Structural Health Monitoring

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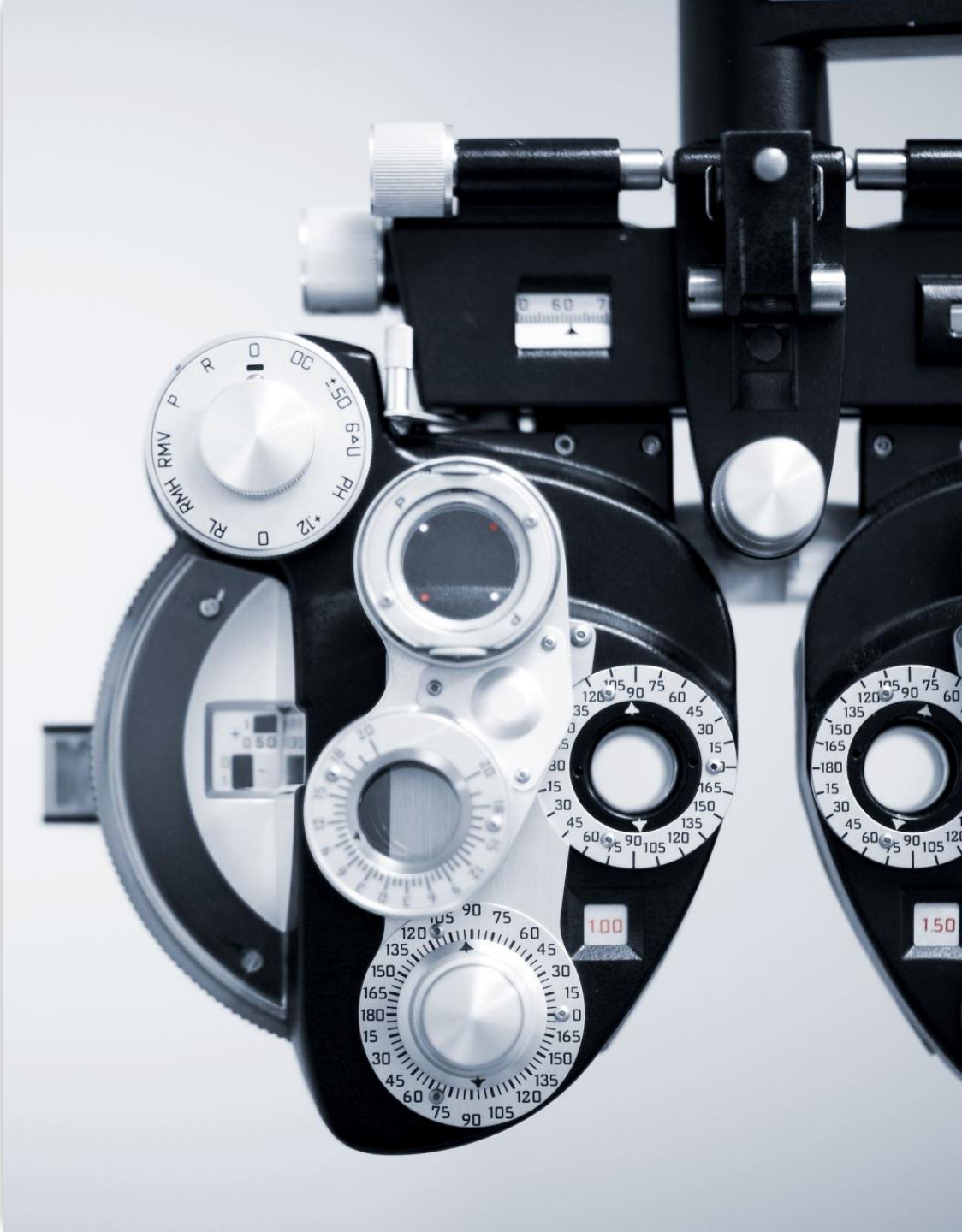
- Application
- Overview of Vibrational Fault Detection Methods
- Device for Data Acquisition
- A Typical Vibrational Analysis – LabView
- Case Scenario with CNC Tool holder
- Overview of Structural Health Monitoring of Wind Turbine System
- Fault Detection Methods in SHM
- Viable Machine Learning (ML)/ AI Methods
- Hybrid Structural Health Monitoring System on Wind Turbines
- Monitoring Methods and Challenges
- Remarks

Structural Health Monitoring (SHM)

- **Structural Health Monitoring (SHM) systems for components and mechanical assemblies** involve the continuous observation and assessment of structural integrity under real operational conditions. In the context of CNC toolholders, Wind Turbines, Systems, to mention a few. SHM integrates sensors—such as accelerometers, strain gauges, or acoustic emission detectors—directly into the System of interest. This allows for real-time detection of anomalies including micro-cracks, wear, imbalance, and resonance-induced fatigue. The collected data is processed using advanced signal analysis techniques (e.g., FFT, PSD, and wavelet analysis) to monitor dynamic behavior, vibration patterns, and stress concentrations. Implementing SHM in Systems significantly enhances predictive maintenance, minimizes unplanned downtime, and extends tool life—ultimately improving the precision and reliability of machining operations.



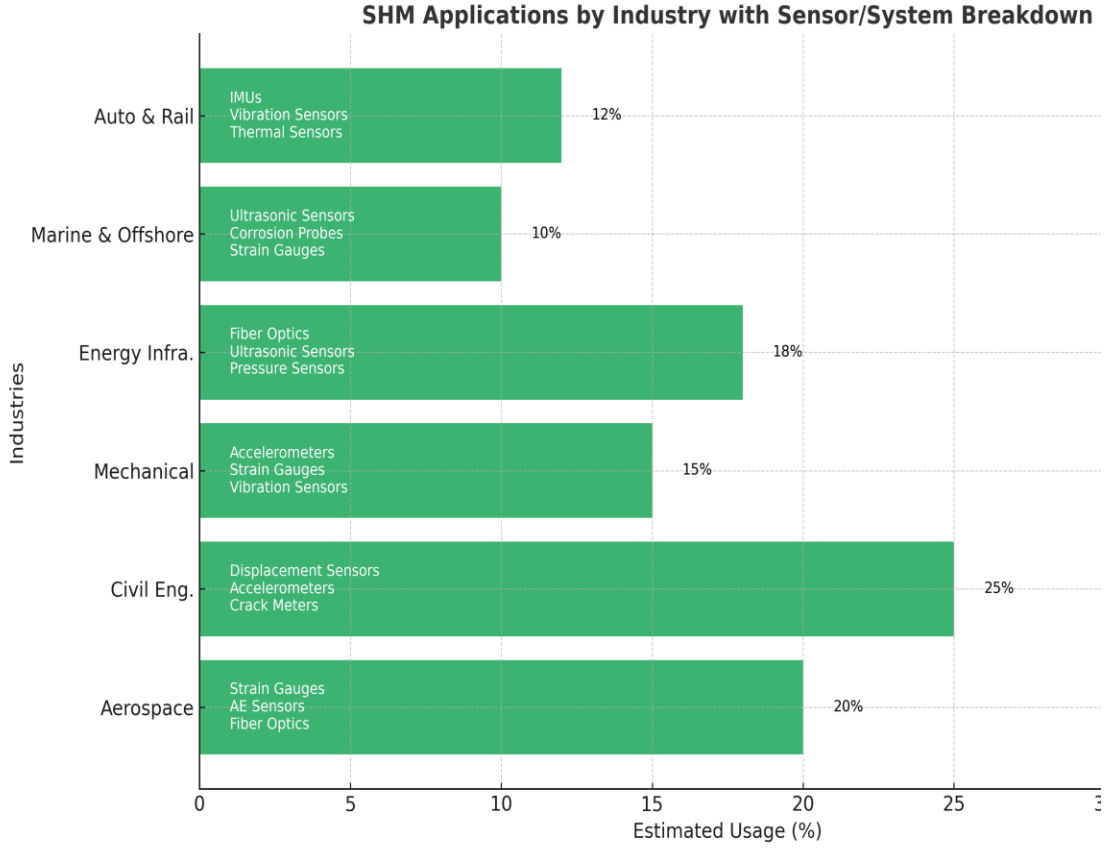
Introduction to Structural Health Monitoring (SHM)

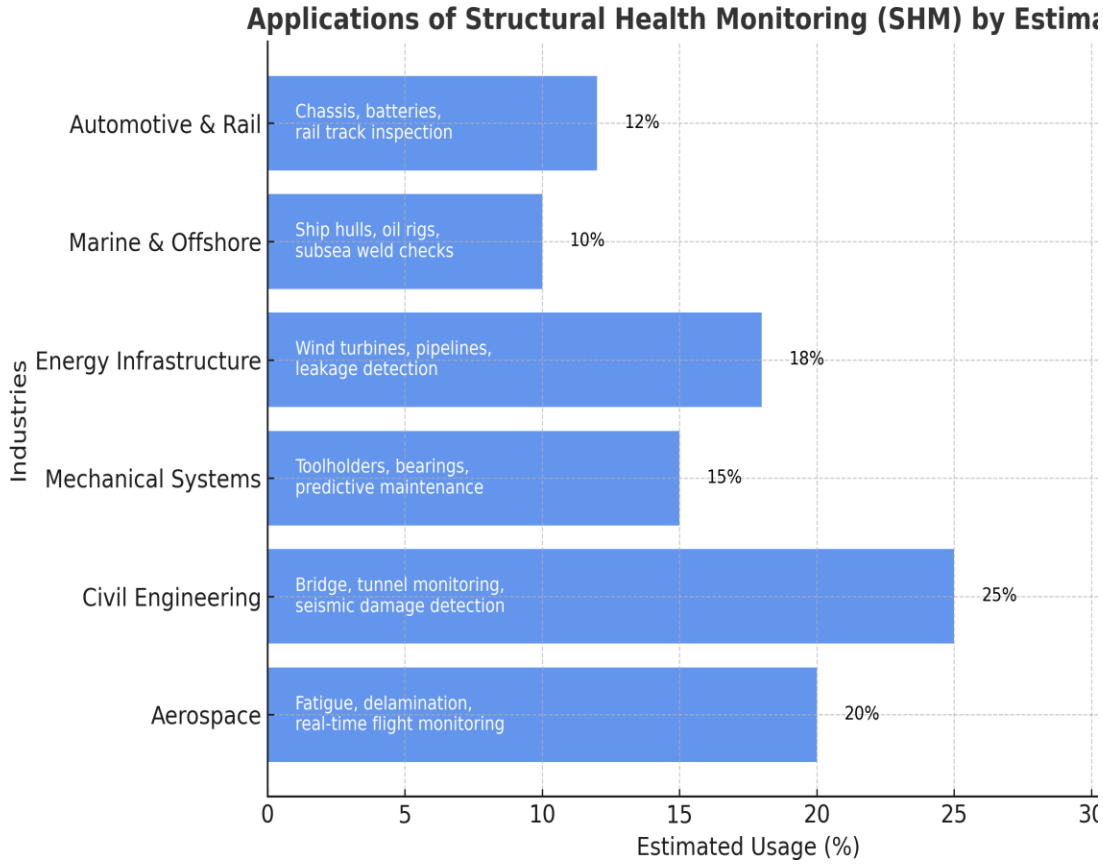
- Structural Health Monitoring (SHM) is the continuous process of assessing the structural integrity of various components and mechanical assemblies. SHM systems utilize integrated sensors to detect potential anomalies, ensuring the reliability and safety of structures over time. Whether analyzed under normal operating conditions or deliberately subjected to external forces through vibrational equipment, the primary goal remains unchanged: to observe and analyze the structure's response using a range of diverse characteristics.

- Key Applications:
- Automotive and Aerospace
- Marine
- CNC Toolholders
- Wind Turbines
- Engines, to mention a few.

- SHM allows real-time detection of:
- Micro-cracks
- Wear
- Imbalance
- Resonance-induced fatigue

- Data collected from sensors like accelerometers and strain gauges is processed using techniques like FFT, PSD, and wavelet analysis.

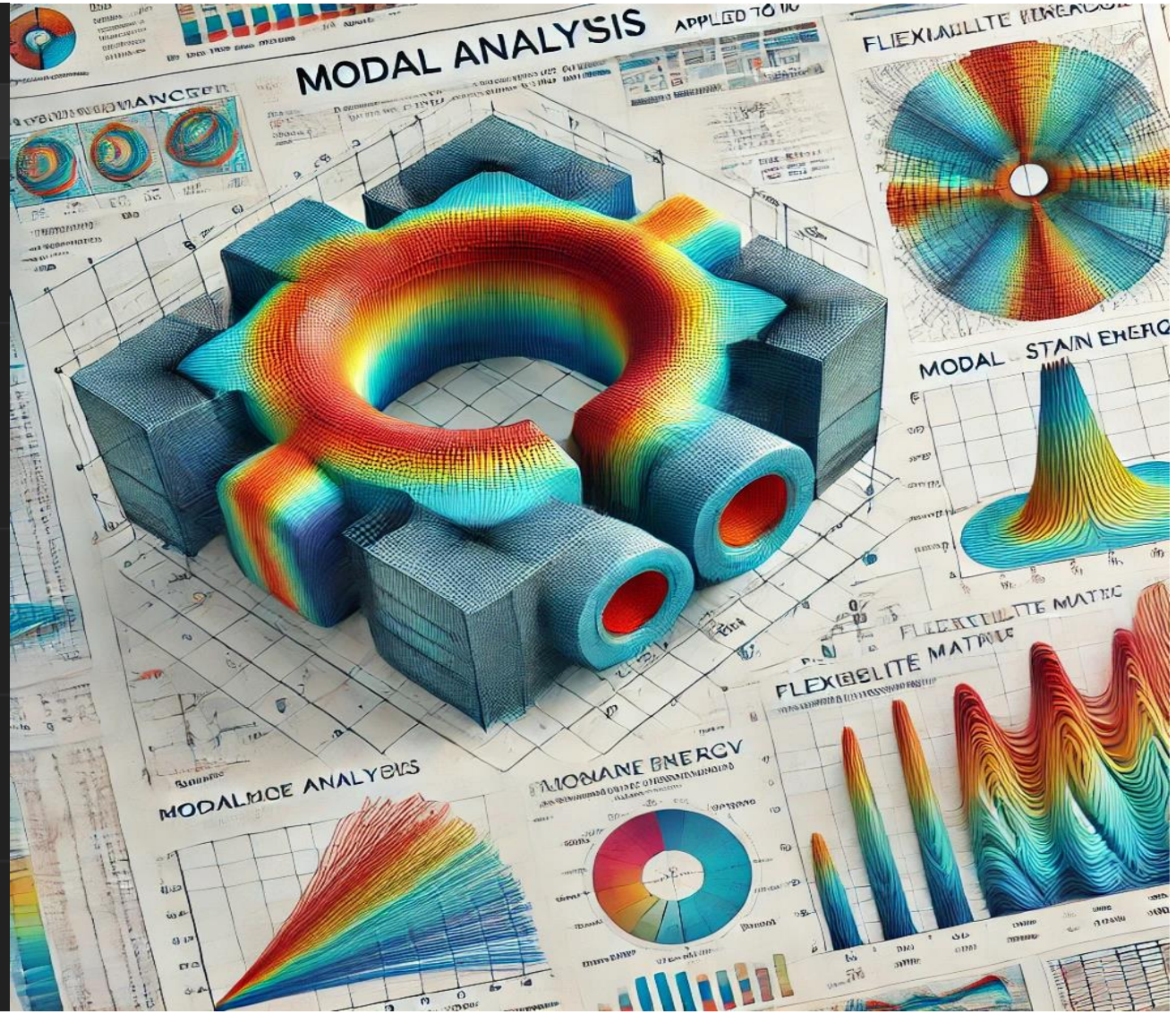

SHM Applications by Industry with Sensor/System Breakdown
Industries
Auto & Rail
Marine & Offshore
Energy Infra.
Mechanical
Civil Eng.
Aerospace
IMUs
Vibration Sensors
Thermal Sensors
Ultrasonic Sensors
Corrosion Probes
Strain Gauges
Fiber Optics
Ultrasonic Sensors
Pressure Sensors
Accelerometers
Strain Gauges
Vibration Sensors
Displacement Sensors
Accelerometers
Crack Meters
Strain Gauges
AE Sensors
Fiber Optics
12%
10%
18%
15%
25%
20%
0
5
10
15
20
25
Estimated Usage (%)


Applications of Structural Health Monitoring (SHM) by Estima
Industries
Automotive & Rail
Marine & Offshore
Energy Infrastructure
Mechanical Systems
Civil Engineering
Aerospace
Chassis, batteries,
rail track inspection
Ship hulls, oil rigs,
subsea weld checks
Wind turbines, pipelines,
leakage detection
Toolholders, bearings,
predictive maintenance
Bridge, tunnel monitoring,
seismic damage detection
Fatigue, delamination,
real-time flight monitoring
12%
10%
18%
15%
25%
20%
0
5
10
15
20
25
Estimated Usage (%)

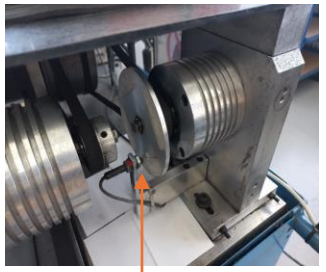
Overview of Vibrational Fault Detection Methods

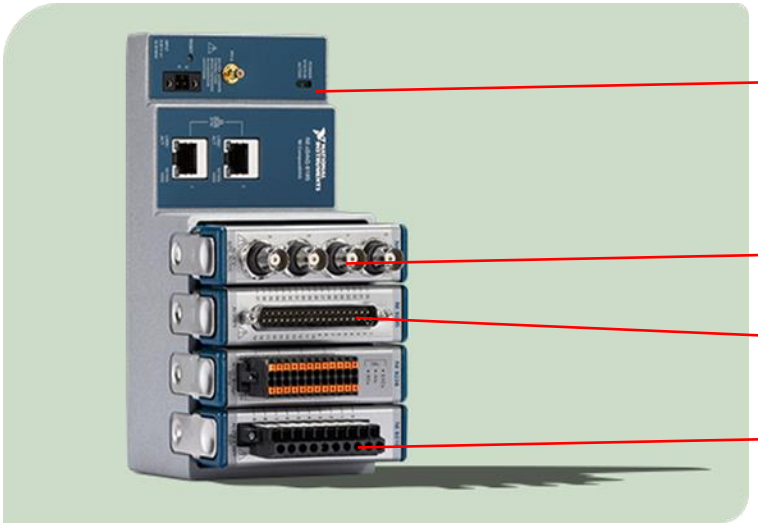
Comparison Of Vibration-Based Damage Detection Methods

	Method	Pros	Cons
1	Natural Frequency	Easy to measure, global indicator of structural changes	Weak sensitivity to minor/local damage, global only
2	Mode Shape	Contains spatial information, helps localize damage	Subtle changes, sensitive to noise, needs high resolution
3	Modal Curvature	Highly sensitive to local damage, good localization	Noise amplification from numerical differentiation
4	Modal Strain Energy	Good for multiple/hidden damages, energy-based	Requires accurate modal data, often needs baseline
5	Modal Flexibility	Effective with limited mode shapes, no baseline needed	Sensitive to noise, limited by available mode shapes



DEVICE FOR DATA ACQUISITION





Chassis with Controller

Modules

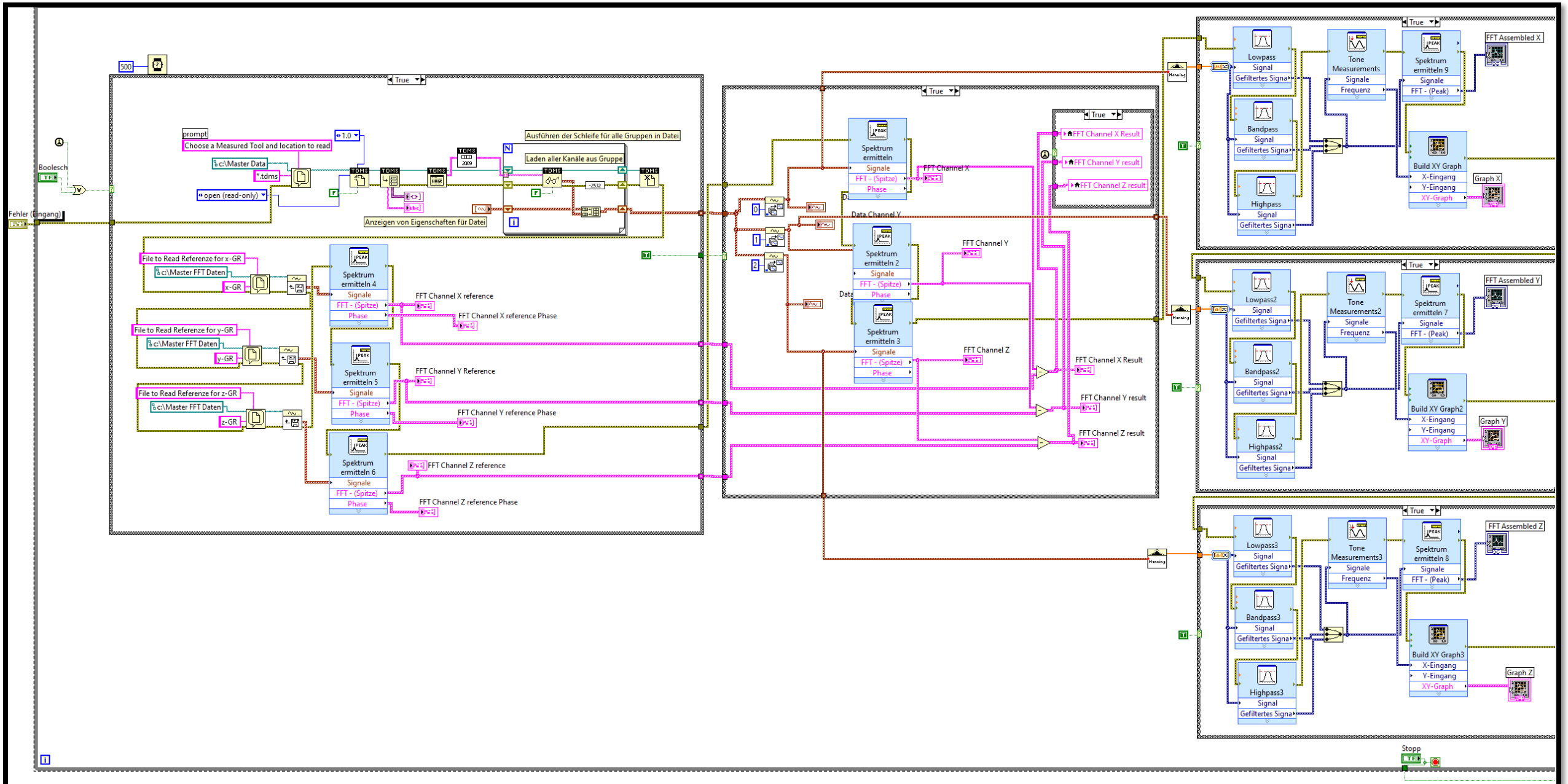
3 axis Accelerometers

RPM control

Temperature

N.B: Measuring System connected to the Teststand. **LABVIEW, Python** could be used for Vibrational Analysis.

A Typical Vibrational Analysis - LabView



Bearing and Gear Simulated Nominal Values for 55_A_TH

Bearing

S/N	RPM	fr	Deep Groov	N_B	BD	PD	Beta	F_Bearing_11	F_Bearing_12	F_Bearing_13	F_Bearing_14
1	1000	16.6666667	30 X 47 X 9	14	4.75	38.5	0	102.2727273	131.0606061	66.51572112	7.305194805
2	2000	33.3333333	6906	14	4.75	38.5	0	204.5454545	262.1212121	133.0314422	14.61038961
3	3000	50		14	4.75	38.5	0	306.8181818	393.1818182	199.5471634	21.91558442
4	4000	66.6666667		14	4.75	38.5	0	409.0909091	524.2424242	266.0628845	29.22077922
5	5000	83.3333333		14	4.75	38.5	0	511.3636364	655.3030303	332.5786056	36.52597403
6	6000	100		14	4.75	38.5	0	613.6363636	786.3636364	399.0943267	43.83116883

S/N	RPM	fr	Deep Groove	N_B	BD	PD	Beta	F_Bearing_21	F_Bearing_22	F_Bearing_23	F_Bearing_24
1	1000	16.6666667	20 X 32 X 7	14	3	26	0	103.2051282	130.1282051	71.26068376	7.371794872
2	2000	33.3333333	6804	14	3	26	0	206.4102564	260.2564103	142.5213675	14.74358974
3	3000	50		14	3	26	0	309.6153846	390.3846154	213.7820513	22.11538462
4	4000	66.6666667		14	3	26	0	412.8205128	520.5128205	285.042735	29.48717949
5	5000	83.3333333		14	3	26	0	516.025641	650.6410256	356.3034188	36.85897436
6	6000	100		14	3	26	0	619.2307692	780.7692308	427.5641026	44.23076923

S/N	RPM	fr	Deep Groove	N_B	BD	PD	Beta	F_Bearing_31	F_Bearing_32	F_Bearing_33	F_Bearing_34
1	1000	16.6666667	25 X 47 X 12	15	6.35	36	0	102.9513889	147.0486111	45.77418708	6.863425926
2	2000	33.3333333	6005	15	6.35	36	0	205.9027778	294.0972222	91.54837416	13.72685185
3	3000	50		15	6.35	36	0	308.8541667	441.1458333	137.3225612	20.59027778
4	4000	66.6666667		15	6.35	36	0	411.8055556	588.1944444	183.0967483	27.4537037
5	5000	83.3333333		15	6.35	36	0	514.7569444	735.2430556	228.8709354	34.31712963
6	6000	100		15	6.35	36	0	617.7083333	882.2916667	274.6451225	41.18055556

S/N	RPM	fr	Deep Groove	N_B	BD	PD	Beta	F_Bearing_31	F_Bearing_32	F_Bearing_33	F_Bearing_34
1	1000	16.6666667	25 X 47 X 12	11	6.75	28.5	0	69.95614035	113.377193	33.21150097	6.359649123
2	2000	33.3333333	6904	11	6.75	28.5	0	139.9122807	226.754386	66.42300195	12.71929825
3	3000	50		11	6.75	28.5	0	209.8684211	340.1315789	99.63450292	19.07894737
4	4000	66.6666667		11	6.75	28.5	0	279.8245614	453.5087719	132.8460039	25.43859649
5	5000	83.3333333		11	6.75	28.5	0	349.7807018	566.8859649	166.0575049	31.79824561
6	6000	100		11	6.75	28.5	0	419.7368421	680.2631579	199.2690058	38.15789474

Key	Nomenclature	General Nomenclature	Acronym
	F_Bearing_11	Ball Pass Frequency of Outer ring	BPFO
	F_Bearing_12	Ball Pass Frequency of Inner ring	BPFO
	F_Bearing_13	Ball Spin Frequency	BSF
	F_Bearing_14	Fundamental Train Frequency	FTF

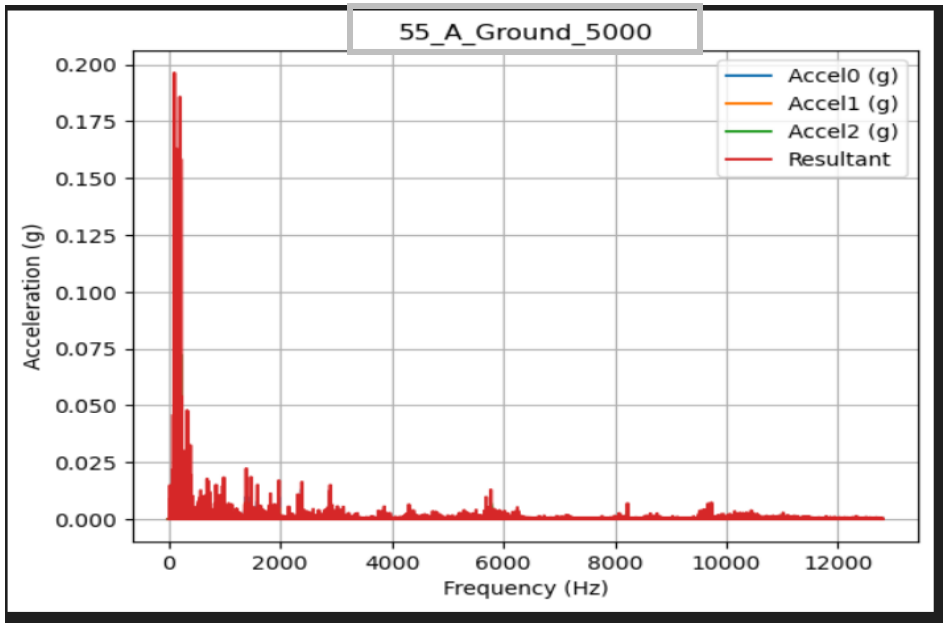
Gear

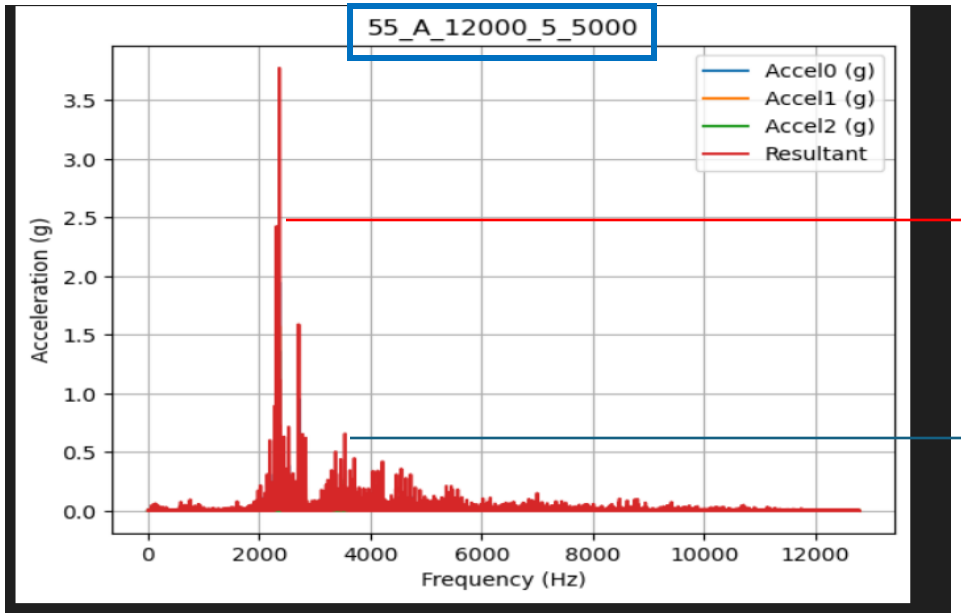
N_P	N_G	N_A	F_Gear_21	F_Gear_22	F_Gear_23
28	28	1	466.6666667	466.6666667	0.5952381
28	28	1	933.3333333	933.3333333	1.19047619
28	28	1	1400	1400	1.78571429
28	28	1	1866.666667	1866.666667	2.38095238
28	28	1	2333.333333	2333.333333	2.97619048
28	28	1	2800	2800	3.57142857

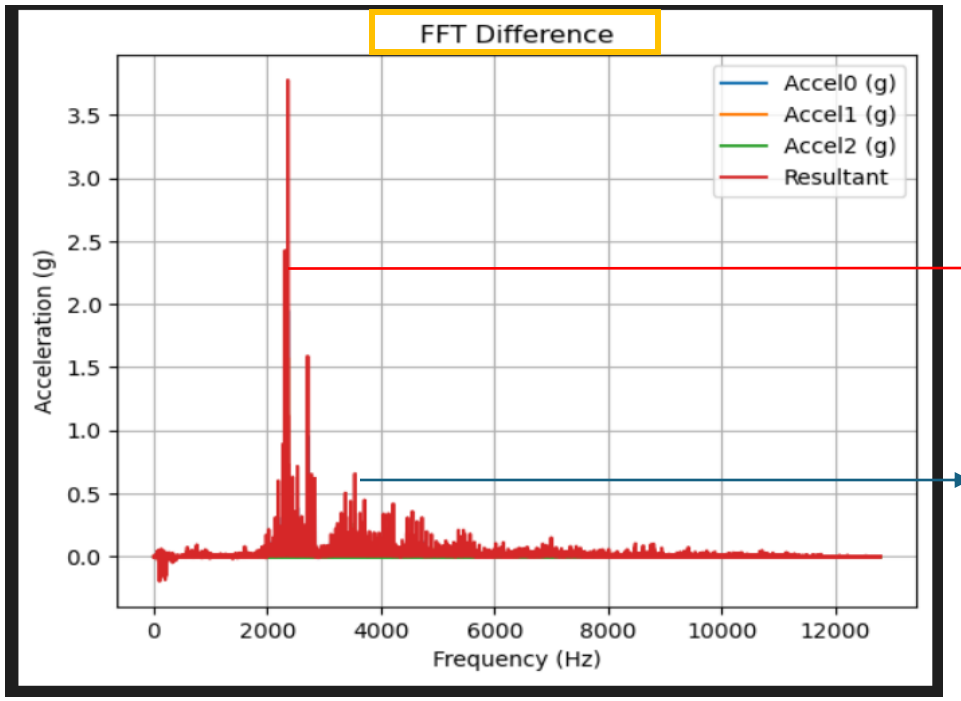
Key	Nomenclature	General Nomenclature	Acronym
	N_P	Pinion Teeth Number	PTN
	N_G	Gear Teeth Number	GTN
	N_A	Number of Assemblies	NA
	F_Gear_21	Gear Mesh Frequency	GMF
	F_Gear_22	Gear Assembly Phase Frequency	GAPF
	F_Gear_23	Hunting Tooth Frequency	HTF

@55_A Toolholder

Implementation of Methodology on Python_Good Assembled Toolholder



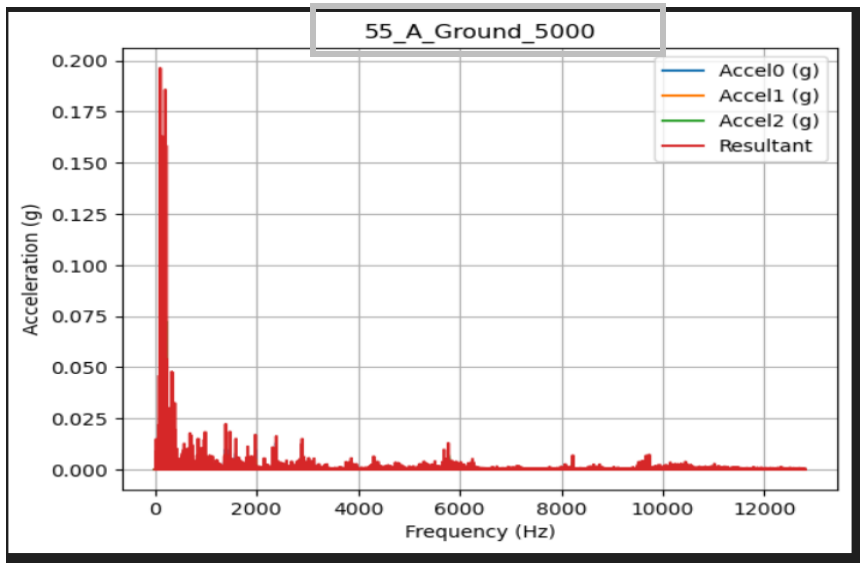


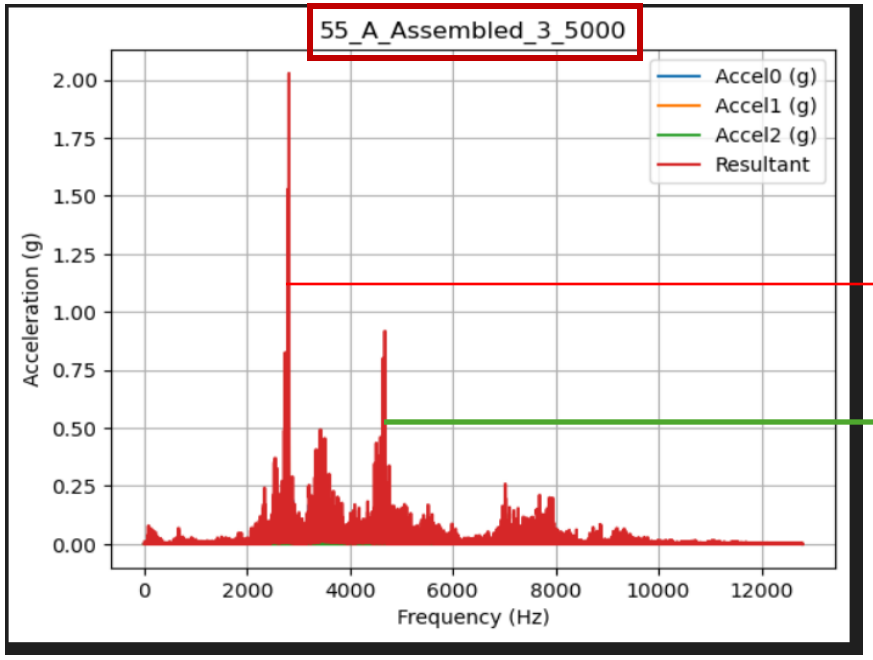


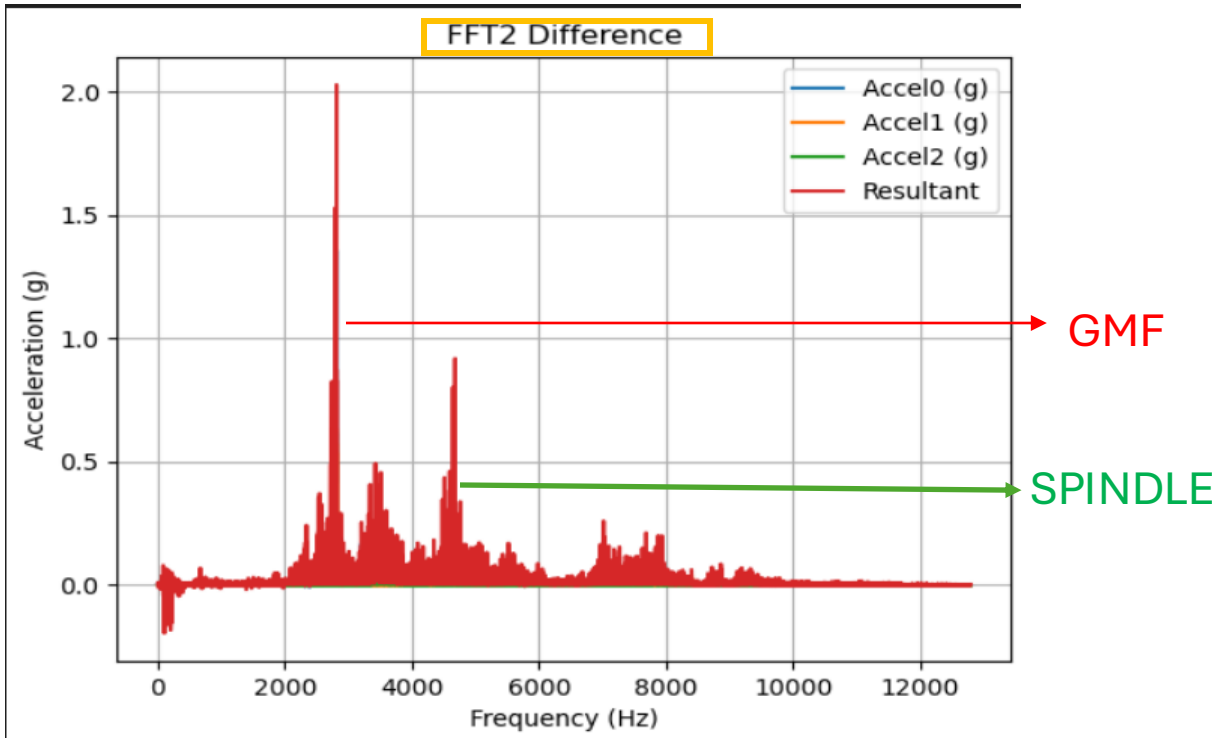
Observation: Neglible Amplitude of Ground, Actual pre-calculated GMF observed

@55_A Tool holder 5

Implementation of Methodology on Python_ Not so Good Assembled Toolholder (GMF Shift)



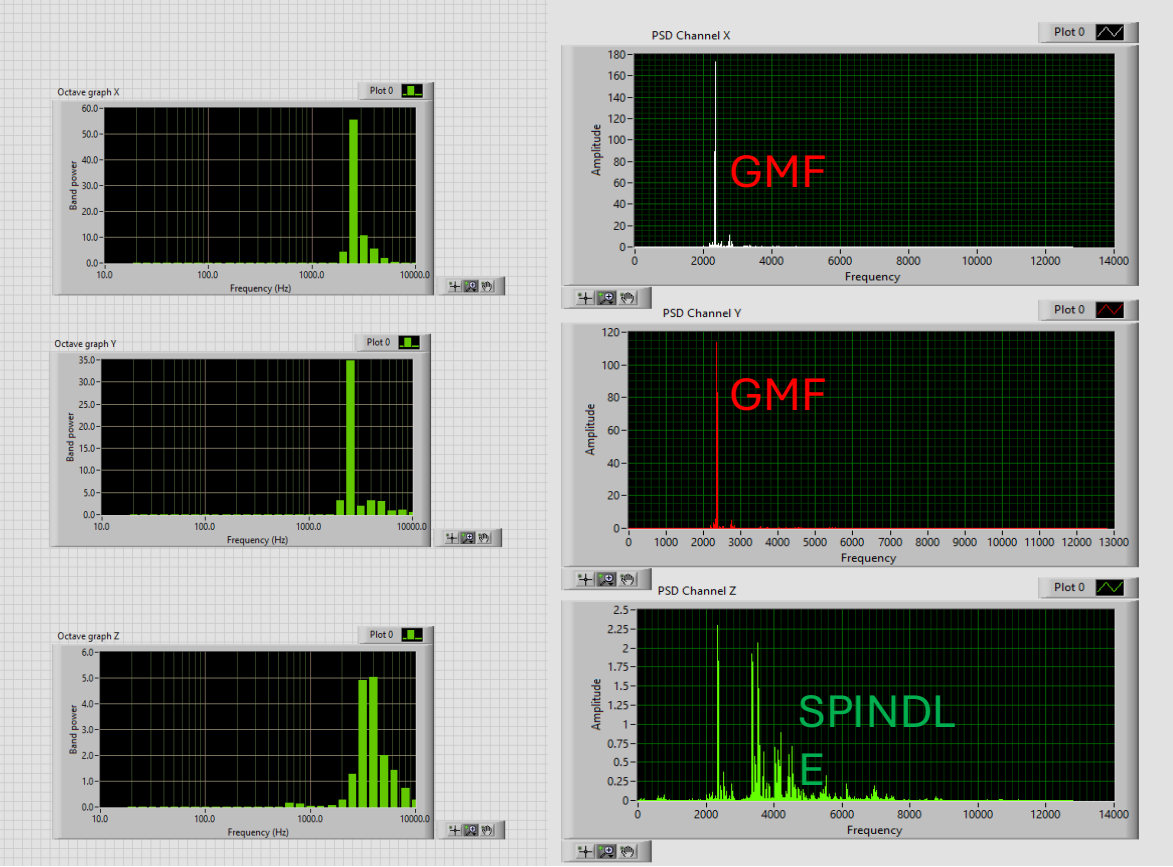




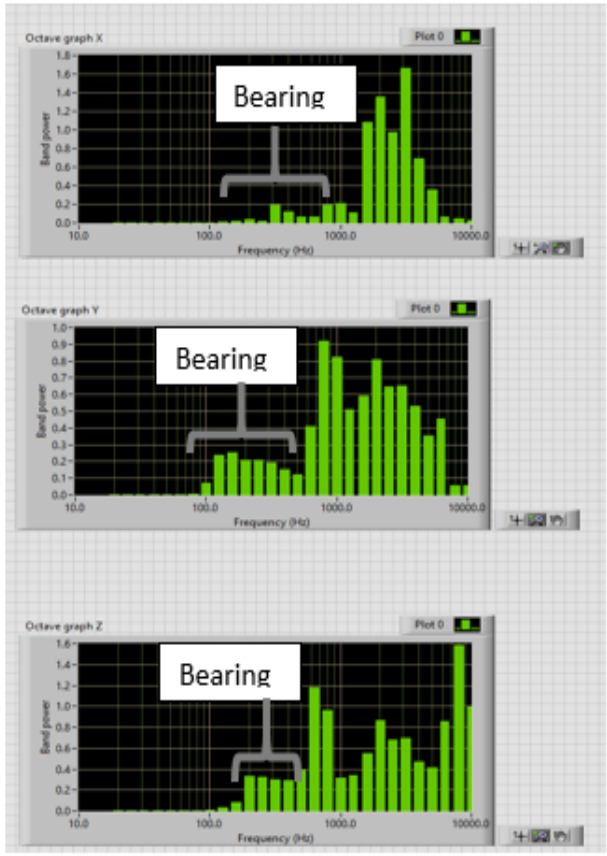
Observation: Neglible Amplitude of Ground but shift in GMF, showing anomaly in operation.

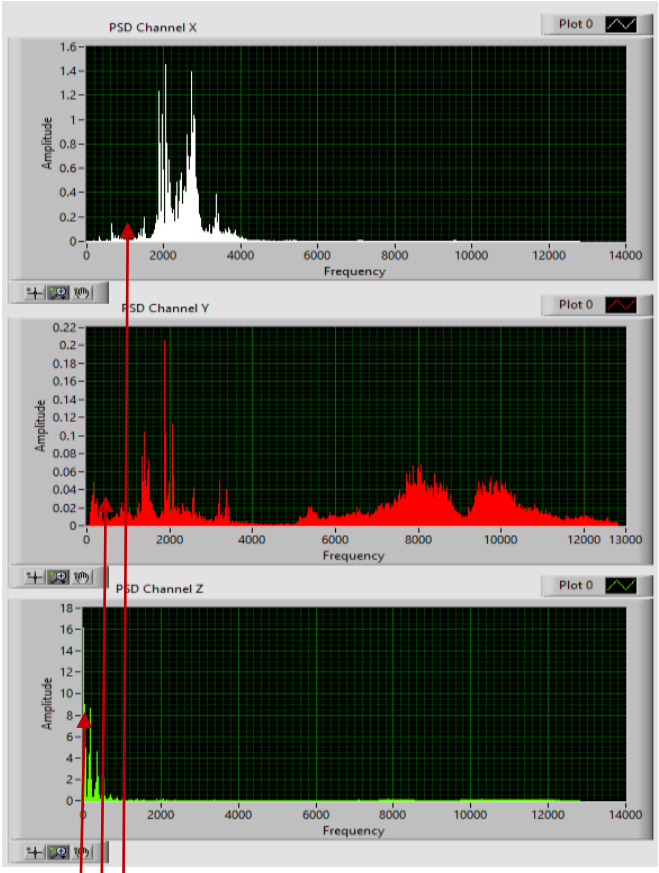
@55_A Tool holder 3

Good Tool holder VS Bad Tool holder(FFt, PSD,Octave)



Good Tool holder



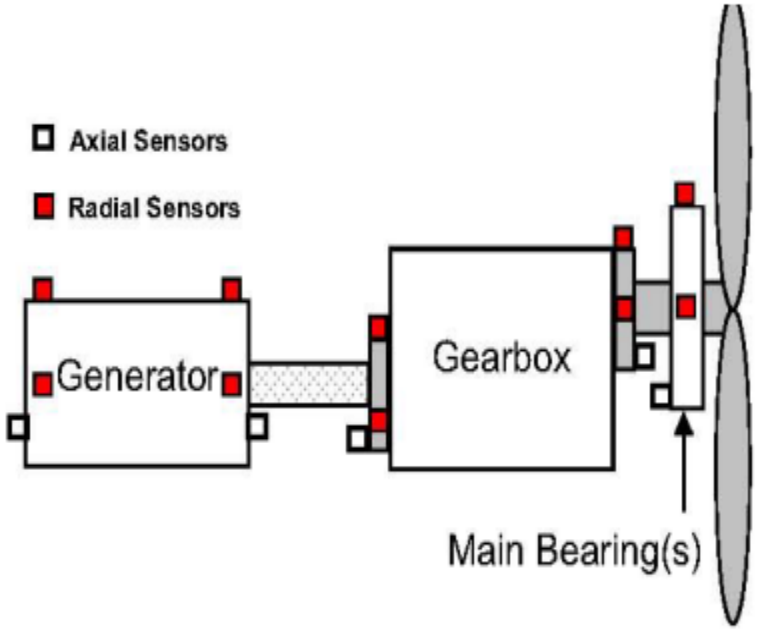


Bad Tool holder

Bearing

Overview of Structural Health Monitoring of Wind Turbine System

- **Sensor Placement**: Accelerometers on blades, gearbox, generator, and tower.
- **Sampling Rate**: ≥2× the highest frequency of interest (e.g., 10 kHz for bearings).
- **Baseline Data**: Compare against healthy turbine signatures.
- **Standards**: Follow IEC 61400-25/26 for wind turbine monitoring.



- Harmonics and sidebands provide diagnostic insights into gear health.
- There are methods like Dirlik or Von misses Stress for Fatigue life Prediction.
- Fatigue Considerations: In vibration scenarios, the stress amplitude and the mean stress are critical. Von Mises stress, which combines both **normal and shear stresses**, can be useful in evaluating these components. Fatigue life prediction involves understanding how the material accumulates damage over time with these cyclic stresses. Von Mises stress can be used to calculate the equivalent stress in multiaxial loading conditions, which helps in assessing potential fatigue damage, but it's not the only stress consideration in vibration fatigue analysis.

Fault Detection Methods in SHM

- **Fault detection in SHM involves identifying deviations from baseline performance using various techniques. In order word there are nominal working conditions which subsequent measurements should be checked against.**

- Common Detection Methods include:

- Vibration Analysis (FFT, PSD, Wavelet)

- Acoustic Emission Detection

- Strain Gauge Monitoring

- Advanced Techniques:

- Machine Learning for Predictive Maintenance

- AI-based models for real-time diagnostics

- Hybrid Technique

- Tandem of Advanced Techniques and Vibrational based Method (Localization and Engineering based reasons are Identified).

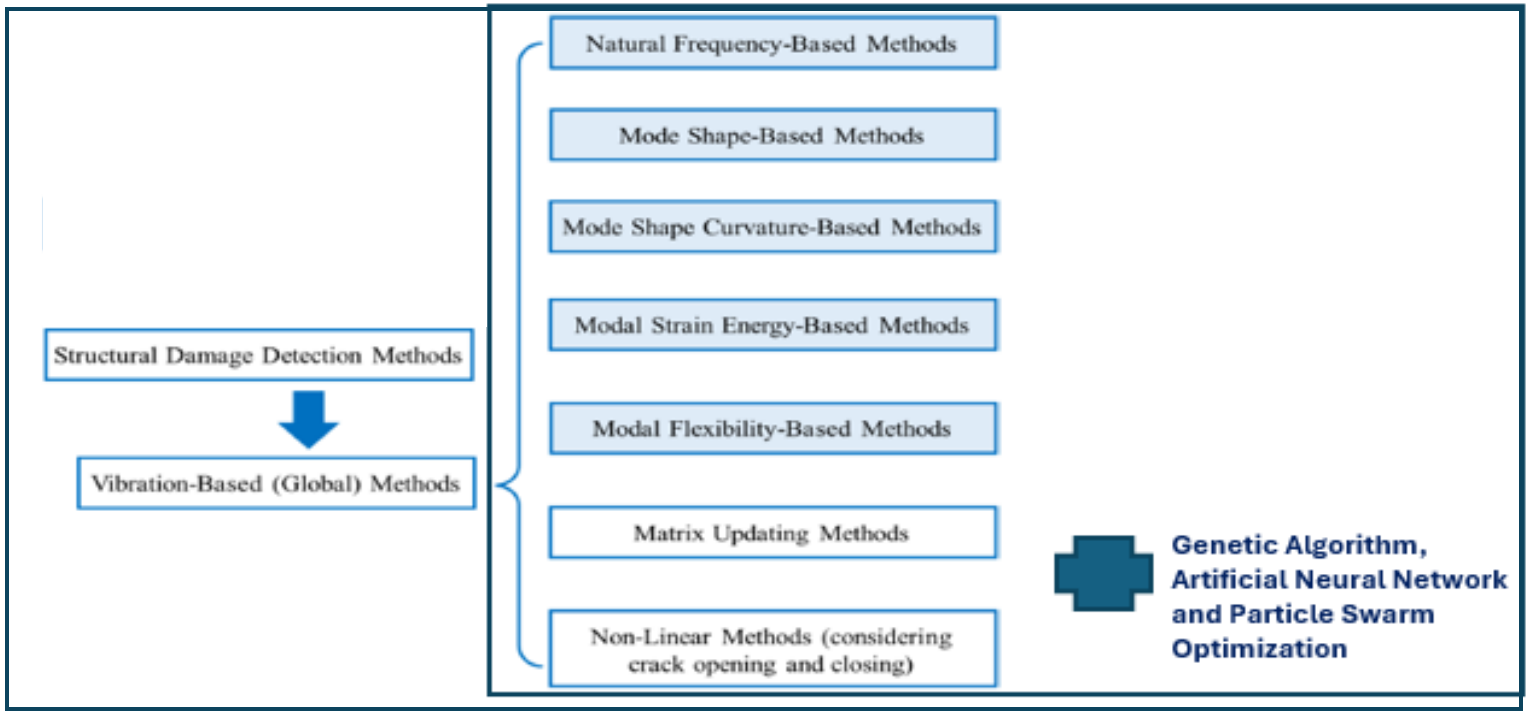
Viable Machine Learning (ML)/ AI Methods

Name of the model	Type of model	Learning type	Application
Neural network	Neural network	Supervised Learning	complex patterns, unstructured data (images, audio, text), and sequential data.
Convolutional Neural Network	Neural network	Supervised Learning	For spectrogram-based detection, Complex Data (Frequency Domain)
Autoencoder	Neural network	Unsupervised Learning	For vibration & sensor data
Random Forest	Decision Tree	Supervised Learning	structured data, interpretable models, and when you want robustness against overfitting.
Isolation Forest	Decision Tree	Unsupervised Learning	For general industrial use
One-Class SVM	Support Vector Machine	Semi-Supervised Learning	For real-time & small datasets

Hybrid Structural Health Monitoring System on Wind Turbines

- Load Sensors, Force Transducers
- Acoustic Sensors, FBG, Image-based Sensors
- Voltage/Current Sensors, Frequency Analyzers
- Hygrometer
- Pressure Transducer
- Microphone, Noise Sensor
- Power Quality Analyzer
- Inclination Sensors, Tilt Sensors
- GPS Receiver

Likely Parameters to Observe



Hybrid System of Vibration and AI/ML

Monitoring Methods and Challenges

Structural Health Monitoring (SHM) Method

Continuous structural integrity monitoring is vital to reliability and sustainability. A multi-sensor network (strain gauges, accelerometers, temperature/acoustic sensors, etc.) enables real-time detection of mechanical, thermal, and electrical anomalies. Data from these sensors feeds into AI-driven diagnostic frameworks, structured across four tiers:

- **Detection:** Pattern recognition to identify deviations from baseline performance.
- **Localization:** Guided-wave systems or Fibre Bragg Grating sensors to pinpoint damage.
- **Classification/Severity:** Hybrid AI models (e.g., physics-informed ML) to categorize faults (cracks, delamination) and assess impact.
- **Prognostics:** Remaining Useful Life (RUL) prediction via fusion of sensor data and simulation.

Remarks

- Structural Health Monitoring (SHM) is revolutionizing how we ensure the safety and longevity of critical infrastructure. By harnessing cutting-edge sensor technologies and real-time data analytics, SHM enables us to keep a constant pulse on the health of structures, from bridges and buildings to aerospace components. Whether monitoring structures in their everyday operational environments or subjecting them to stress through controlled tests, SHM empowers engineers to spot potential issues before they escalate into costly or catastrophic failures. This proactive approach not only extends the lifespan of vital assets but also enhances safety, reduces maintenance costs, and fosters more informed decision-making. As we move toward more connected, data-driven systems, SHM will continue to be at the heart of smarter, safer infrastructure management.

This field is incredibly dynamic and full of potential, and I'm excited about **the opportunity to connect, share insights, and continuously learn and grow together** as we explore new developments and innovations in this space!