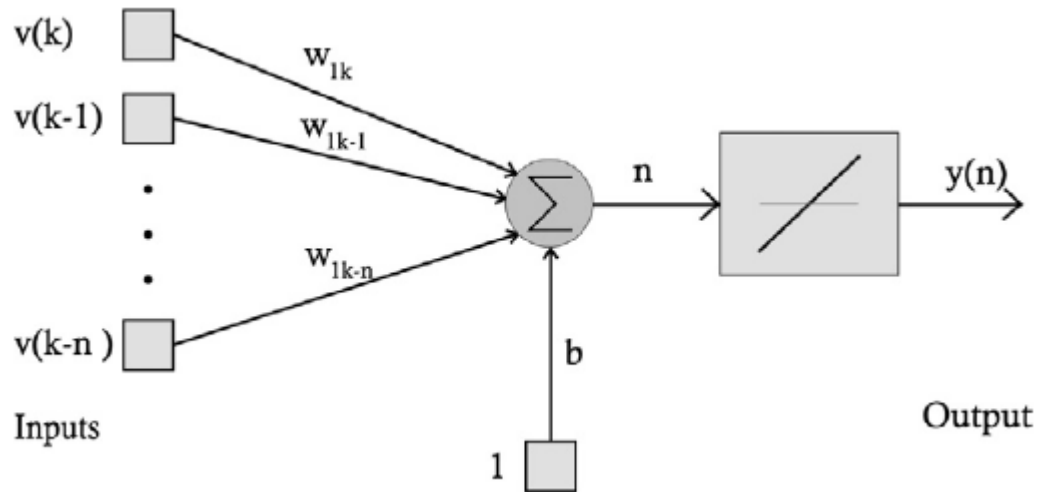
$n_0$ : Number of data samples.

$u(n)$ : Motor vibration signal.

$y(n)$ : Estimated irrelevant part of the vibration signal (non-bearing fault components).

# Bearing Fault Diagnosis & Classification

Adaptive Linear Neuron (ADALINE) neural network with purelin activation functions



The structure of ADALINE used as an intelligent filter.

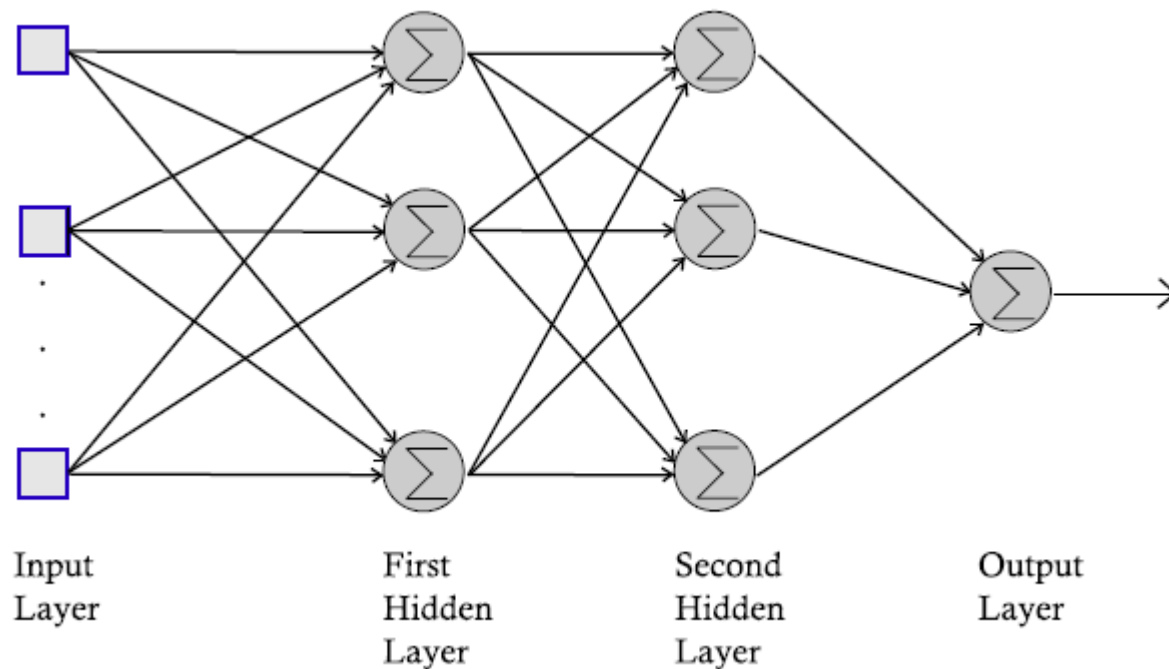
The network input  $p$  and the target  $t$  are considered as follows:

$$p = \begin{bmatrix} \text{healthy}(k) \\ \text{healthy}(k-1) \\ \vdots \\ \text{healthy}(k-n_0) \end{bmatrix} \quad n_0 = 1, 2, \dots \quad t = [\text{healthy}(k)] \quad k = 1, 2, \dots$$

$\text{healthy}(k)$  is the sampled vibration signal of a healthy induction motor ( $k$  is the indices for the number of samples).

# Bearing Fault Diagnosis & Classification

Fault classification based on pattern recognition for healthy and defective bearings in four categories, including healthy condition, inner race defect, outer race defect and double holes in outer race.



The structure of a multi-layer perceptron network.

# Bearing Fault Diagnosis & Classification

The input prototypes for network training are defined as:

$$p = \begin{bmatrix} \text{first central moment (RMS}^2) \\ \text{second central moment (variance)} \\ \text{third central moment (skewness)} \\ \text{forth central moment (kurtosis)} \end{bmatrix}$$

First central moment ( $RMS^2$ )

$$RMS^2 = \frac{1}{N} \sum_{j=1}^N (x_j^i - \mu^i)$$

$$\mu^i = \frac{1}{N} \sum_{j=1}^N x_j^i$$

Second central moment (variance)

$$\sigma^2 = \frac{1}{N-1} \sum_{j=1}^N (x_j^i - \mu^i)^2$$

Third, third central moment (skewness)

$$SK = \frac{1}{(N-1)\sigma^3} \sum_{j=1}^N (x_j^i - \mu^i)^3$$

Forth central moment (kurtosis)

$$KU = \frac{1}{(N-1)\sigma^4} \sum_{j=1}^N (x_j^i - \mu^i)^4$$

$N$  is the total number of samples

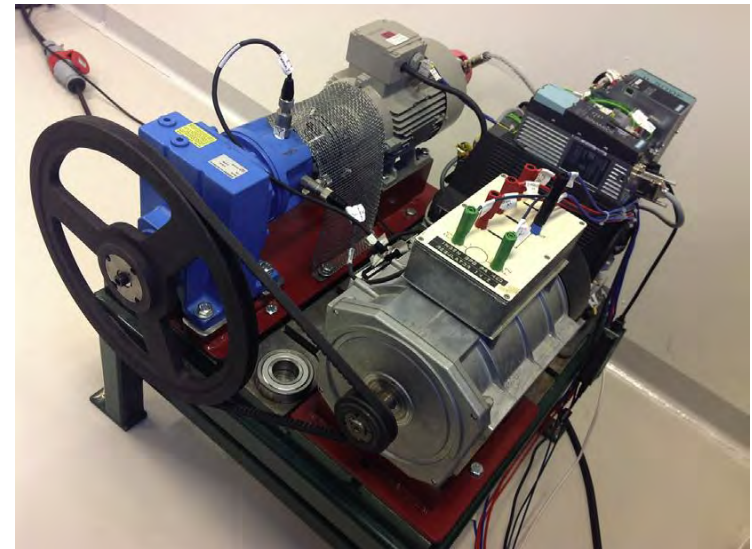
# Bearing Fault Diagnosis & Classification

## Experimental setup and results

### ❑ Characterization

- A three-phase, 1.2 kW, 380 V, 1500 rpm, four pole induction motor is used to collect experimental data.
- Both shaft-end and fan-end bearings are 6205-2Z.
- The vibration signal is sampled by Advantech PCI-1711 data acquisition card with 32 kHz sampling frequency using B&K 4395 accelerometer.

Experimental setup of bearing defect diagnosis.





# Bearing Fault Diagnosis & Classification

In the design of RNFC filter a unit sample data delay ( $n_0 = 1$ ) is selected. Therefore input prototypes are defined as:

$$p1 = \begin{bmatrix} \text{healthy signal}(k) \\ \text{healthy signal}(k-1) \end{bmatrix} \quad k = 1, 2, \dots$$

In this section target is considered as:

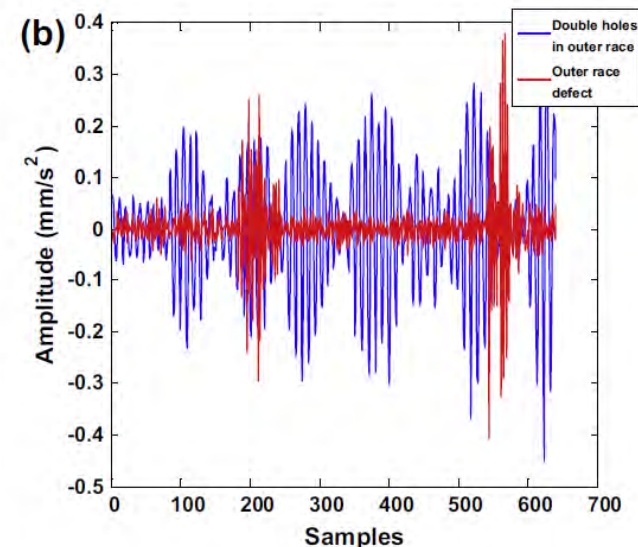
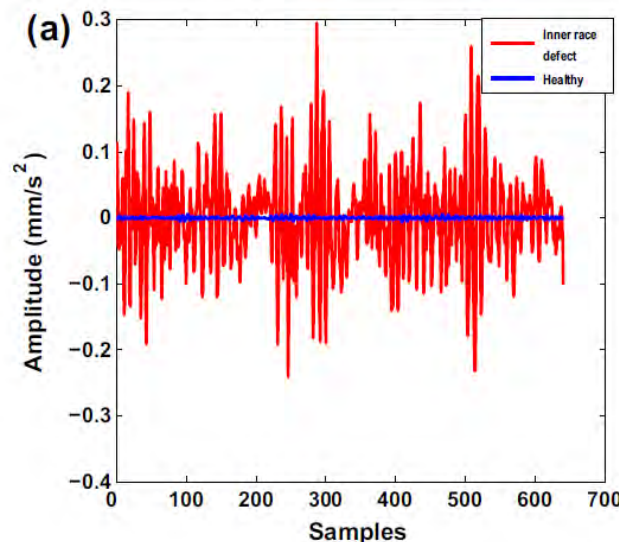
$$t = [\text{healthy}(k)] \quad k = 1, 2, \dots$$

After training is completed, the test input must be extracted from the sampled vibration signal in the form of input patterns.

$$p^{test} = \begin{bmatrix} \text{sampled vibration signal}(k) \\ \text{sampled vibration signal}(k-1) \end{bmatrix} \quad k = 1, 2, \dots$$

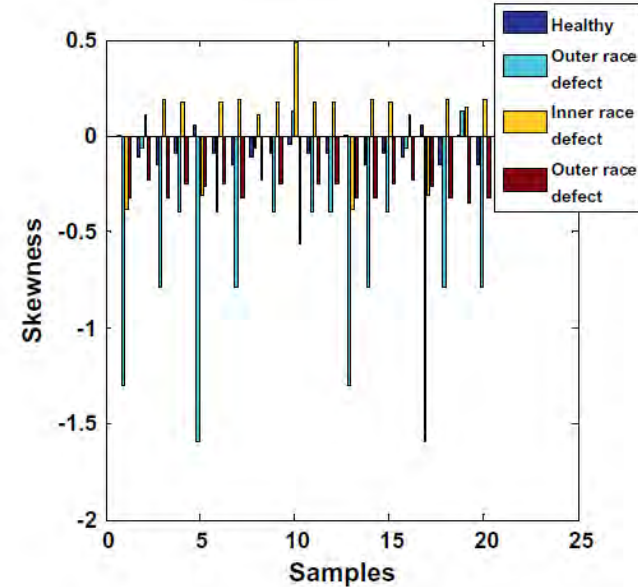
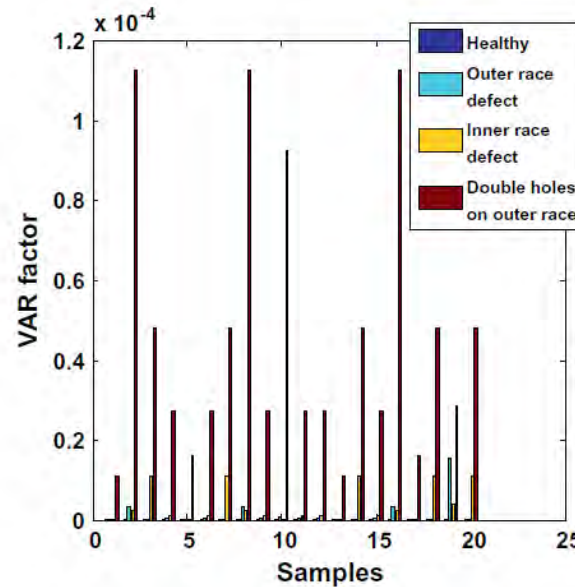
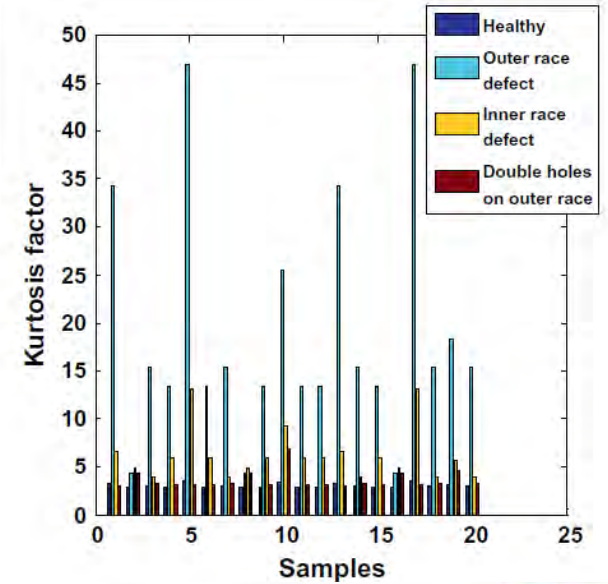
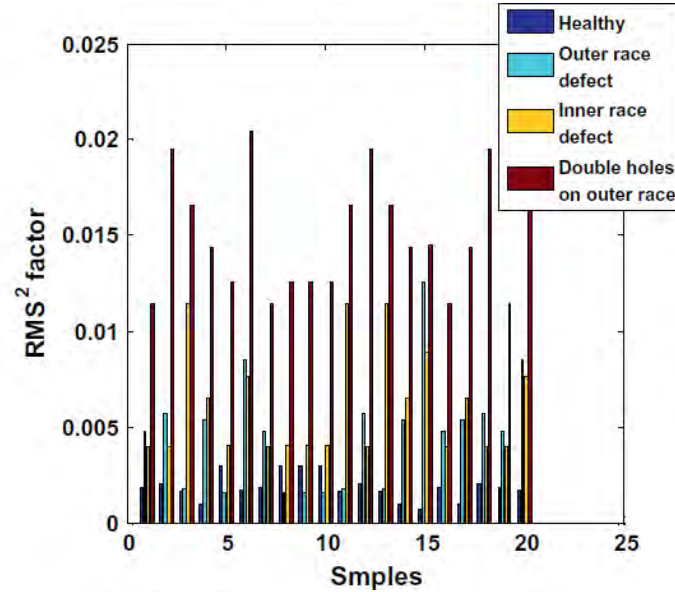
RNFC filter output of four fault categories;

- (a) healthy and inner race fault and
- (b) outer race fault and double hole in outer race.



# Bearing Fault Diagnosis & Classification

Time-domain features of test data.





# Bearing Fault Diagnosis & Classification

**Table 1**

Fault detection using RNFC filter.

Net number	Neurons number	Correct classification percent			
		Healthy (%)	Inner race defect (%)	Outer race defect (%)	Double holes in outer race (%)
1	[4 3 2]	100	100	100	100
2	[4 8 2]	100	100	100	100
3	[4 3 5 2]	100	100	100	100
4	[4 10 3 5 2]	0	0	0	0

**Table 2**

Direct fault detection (fault classification without RNFC filter).

Net number	Neurons number	Correct classification percent			
		Healthy (%)	Inner race defect (%)	Outer race defect (%)	Double holes in outer race (%)
1	[4 3 2]	0	16	60	56
2	[4 8 2]	16	28	16	12
3	[4 3 5 2]	32	12	30	64
4	[4 10 3 5 2]	0	0	0	0

# Bearing Fault Diagnosis & Classification

**Table 3**

Fault detection using ANFIS.

Correct classification percent			
Healthy (%)	Inner race defect (%)	Outer race defect (%)	Double holes in outer race (%)
16	32	51	70

**Table 4**

Fault detection in presence of low-quality sampled signals using RNFC filter.

Net number	Neurons number	Correct classification percent							
		Healthy (%)		Inner race defect (%)		Outer race defect (%)		Double holes in outer race (%)	
		With filter	Without filter	With filter	Without filter	With filter	Without filter	With filter	Without filter
1	[4 3 2]	100	4	96	0	80	34	100	44
2	[4 8 2]	100	24	100	20	100	78	100	0
3	[4 3 5 2]	100	72	100	8	96	48	100	24

# Headlines

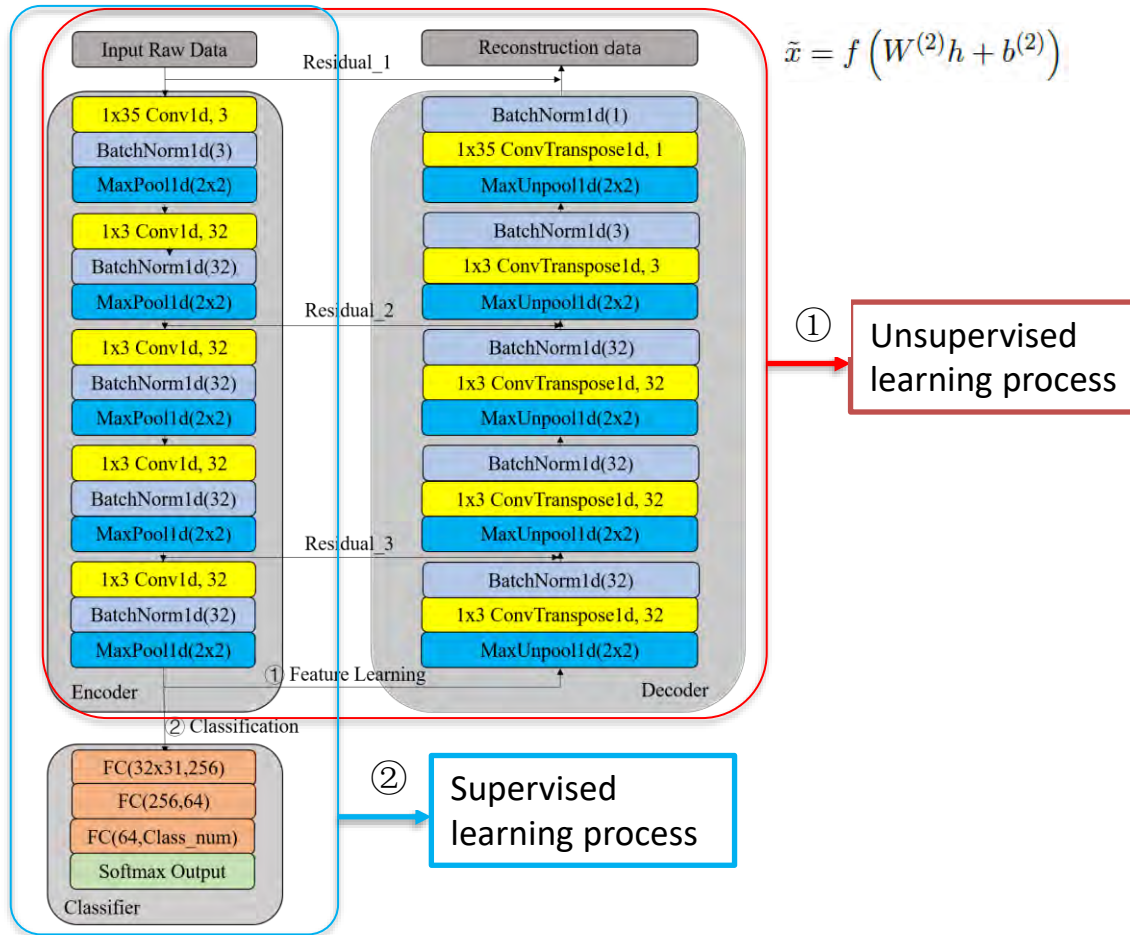
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# Residual wide-kernel deep convolutional auto-encoder (RWKDCAE)

The objective of AE is to minimize

$$\tilde{x} = f(W^{(2)}h + b^{(2)})$$

$$Loss = |x - \tilde{x}|^2$$

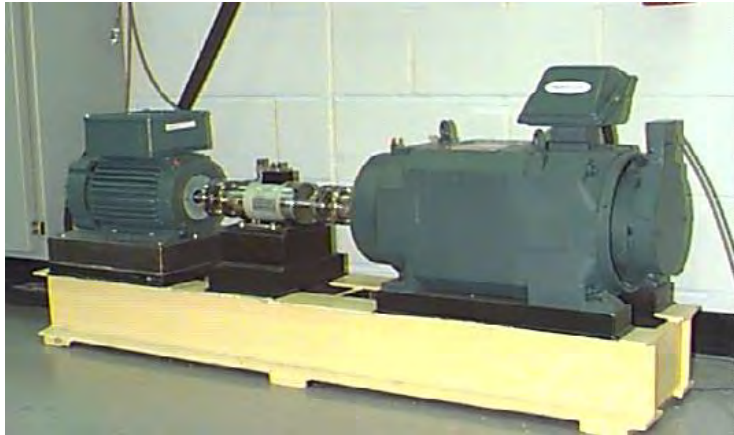


- ❑ The wide-kernel convolutional layer is introduced in the convolutional auto-encoder that can ensure the model can learn effective features from the data without any signal processing.
- ❑ The residual learning block is introduced in convolutional auto-encoder that can ensure the model with sufficient depth without gradient vanishing and overfitting problems.
- ❑ Convolutional auto-encoder can learn constructive features without massive data.

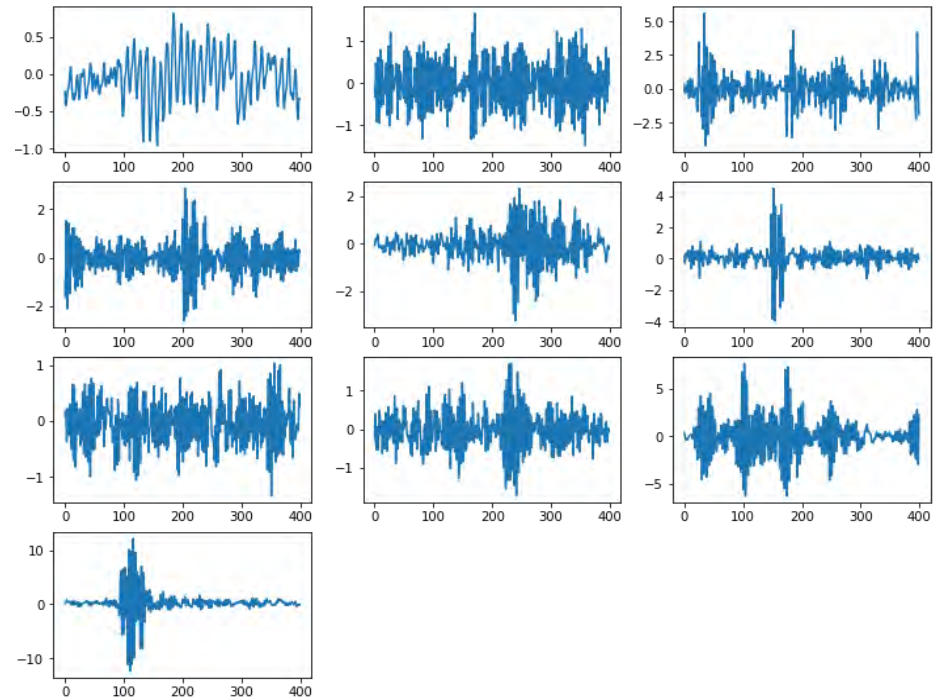
# Bearing Dataset

## Case Western Reserve University (CWRU) Bearing Fault Dataset

- CWRU bearing dataset is made up of nine fault categories and one normal condition.
- The nine types of faults are divided into three main types, which is the inner raceway fault, the outer raceway fault and the ball fault.
- There are three fault diameters for each fault type, which are 0.007 inches, 0.014 inches and 0.021 inches.



CWRU bearing test rig

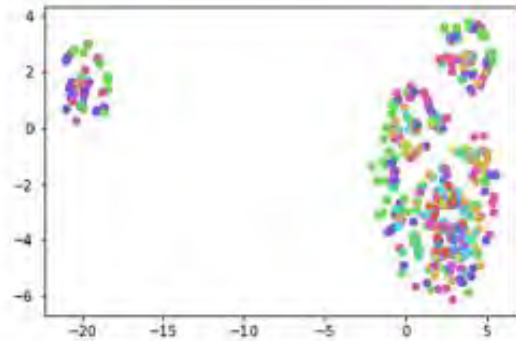


CWRU bearing fault waveform

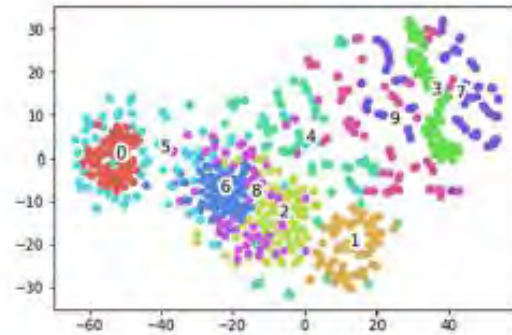


# Bearing Fault Diagnosis & Classification

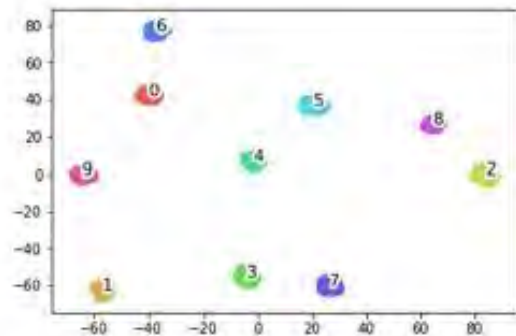
Firstly, it is necessary to compare the feature learning ability of the proposed model, which is compared with standard auto-encoder.



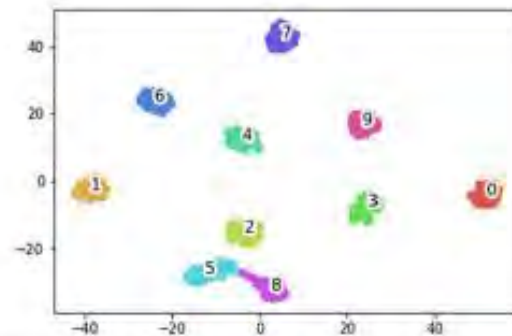
(a) encoder data of standard Auto-encoder by unsupervised learning



(b) encoder data of the proposed model by unsupervised learning



(c) encoder data of the proposed model by supervised learning



(d) frequency-domain data transform from FFT

Feature visualization of CWRU bearing dataset

- the feature that learned by a Standard auto-encoder by unsupervised learning process.
- the feature that learned by the proposed model by unsupervised learning process.
- the feature that learned by the proposed RWKDCAE model by supervised learning process.
- the frequency-domain signals.

# Bearing Fault Diagnosis & Classification

Secondly, in order to directly show the feature extraction ability of the proposed RWKDCAE model, the testing datasets are from the same working conditions of the training datasets.

CWRU bearing dataset

	Subsets				
	A	B	C	D	E
Training Set	1hp	2hp	3hp	1-3hp	1-2hp
Testing Set	1hp	2hp	3hp	1-3hp	3hp

Result of the proposed model and compare it with existing methods

Fault diagnosis methods	Dataset					Feature size	Feature extraction	
	A	B	C	D	E			
ISA Trans. 2020	DAE				71.26%	1024	No	
	MLP				70.11%	1024	No	
	CNN				99.62%	1024	No	
Sensors 2017	ResNet18				100%	1024	No	
	WKDCNN				100%	1024	No	
TII, 2018	VGG-16	99.30%	90.66%	99.72%	98.85%	96.47%	1024	Yes
	VGG-16TL	100%	100%	99.96%	99.95%	98.80%	1024	Yes
WKDCAE	100%	100%	100%	99.92%	99.42%	1024	No	
RWKDCAE	100%	100%	100%	100%	99.85%	1024	No	

# Bearing Fault Diagnosis & Classification

In order to show the robust capability of the proposed model when it deals with the real-time datasets, it is necessary to test the performance of the model in the noise working conditions.

CWRU bearing dataset

Load	Model	SNR (dB)					
		0	2	4	6	8	10
A	1-DCNN	96.00%	98.33%	99.33%	99.33%	99.33%	99.33%
	1-D WDCNN	96.67%	99.00%	99.00%	99.67%	99.67%	99.67%
	RWKDCAE	99.00%	99.33%	99.67%	99.67%	100%	100%
B	1-DCNN	97.00%	99.33%	99.67%	99.67%	100%	100%
	1-D WDCNN	97.67%	99.33%	99.67%	99.67%	100%	100%
	RWKDCAE	99.33%	100%	100%	100%	100%	100%
C	1-DCNN	96.67%	98.00%	99.33%	100%	100%	100%
	1-D WDCNN	97.67%	98.00%	99.67%	100%	100%	100%
	RWKDCAE	98.00%	100%	100%	100%	100%	100%
D	1-DCNN	97.83%	98.33%	98.33%	98.67%	99.33%	99.33%
	1-D WDCNN	98.25%	98.75%	98.75%	98.92%	99.42%	99.42%
	RWKDCAE	99.08%	99.17%	99.42%	99.58%	99.67%	99.83%



# Bearing Fault Diagnosis & Classification

Lastly, it is difficult to get enough data with labels, so it is necessary to test the proposed model with very limited training samples. The results are shown as follows:

CWRU bearing dataset

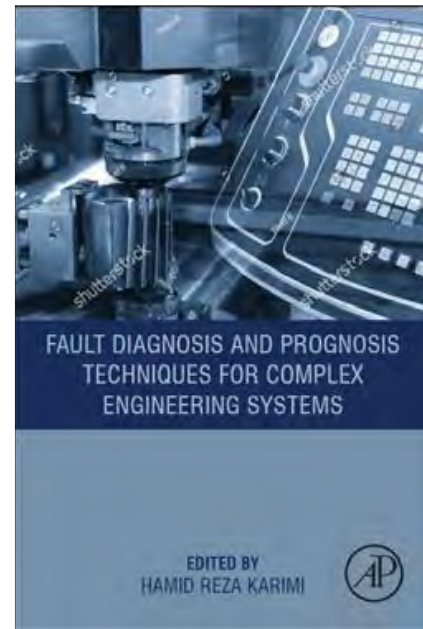
Proportion	Models	Datasets			
		A	B	C	D
10%	1-DCNN	88.00%	87.57%	94.78%	97.44%
	1-D WDCNN	89.67%	88.78%	95.44%	98.05%
	RWKDCAE	90.22%	92.78%	98.33%	99.53%
30%	1-DCNN	97.57%	98.00%	99.00%	99.21%
	1-D WDCNN	98.57%	99.00%	99.86%	99.36%
	RWKDCAE	98.86%	99.86%	100%	99.68%
50%	1-DCNN	98.80%	99.40%	100%	99.75%
	1-D WDCNN	98.80%	99.40%	100%	99.76%
	RWKDCAE	99.80%	100%	100%	99.90%

# Conclusions

- ❑ Proposing new deep learning model, RWKDCAE, for rotating machinery fault diagnosis with limited raw time-domain vibration signal.
- ❑ Firstly, the one-dimensional wide-kernel convolutional layer was introduced into Convolutional Auto-encoder to avoid feature extraction before training and could extract features from raw limited vibration signals.
- ❑ Secondly, the residual learning block was introduced to avoid overfitting and gradient vanishing in the deep learning model.
- ❑ Thirdly, the feature extraction effects of Standard Auto-encoder and the proposed model during unsupervised learning are compared.
- ❑ Then, CWRU bearing dataset was used to test the performance of RWKDCAE in the same working condition, different working conditions, noise signals and different numbers of the training samples.

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**Thanks for your attention.**