Infrared and Vibration based Bearing Fault Detection Using Neural Networks

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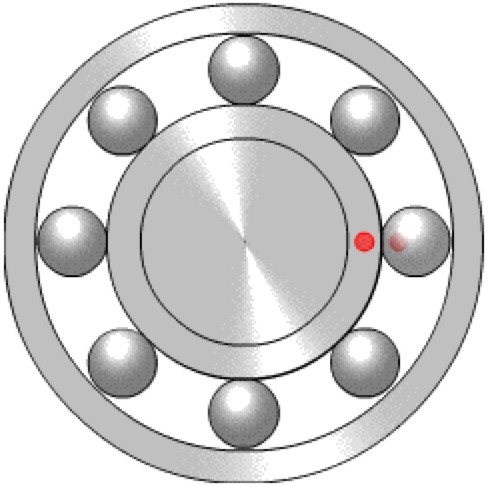
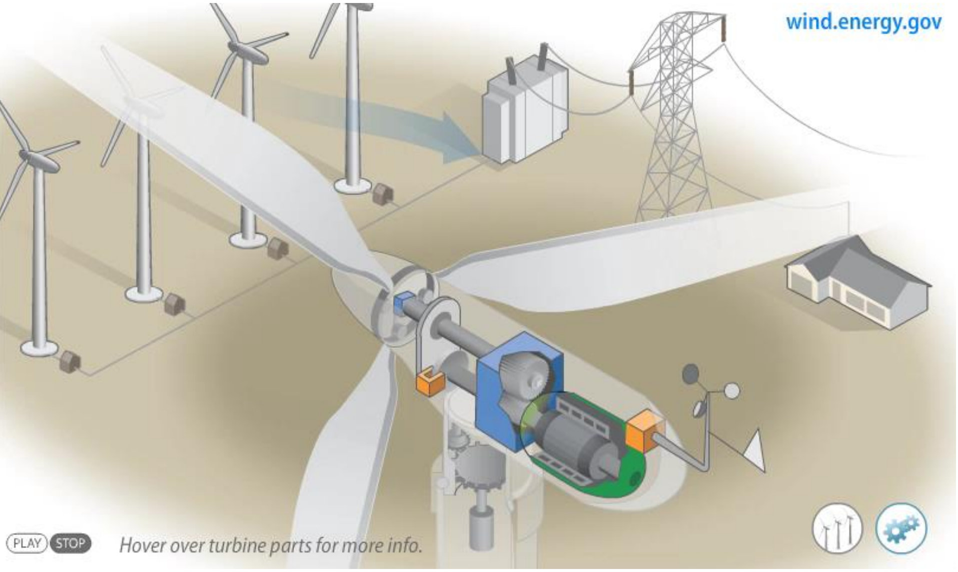
Overview

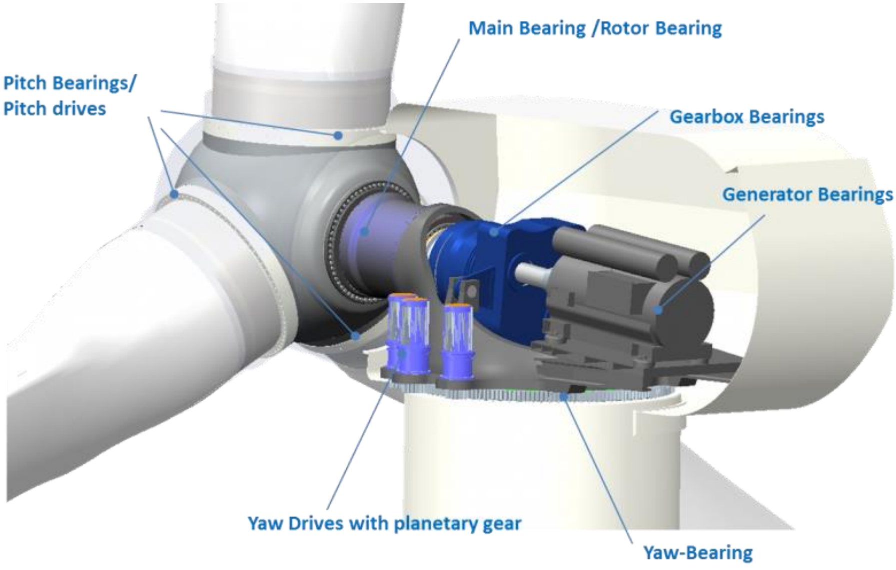
- Bearings and bearing fault causes
- Experiments and data set creation
- Fault-detection architecture
- Results
- Conclusion

Bearings: what they do



Bearings: example where they are used





Bearing failure

- Downtime
- Costs
- Fault propagation
- Reduced lifetime

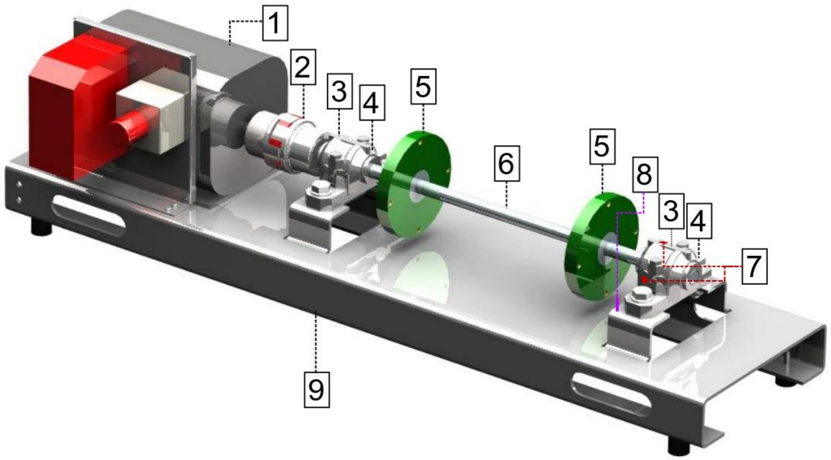
- Bearing failure
  - Improper lubrication
    - Delayed lubrication renewal 20%
    - Inadequate lubrication 15%
    - Lubricant contamination 25 %
    - Unsuitable lubrication 20 %
  - Inadequate bearing selection 10%
  - Improper mounting 5%
    - Load imbalance
    - Misalignment
  - Indirect failures 4%
  - Manufacturing errors 1%

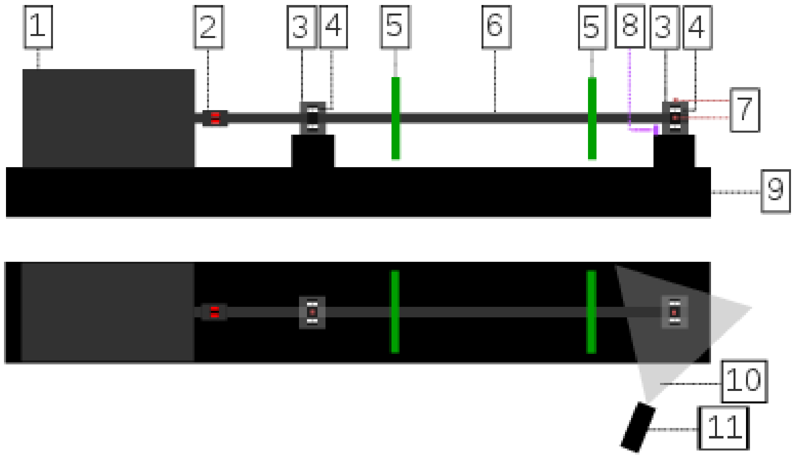
[1] C. Radu, The most common causes of Bearing Failure and Importance of Bearing Lubrication, RKB Technical review, 2010

Goal

Detect and **identify** which **fault(s)/ condition(s)** is/are present using **thermal imaging** and **vibration data**

Setup & faults/conditions





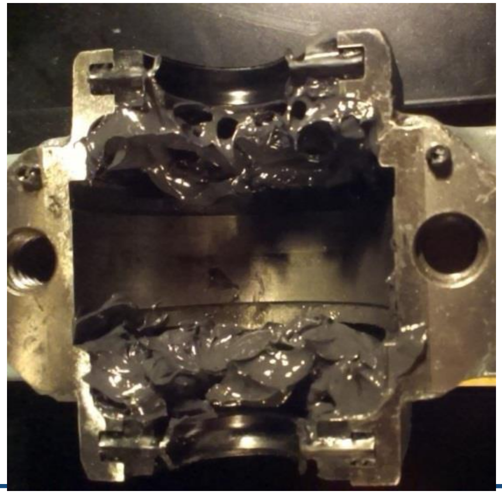
1. Servo-motor
2. Coupling
3. Bearing housing
4. Bearing
5. Disk
6. Shaft
7. Accelerometer
8. Thermocouple
9. Metal plate
10. Field of view
11. Thermal camera

Setup & faults/conditions

Mildly reduced lubrication (MRL)

Heavily reduced lubrication (HRL)

No fault (NF)

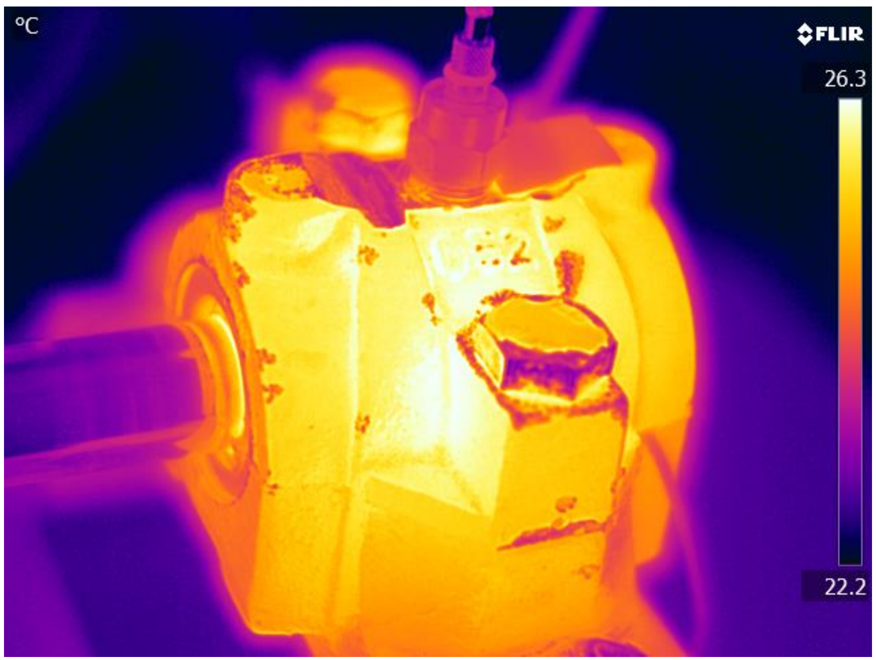


Outer raceway fault (ORF)

Data:

40 recordings (5 bearings * 8 faults/conditions)
1 hour video per recording
10 minute vibrations per recording

Corrected for ambient temperature.

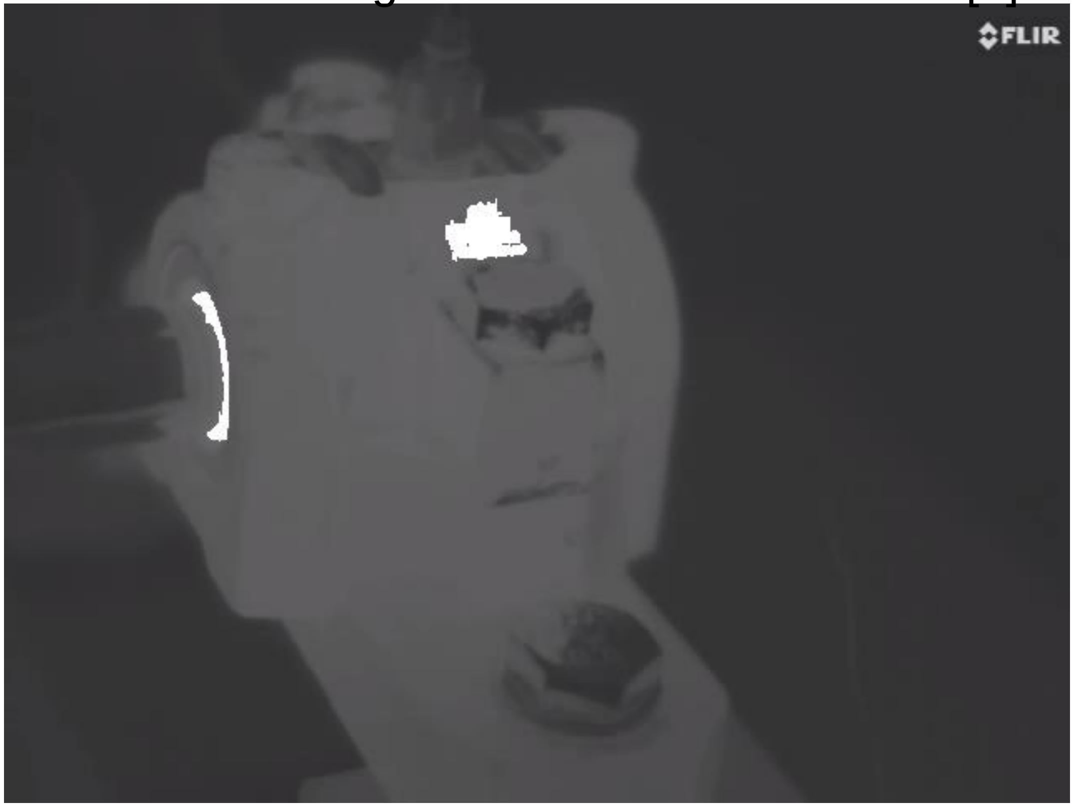


	Bearing 1	Bearing 2	Bearing 3	Bearing 4	Bearing 5
NF	1	2	3	4	5
NF-IM	6	7	8	9	10
MRL	11	12	13	14	15
MRL-IM	16	17	18	19	20
HRL	21	22	23	24	25
HRL-IM	26	27	28	29	30
ORF	31	32	33	34	35
ORF-IM	36	37	38	39	40

Multi-sensor solution:

Thermal images - preprocessing:

Region of interest detection using Gaussian mixture models [2]

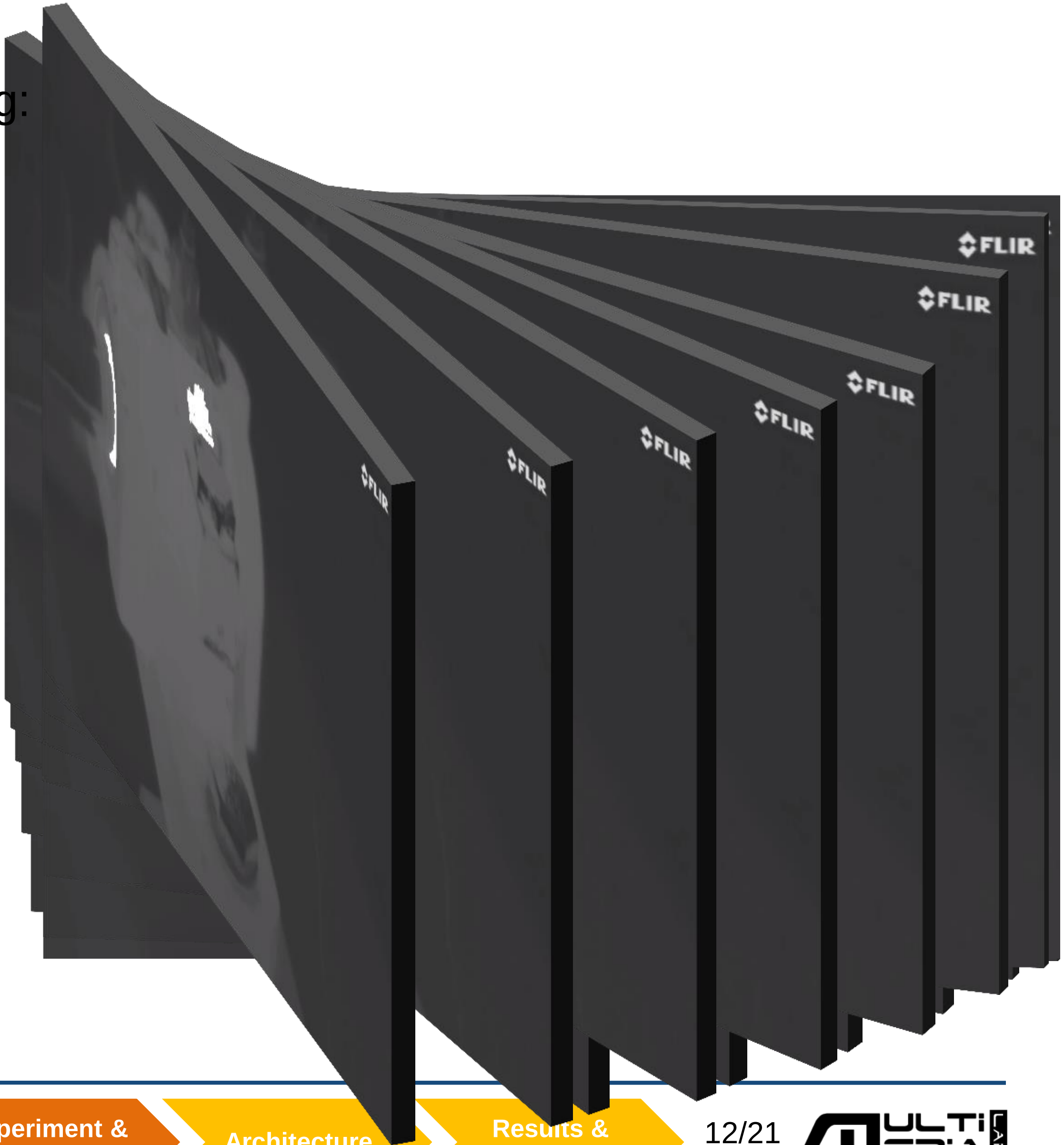


[2] Z. Zivkovic. Improved adaptive gaussian mixture model for background subtraction. ICPR 2004. pages 28–31 Vol.2, Aug 2004.

Multi-sensor solution:

Thermal images - preprocessing:

Use ROI as timeseries



Multi-sensor solution:

Thermal images - preprocessing:

Use ROI as timeseries

Multi-sensor solution:

Thermal images – dataformat:

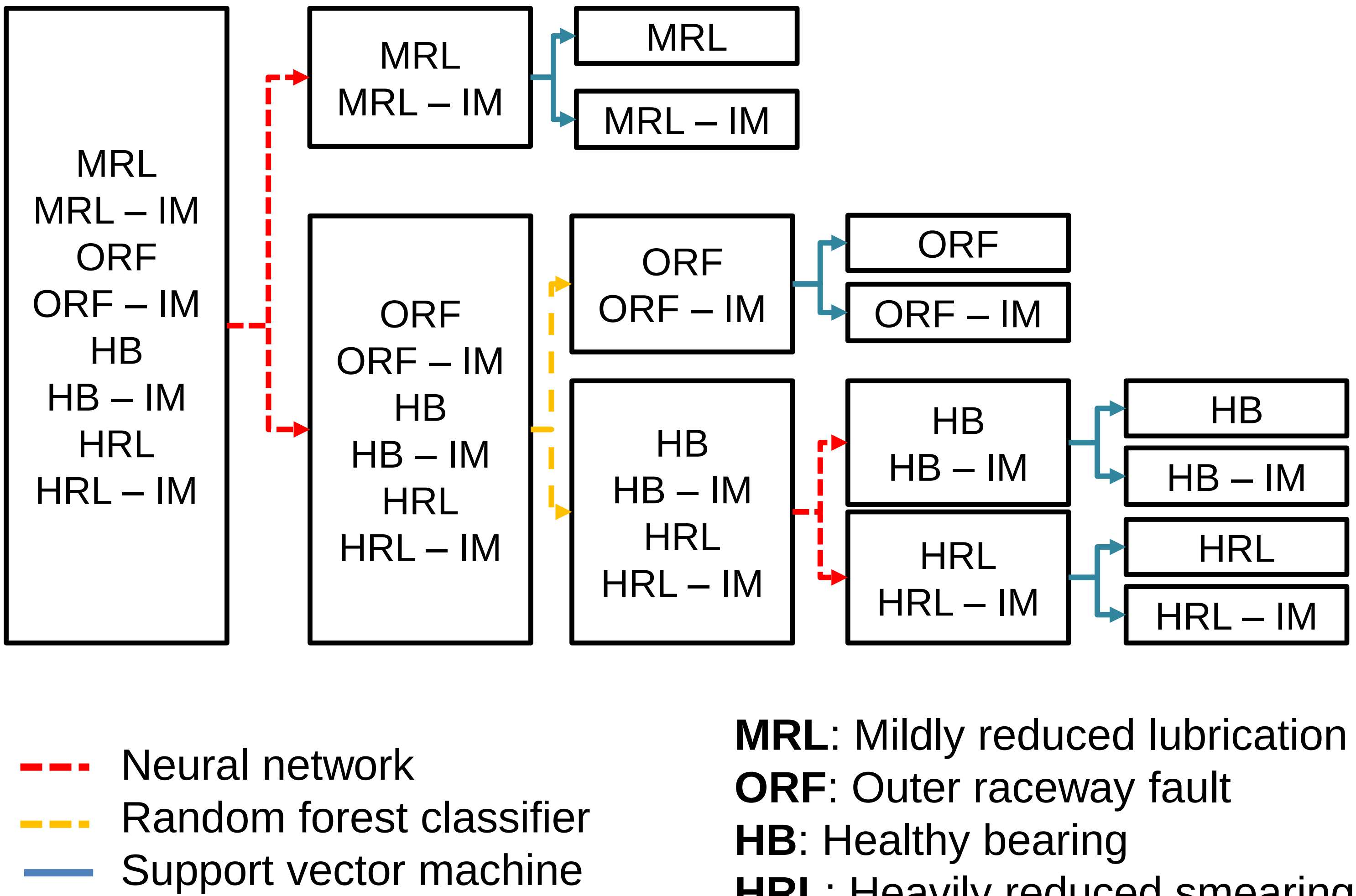
Use ROI as **timeseries**

1 hour

$I_t(x,y)$	$I_{t+1}(x,y)$	…	$I_{225}(x,y)$

- 500 pixels from the seal
- 1000 pixels from the top of the housing

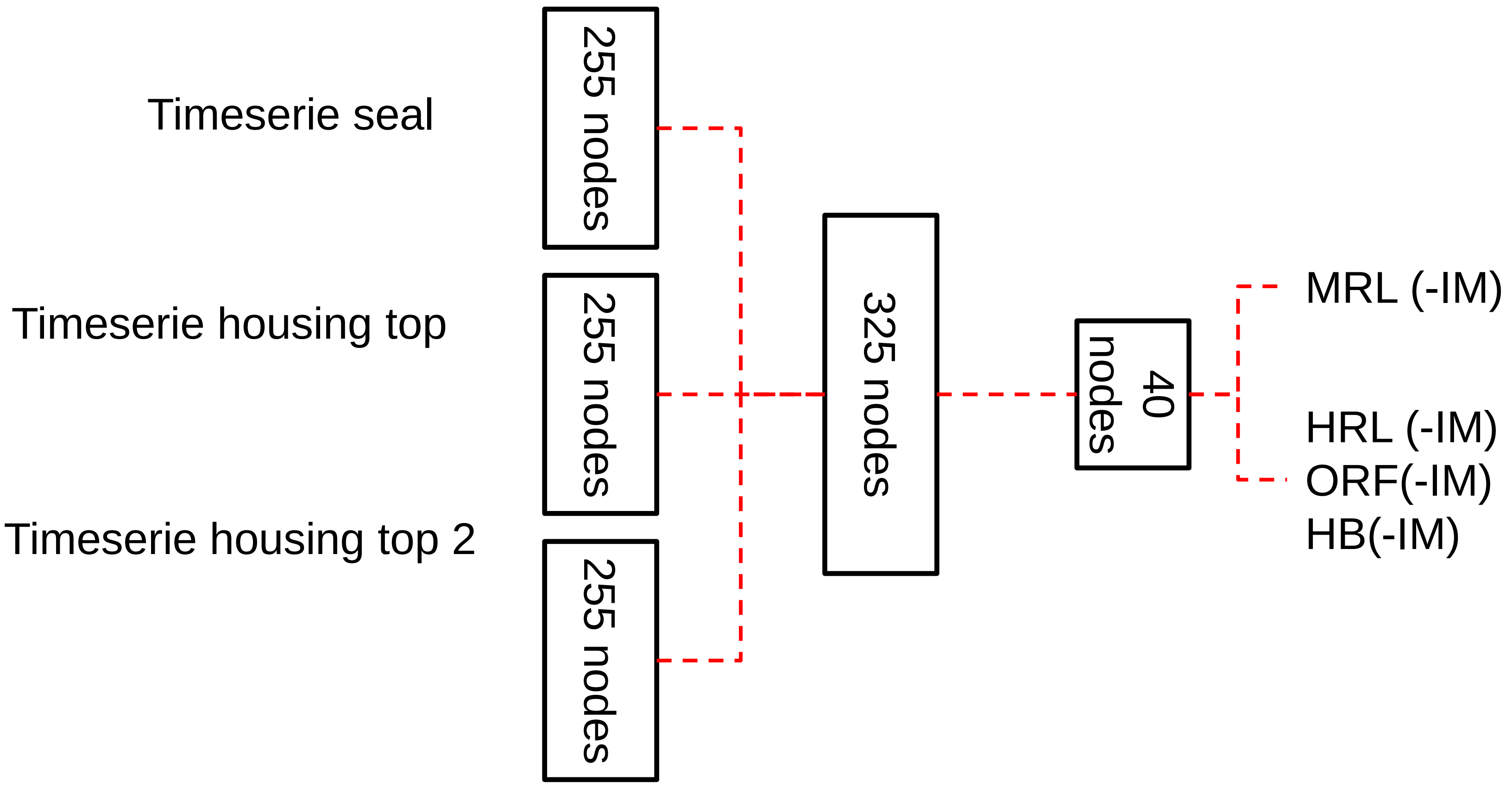
Fault detection architecture



MRL: Mildly reduced lubrication
ORF: Outer raceway fault
HB: Healthy bearing
HRL: Heavily reduced smearing

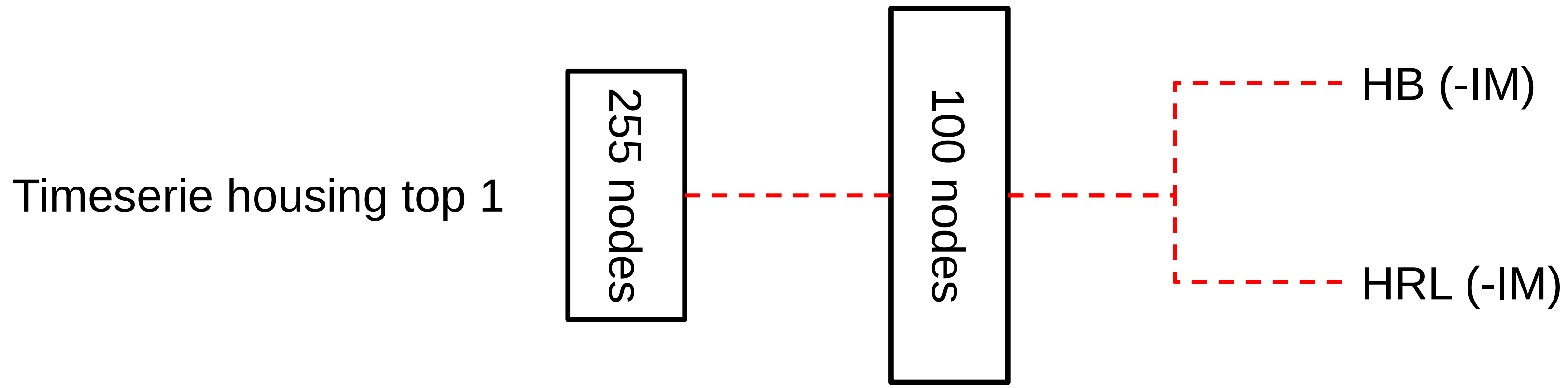
Multi-sensor solution – Neural network 1:

Architecture: 675 ➔ 325 ➔ 40 ➔ 2



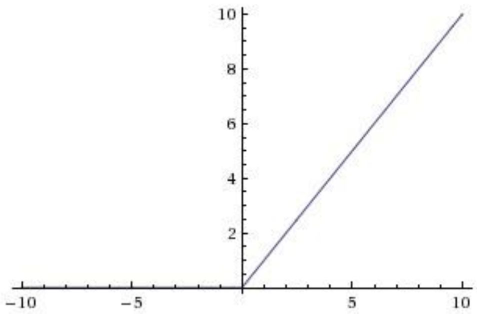
Multi-sensor solution – Neural network 2:

Architecture: 255 ➔ 100➔ 2



Neural network techniques used:

- Training: Stochastic gradient descent + momentum with Backpropagation
- Activation function hidden nodes: Rectified linear units
- Activation output nodes: Softmax
- Loss function: Cross entropy



Vibration part:

Data	Features	Classification model	Classes
Vibration data	Peak to peak features Kurtosis features	Random forest	ORF (-im) HRL (-IM) HB(-IM)
Vibration data	Amplitude at the rotation frequency (25 Hz)	Linear SVM	Imbalance Balance

Results

Fault	IR-based precision	Multi-sensor precision
HB	50 %	100 %
HB - IM	70 %	100 %
MRL	100 %	100 %
MRL - IM	80 %	80 %
HRL	70 %	100 %
HRL - IM	70 %	90 %
ORF	30 %	100 %
ORF - IM	40 %	100 %
Average	63,75 %	96,25 %

Acknowledgment

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Thank you for listening !

Questions ?