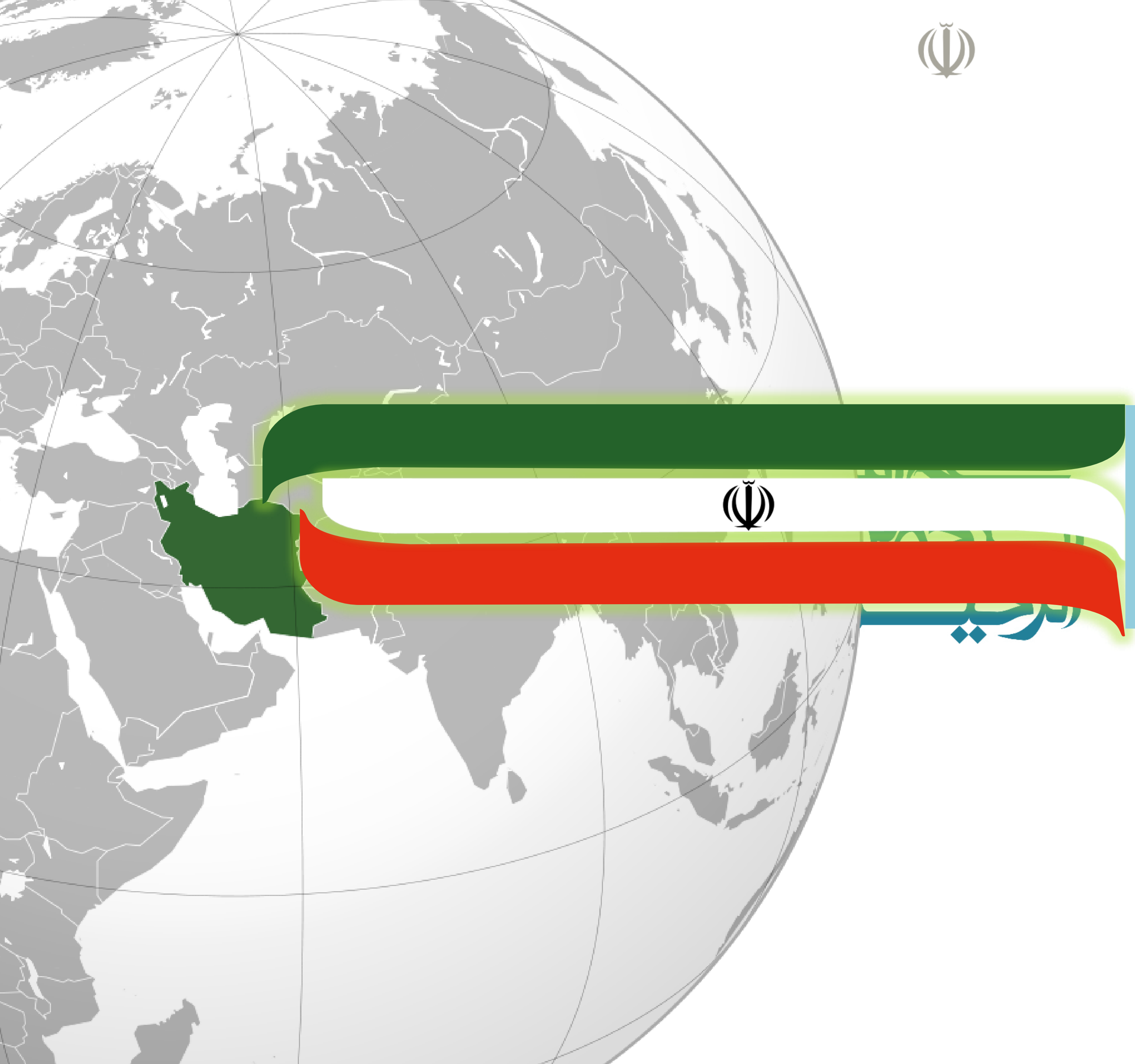

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ستاد ملی هفته پژوهش و فناوری

شماره: ۱۷۲۶۰/ ۶۵۸۵/ ۱۴۰۰

تاریخ: ۱۴۰۰/۰۹/۲۷

گواهی می شود:

در بیست و دومین نمایشگاه دستاوردهای پژوهش، فناوری و فن بازار - آذر ۱۴۰۰

فـــناوری: سامانه نگهداری و تعمیرات هوشمند

متعلق به: بهپویان امین منتظر

با همکاری: محمدعلی تیشه وری

در سامانه ارزیابی فناوری ایران (سافا)، حائز سطح آمادگی فناوری (TRL) ۷ گردید.

(عدد ۹ بیانگر بالاترین و عدد ۱ پایین ترین سطح فناوری می باشد که از طریق فرآیند داوری و بر اساس مستندات ارایه شده در قالب خوداظهاری تعیین شده است.)

دکتر علی باستی

رئیس پارک علم و فناوری گیلان و
دبیر اجرایی بیست و دومین نمایشگاه
دستاوردهای پژوهش، فناوری و فن بازار

✓ شرکت دانش بنیان در حوزه طراحی نرم افزارهای هوشمند

(معاونت علمی و فناوری ریاست جمهوری)

✓ شرکت دانش بنیان برتر

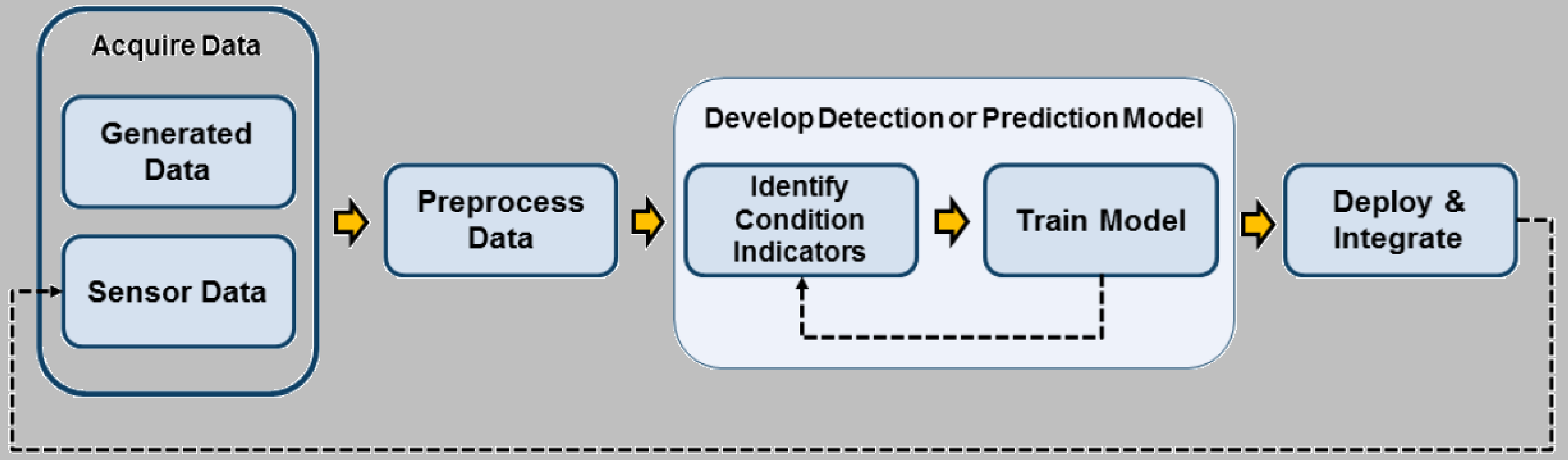
- استان خراسان رضوی (۹۶ و ۹۸ و ۱۴۰۰)
- وزارت نیرو (۹۹)(حوزه آبفا)

✓ ۳ گرید خدمات مشاوره/ آب و فاضلاب، اتوماسیون صنعتی و بهینه سازی

✓ پروژه پژوهشی منتخب وزارت نیرو در سال ۱۳۹۷

✓ طرح برگزیده جهت رونمایی در نمایشگاه تستا ۱۴۰۰

Workflow For Predictive Maintenance Algorithm Development



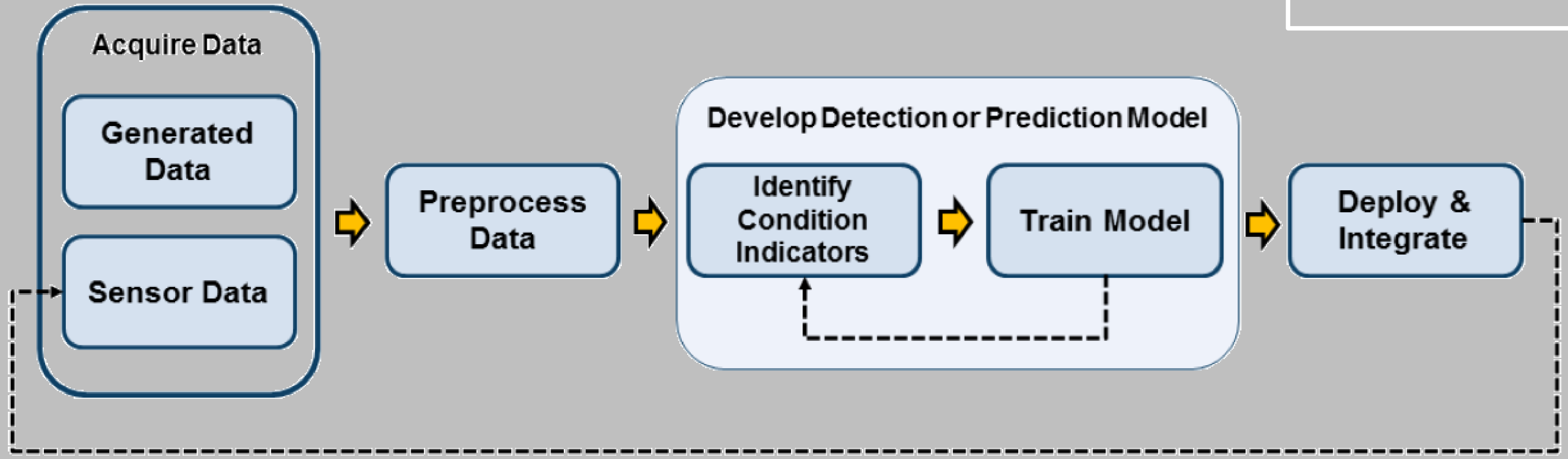
you might have access to measured data from:

- Normal system operation
- The system operating in a faulty condition
- Lifetime record of system operation (run-to-failure data)

Vibration	Tachometer	Age
[time-series data]	[time-series data]	[scalar]

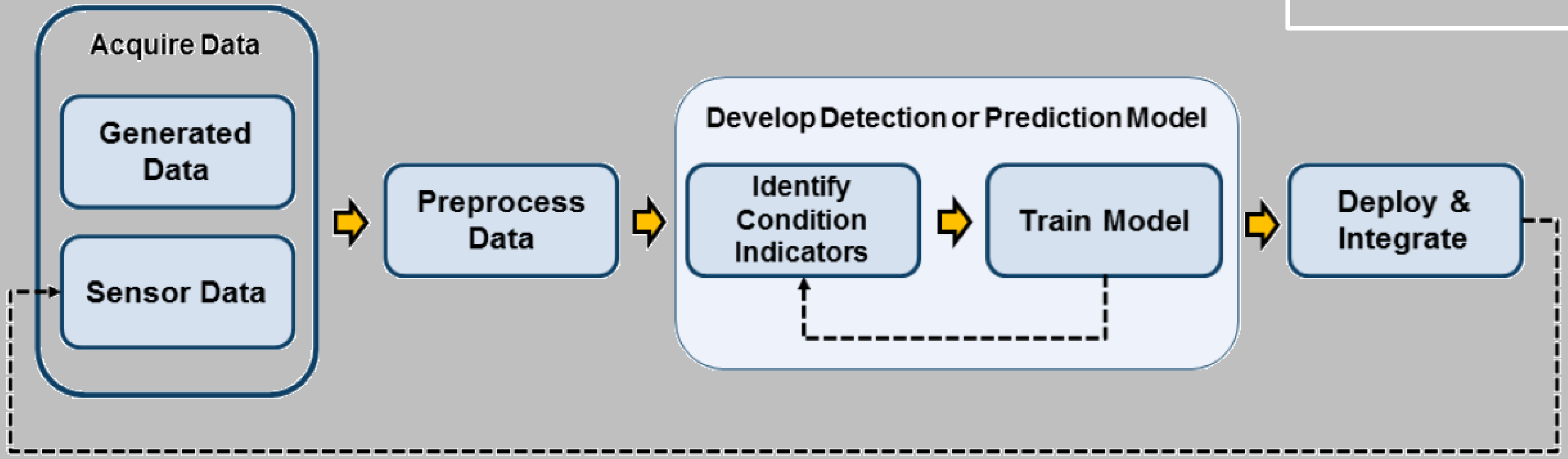
EngineID	Vibration	Tachometer	Age
01	[time-series data]	[time-series data]	9,500
02	[time-series data]	[time-series data]	48,000
...	...	...	...
N	[time-series data]	[time-series data]	16,700

EngineID	Vibration	Tachometer	Age
01	[time-series data]	[time-series data]	9,500
01	[time-series data]	[time-series data]	21,250
01	[time-series data]	[time-series data]	44,800
02	[time-series data]	[time-series data]	14,000
02	[time-series data]	[time-series data]	48,000
...	...	...	...



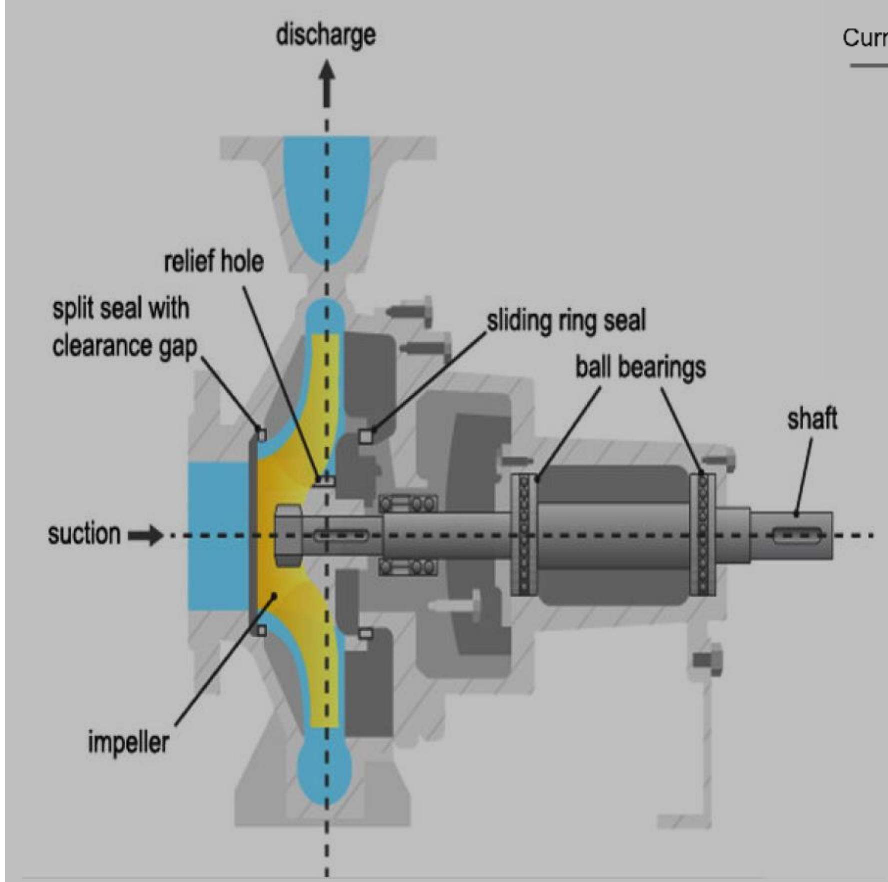
Data preprocessing can include:

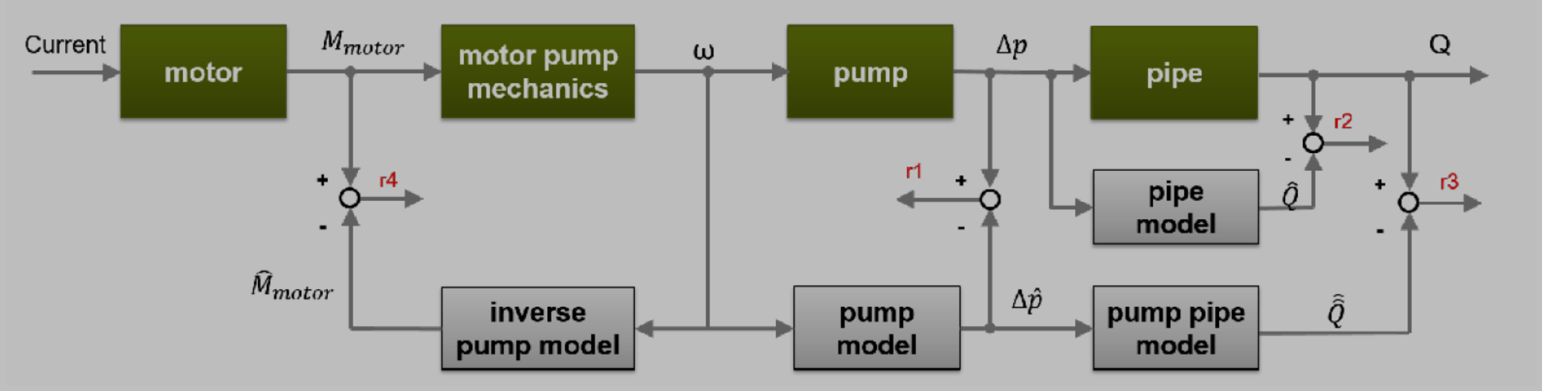
- Outlier and missing-value removal, offset removal, and detrending.
- Noise reduction, such as filtering or smoothing.
- Transformations between time and frequency domain.
- More advanced signal processing such as short-time Fourier transforms and transformations to the order domain



Examples of signal-based condition indicators include:

- The mean value of a signal that changes as system performance changes
- A quantity that measures chaotic behavior in a signal, the presence of which might be indicative of a fault condition
- The peak magnitude in a signal spectrum, or the frequency at which the peak magnitude occurs, if changes in such frequency-domain behavior are indicative of changing machine conditions

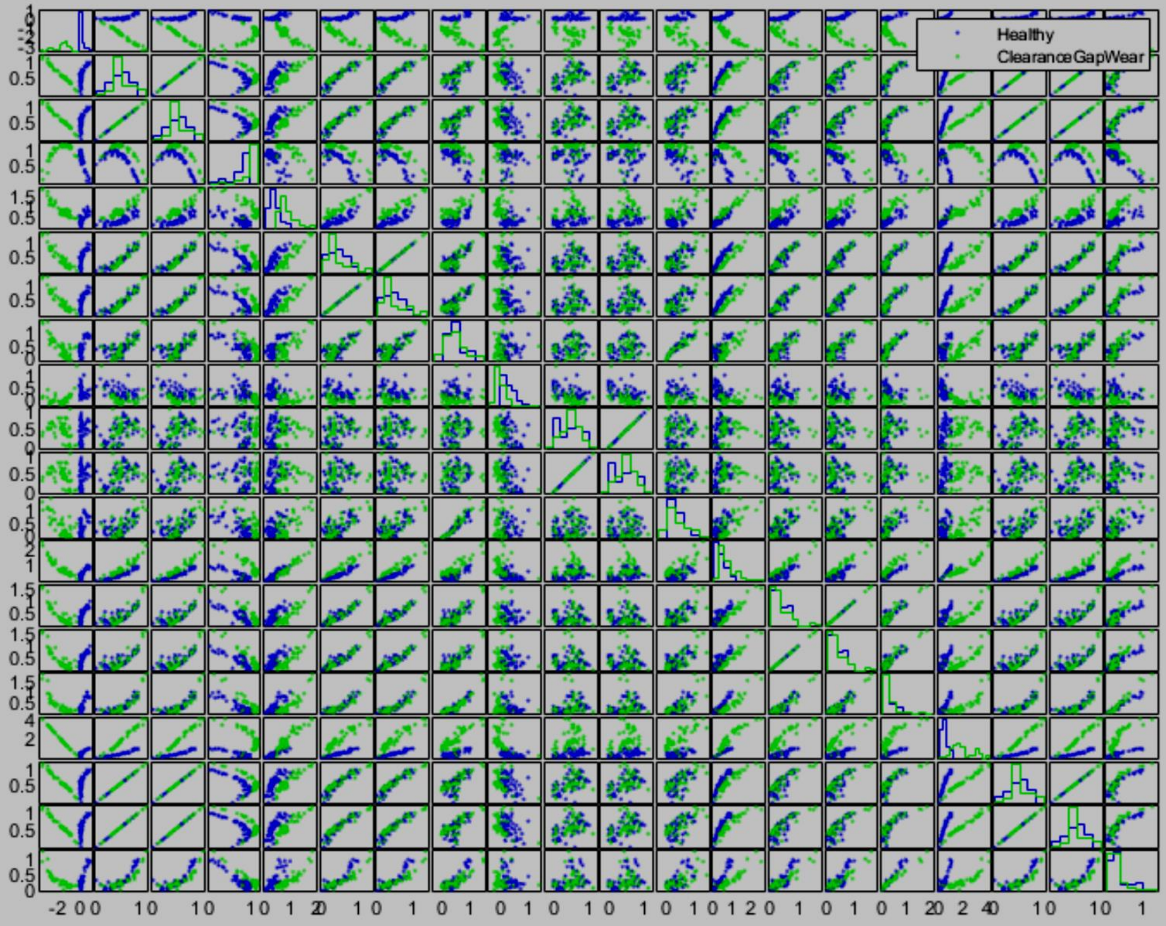


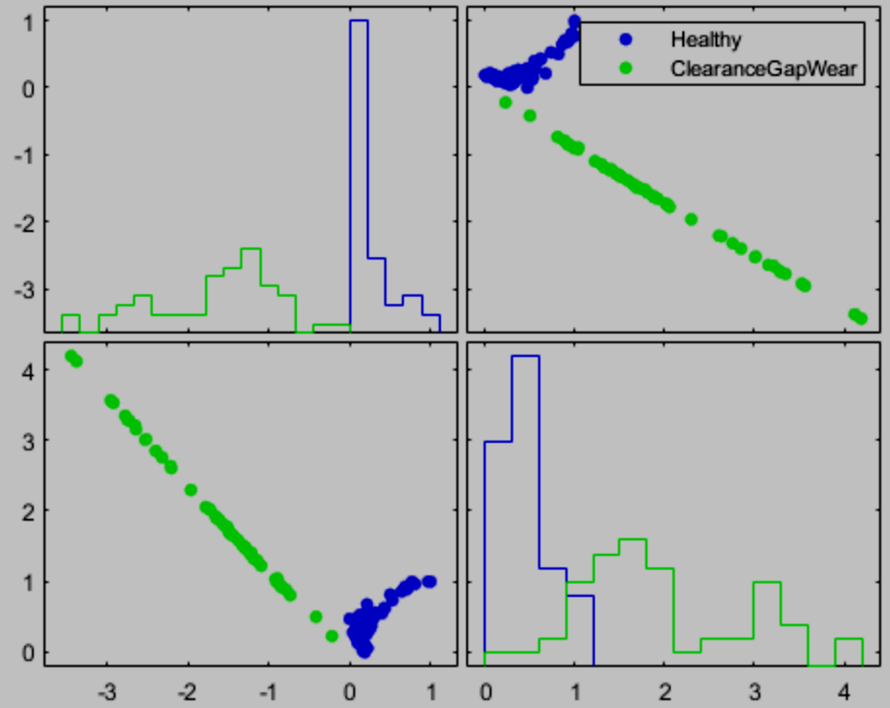


r1 = dp - dpest
r2 = Q - Qest_pipe
r3 = Q - Qest_pump_pipe

1 Healthy pump
2 Fault 1: Wear at clearance gap
3 Fault 2: Small deposits at impeller outlet
4 Fault 3: Deposits at impeller inlet
5 Fault 4: Abrasive wear at impeller outlet
6 Fault 5: Broken blade
7 Fault 6: Cavitation
8 Fault 7: Speed sensor bias
9 Fault 8: Flowmeter bias
10 Fault 9: Pressure sensor bias

همایش مدیریت دارایی فیزیکی





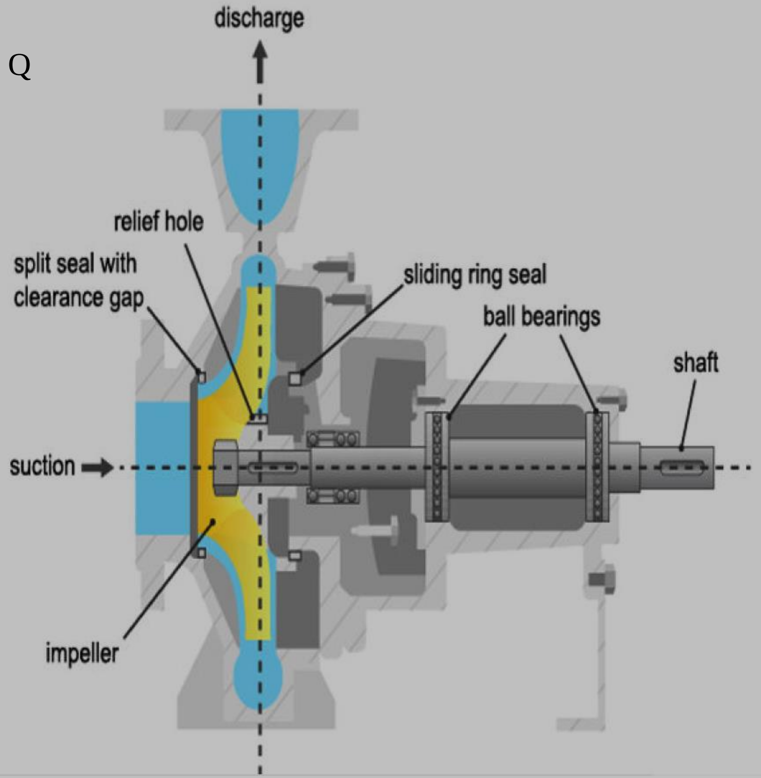
Mean and Norm1

Signal-Based Condition Indicators:
Time-Domain Condition Indicators
Frequency-Domain Condition Indicators

Model-Based Condition Indicators:
Static Models
Dynamic Models
State Estimators

The following signals are typically measured:

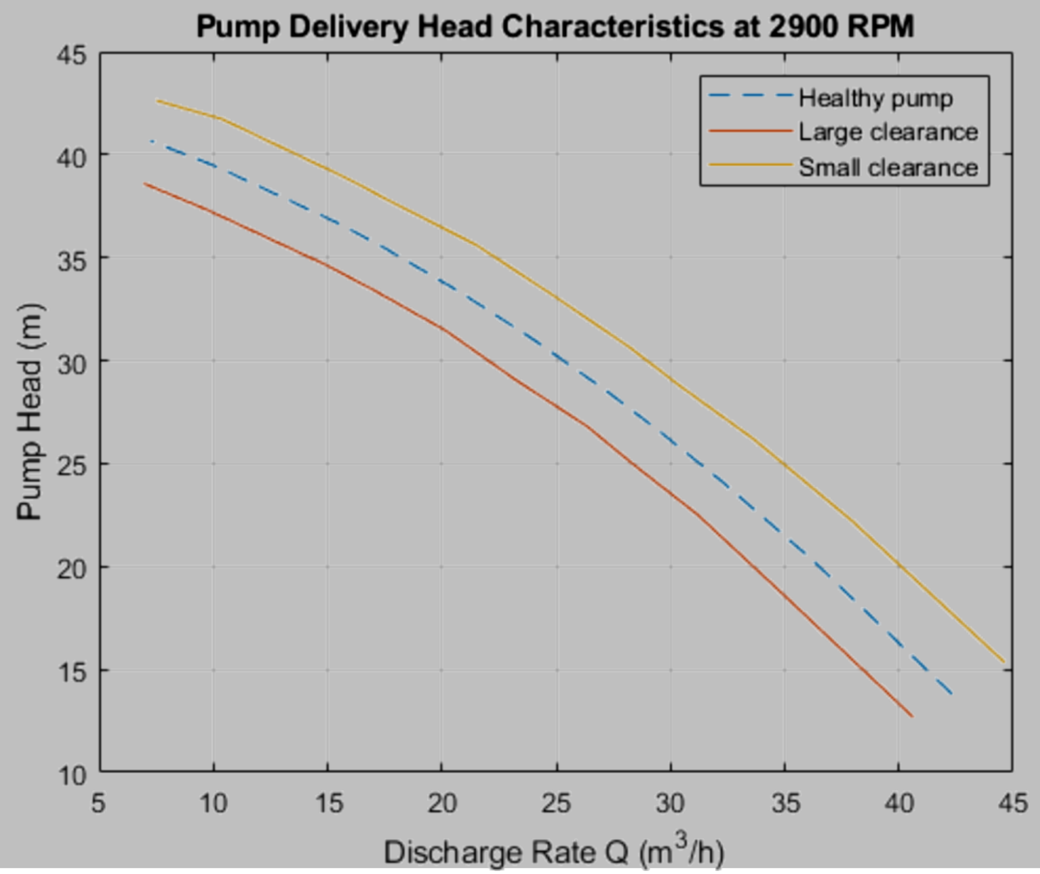
- Pressure difference between the inlet and outlet Δp
- Rotational speed ω
- Motor torque Mmot and pump torque Mp
- Fluid discharge (flow) rate at the pump outlet Q
- Driving motor current, voltage, temperature
- Fluid temperature, sediments



- **Cavitation:** Development of vapor bubbles inside the fluid if static pressure falls below vapor pressure. Bubbles collapse abruptly leading to damage at the blade wheels
- **Gas in fluid:** A pressure drop leads to dissolved gas in the fluid. A separation of gas and liquid and lower head results.
- **Dry Run:** Missing fluid leads to lack of cooling and overheating of bearing. Important for starting phase.
- **Erosion:** Mechanical damage to the walls because of hard particles or cavitation
- **Corrosion:** Damage by aggressive fluids
- **Bearing wear:** Mechanical damage through fatigue and metal friction, generation of pitting and tears
- **Plugging of relief bore holes:** Leads to overloading/damage of axial bearings
- **Plugging of sliding ring seals:** Leads to higher friction and smaller efficiency
- **Increase of split seals:** Leads to loss of efficiency
- **Deposits:** Deposits of organic material or through chemical reactions at the rotor entrance or outlet reduce efficiency and increase temperature.
- **Oscillations:** Rotor imbalance through damage or deposits at the rotor. Can cause bearing damage.

Fault Detection Techniques

1. Parameter estimation
2. Residue generation

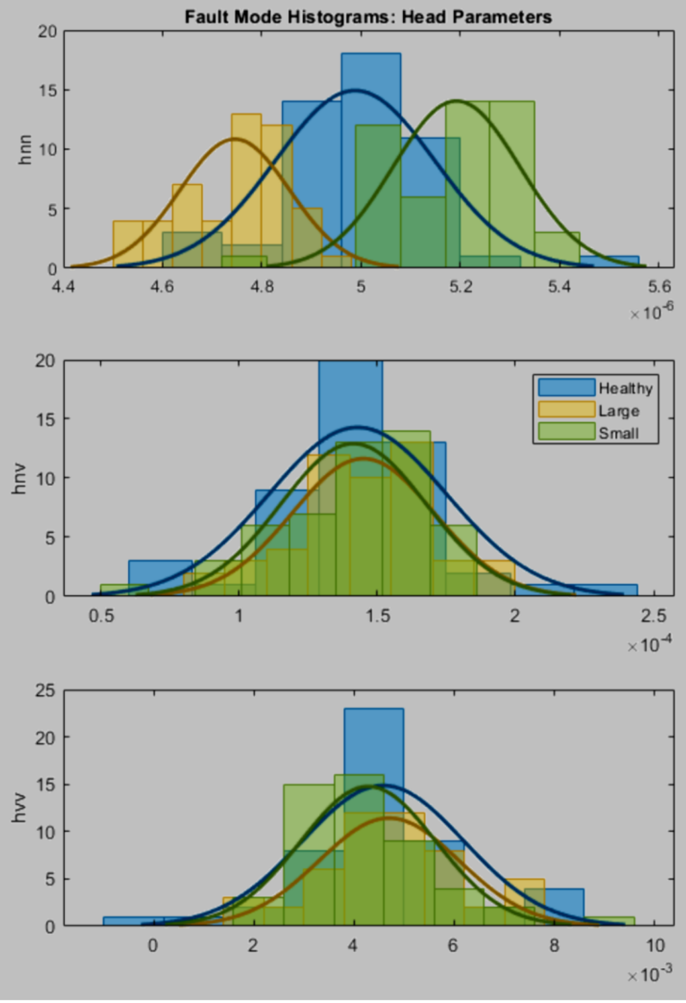


$$H \approx h_{nn}\omega^2 - h_{nv}\omega Q - h_{vv}Q^2$$

$$M_p \approx k_0\omega Q - k_1 Q^2 + k_2\omega^2$$

	hnn	hnv	hvv
Healthy	5.1164e-06	8.6148e-05	0.010421
Large Clearance	4.849e-06	8.362e-05	0.011082
Small Clearance	5.3677e-06	8.4764e-05	0.0094656

	k0	k1	k2
Healthy	0.00033347	0.016535	2.8212e-07
Large Clearance	0.00031571	0.016471	3.0285e-07
Small Clearance	0.00034604	0.015886	2.6669e-07

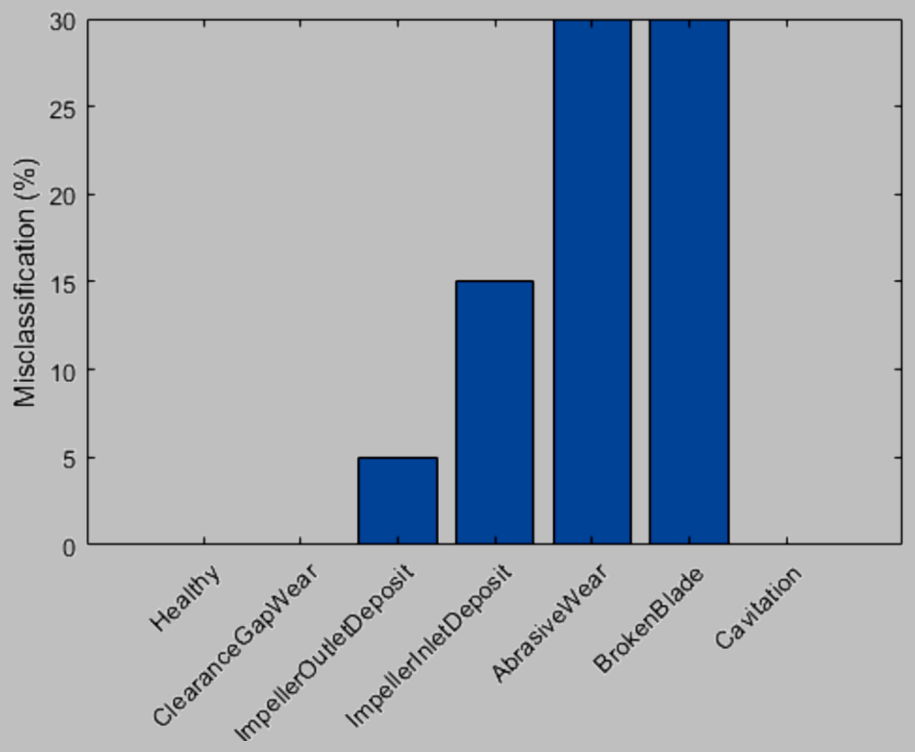


Multi-Class Classification of Fault Modes Using Tree Bagging

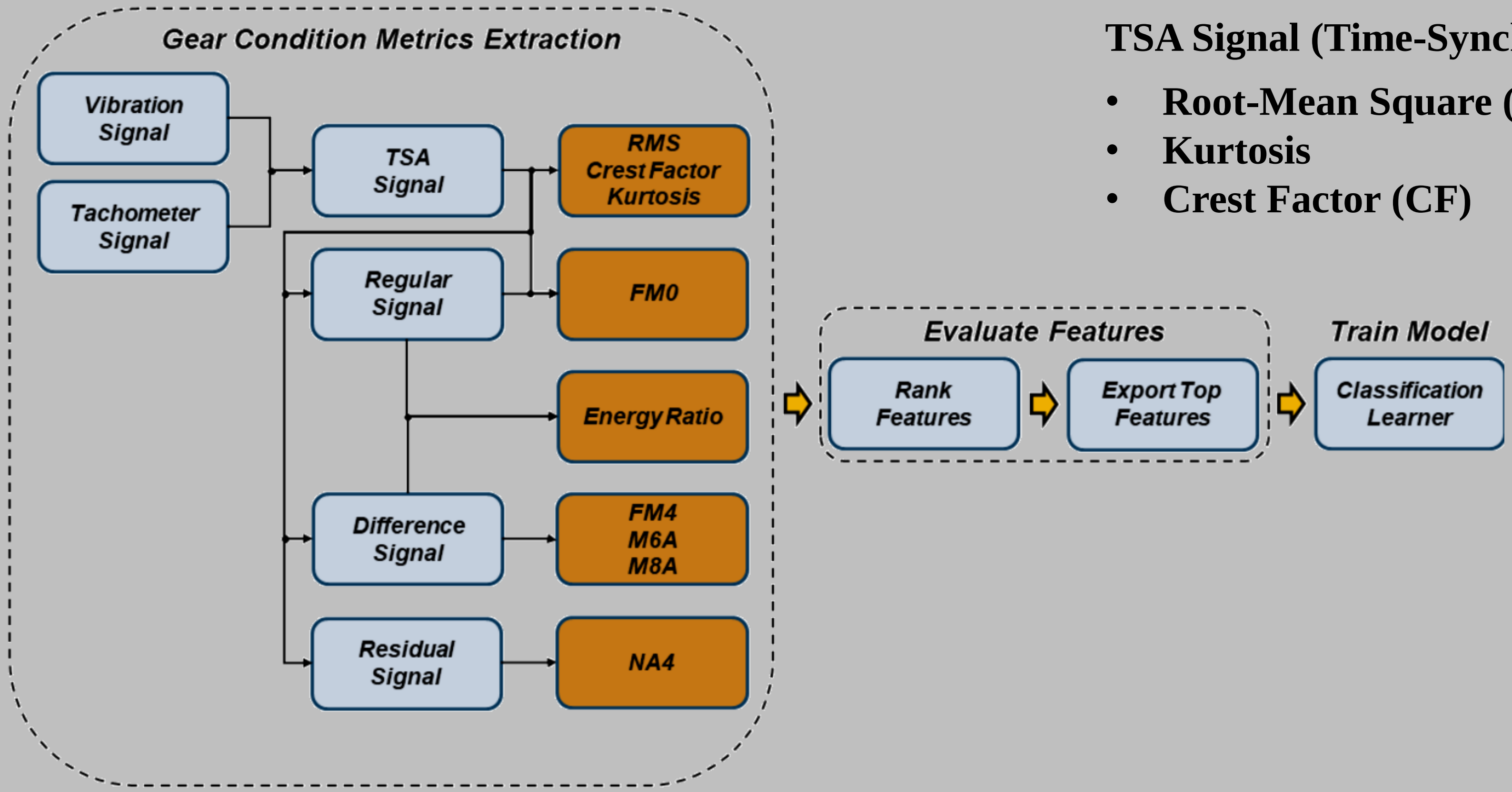
1. Healthy operation
2. Wear at clearance gap
3. Small deposits at impeller outlet
4. Deposits at impeller inlet
5. Abrasive wear at impeller outlet
6. Broken blade
7. Cavitation

A summary of the fault diagnosis workflow follows:

1. Run the test pump at its nominal speed. Turn the discharge valve to various settings to control the flow rate. For each valve position, note down the pump speed, flow rate, pressure differentials and torque
2. Estimate parameters for the pump head and pump torque characteristic (steady state) equations.
3. If the uncertainty/noise is low and the parameter estimates are reliable, the estimated parameters can be directly compared to their nominal values. Their relative magnitudes would indicate the nature of the fault.
4. In a general noisy situation, use the anomaly detection techniques to first check if there is a fault present in the system at all. This can be done very quickly by comparing the estimated parameter values against the mean and covariance values obtained from a historical database of healthy pumps.
5. If a fault is indicated, use the fault classification techniques (such as likelihood ratio tests or output of a classifier) to isolate the most probable cause(s). The choice of classification technique would depend upon sensor data available, their reliability, the severity of the fault and availability of historical information regarding the fault modes.

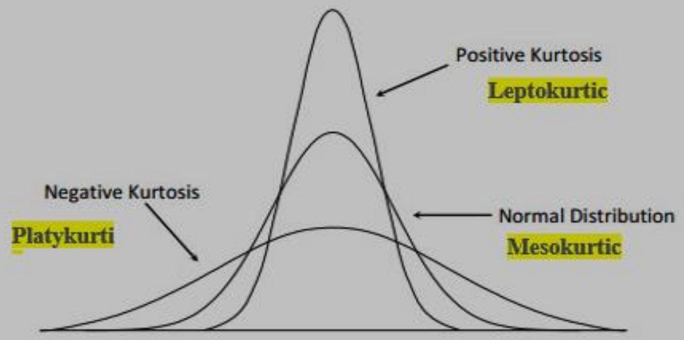


Condition Indicators for Gear Condition Monitoring

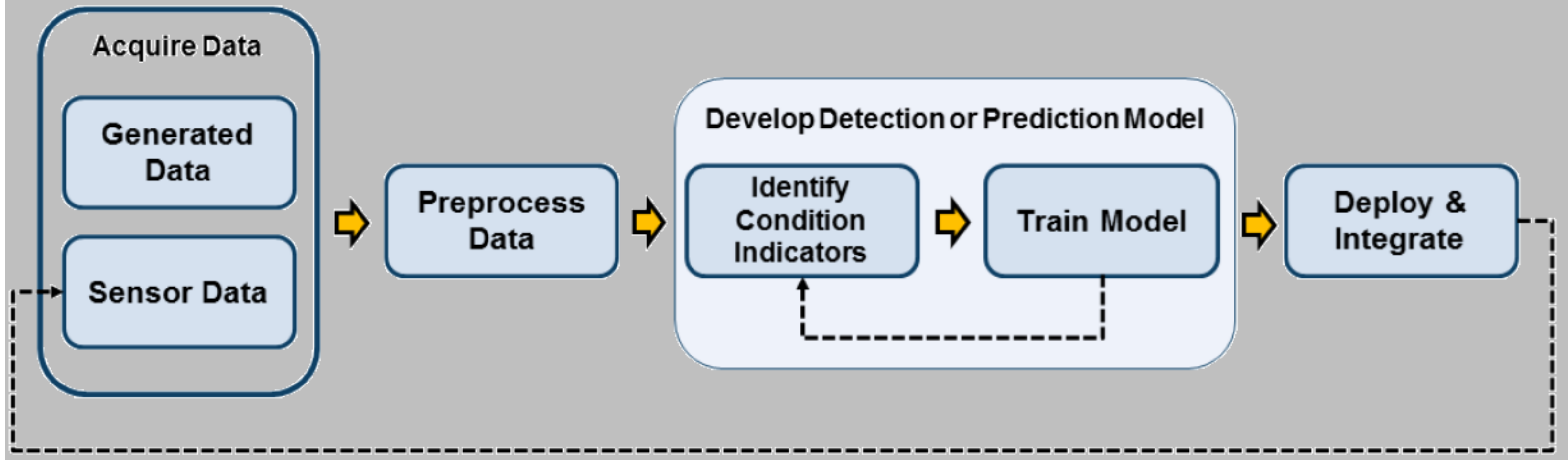


TSA Signal (Time-Synchronous Averaged)

- Root-Mean Square (RMS)
- Kurtosis
- Crest Factor (CF)



Decision Models for Fault Detection and Diagnosis

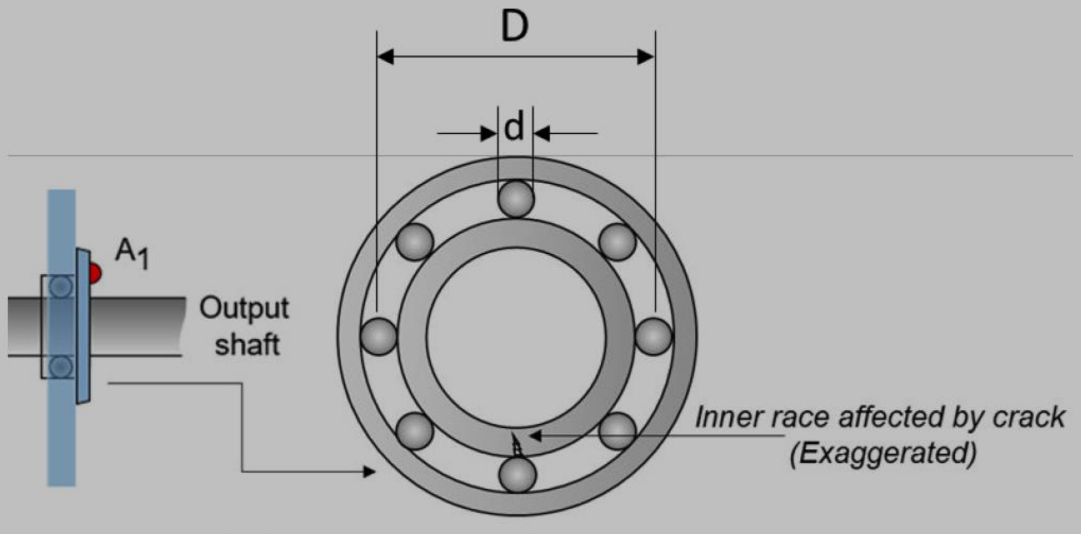


Some examples of decision models for condition monitoring include:

- A threshold value or set of bounds on a condition-indicator value that indicates a fault when the indicator exceeds it
- A probability distribution that describes the likelihood that any particular value of the condition indicator is indicative of any particular type of fault
- A classifier that compares the current value of the condition indicator to values associated with fault states, and returns the likelihood that one or another fault state is present

- **Feature Selection: PCA**
- **Statistical Distribution Fitting**
- **Machine Learning**
- **Regression with Dynamic Models**
- **Control Charts**
- **Changepoint Detection**

Rolling Element Bearing Fault Diagnosis

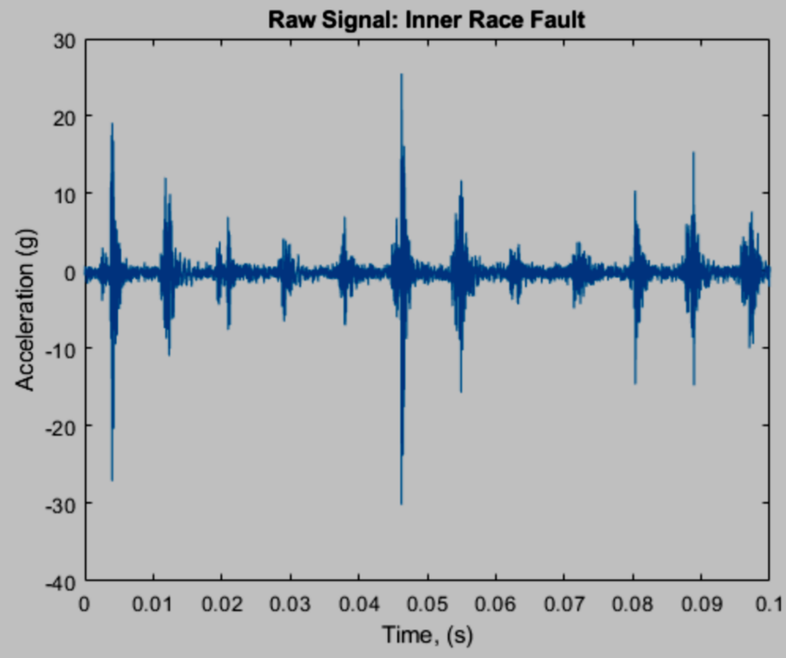


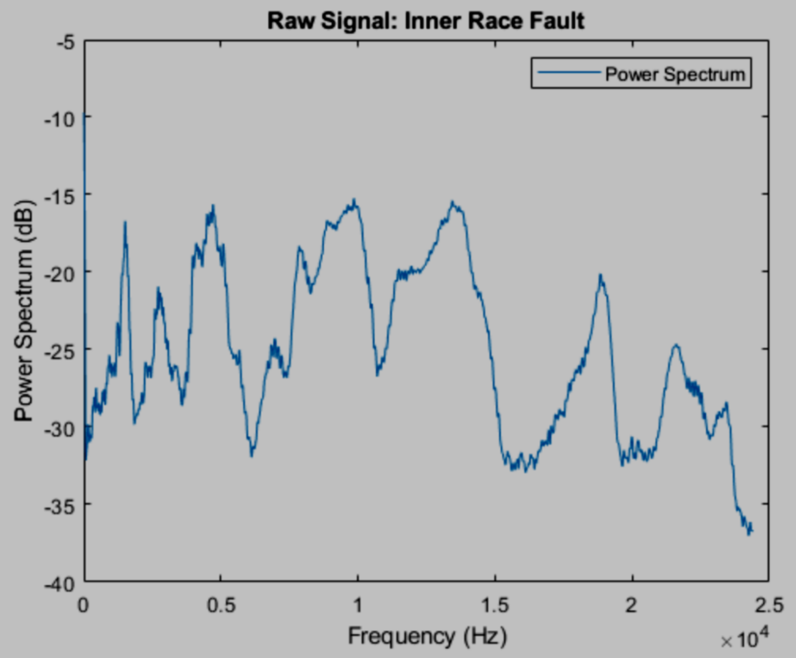
Ball bearing cross−section (Magnified)

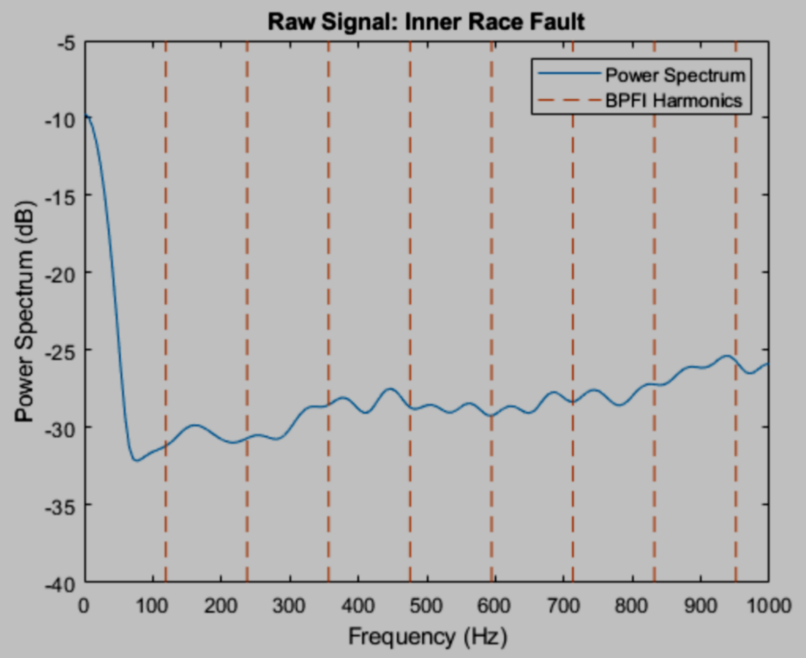
Localized faults in a rolling element bearing may occur in the outer race, the inner race, the cage, or a rolling element.

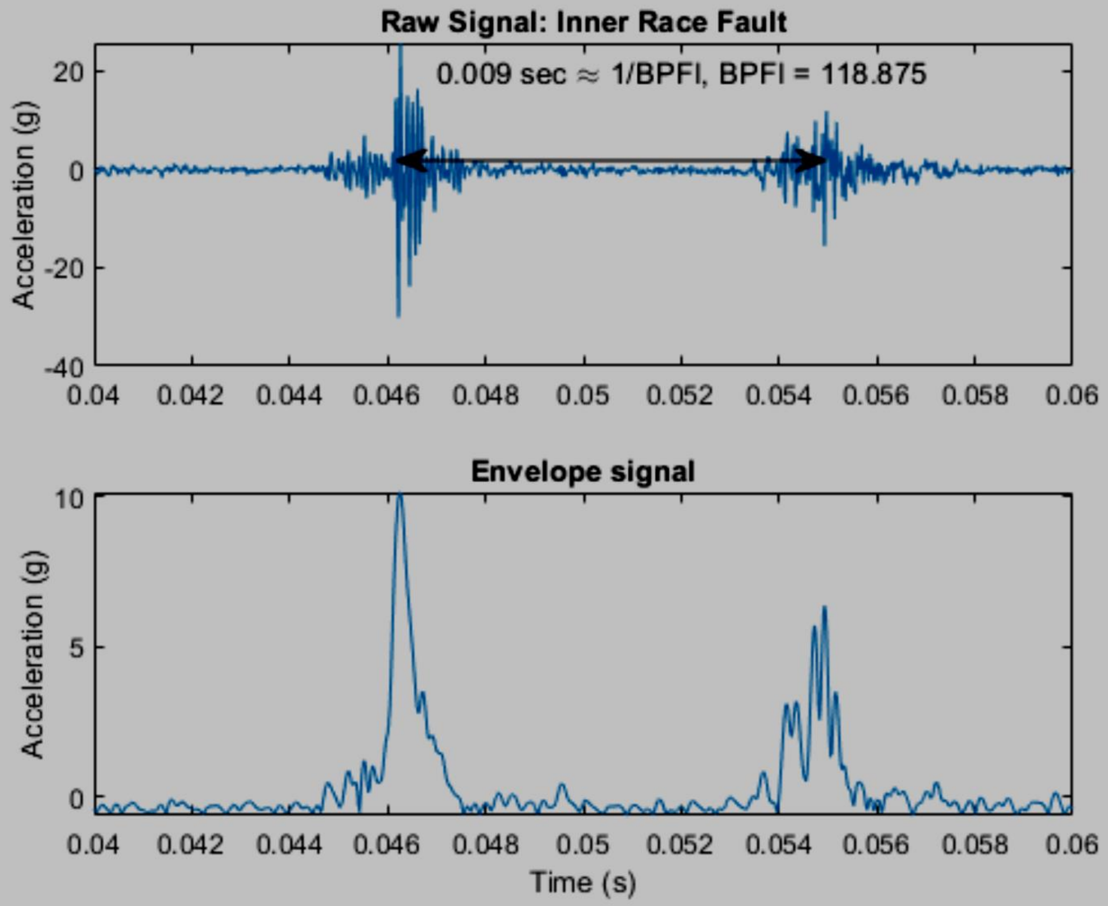
High frequency resonances between the bearing and the response transducer are excited when the rolling elements strike a local fault on the outer or inner race, or a fault on a rolling element strikes the outer or inner race.

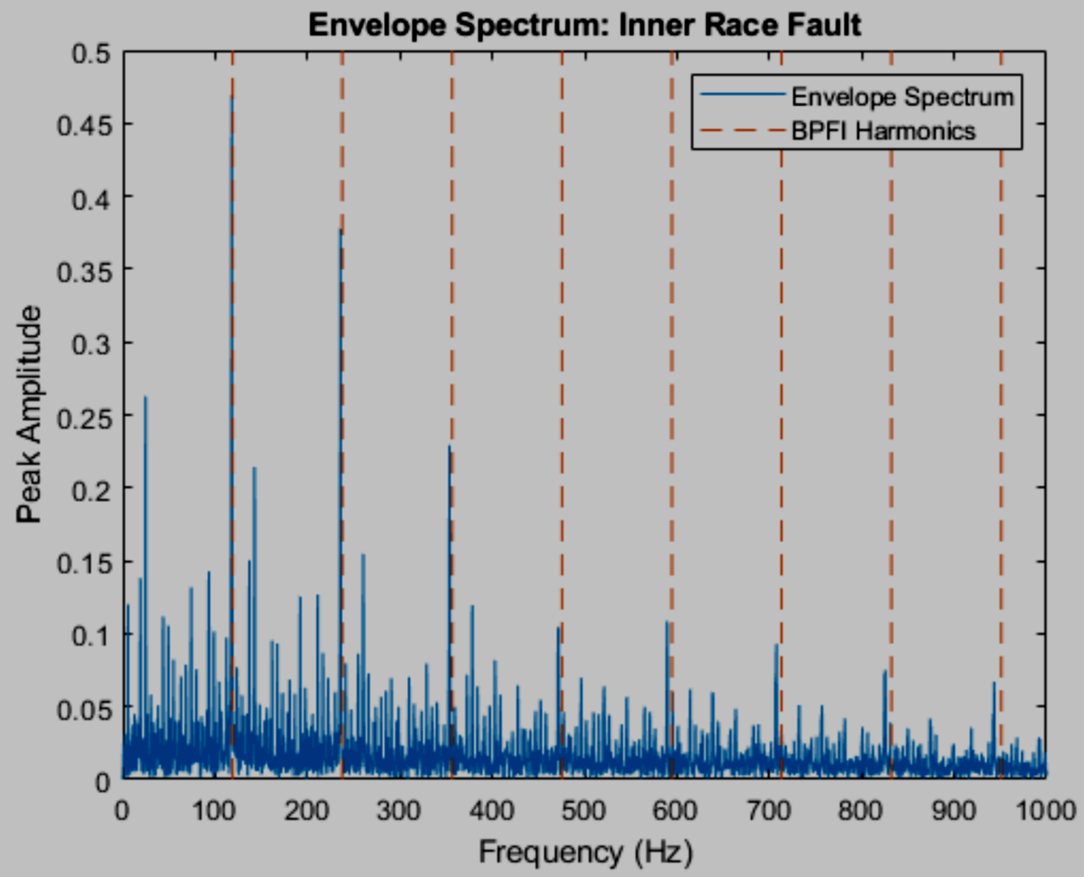
Each data set contains an acceleration signal "gs", sampling rate "sr", shaft speed "rate", load weight "load", and four critical frequencies representing different fault locations: ballpass frequency outer race (BPFO), ballpass frequency inner race (BPFI), fundamental train frequency (FTF), and ball spin frequency (BSF).

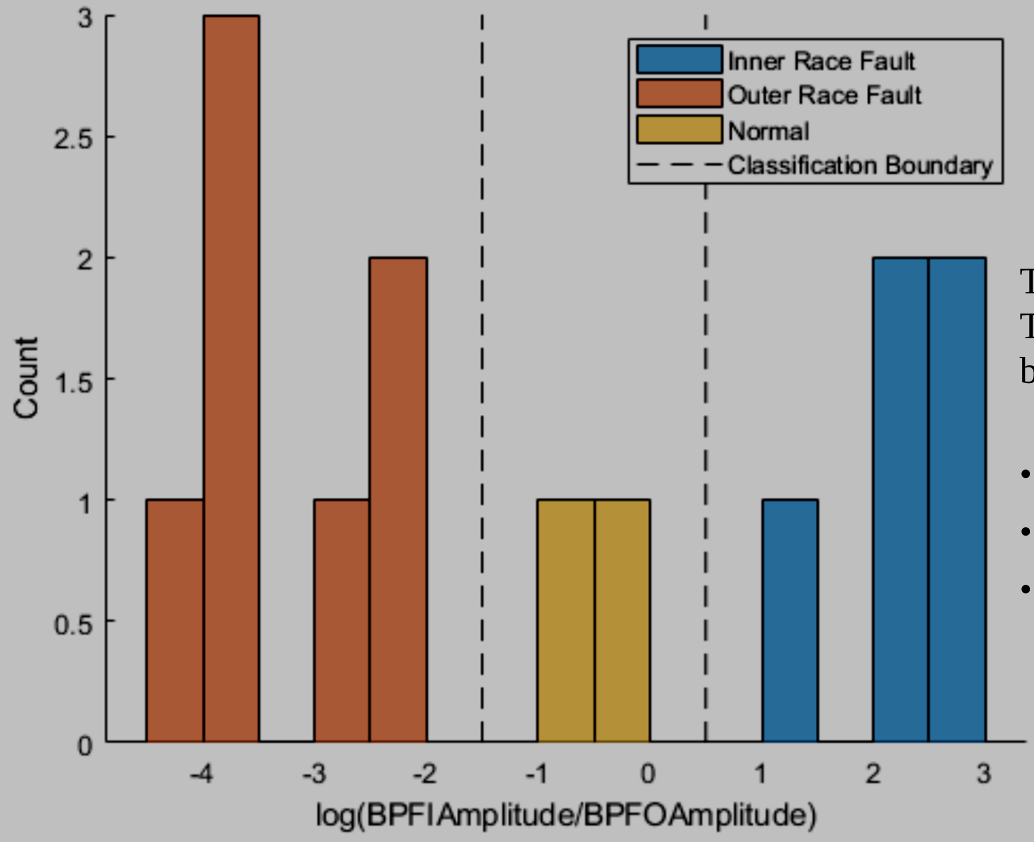

Raw Signal: Inner Race Fault
Acceleration (g)
Time, (s)
30
20
10
0
-10
-20
-30
-40
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1


Raw Signal: Inner Race Fault
Power Spectrum
Power Spectrum (dB)
Frequency (Hz)
-5
-10
-15
-20
-25
-30
-35
-40
0
0.5
1
1.5
2
2.5
$\times 10^4$


Raw Signal: Inner Race Fault
Power Spectrum
BPFI Harmonics
Power Spectrum (dB)
Frequency (Hz)
-5
-10
-15
-20
-25
-30
-35
-40
0
100
200
300
400
500
600
700
800
900
1000


Raw Signal: Inner Race Fault
0.009 sec ≈ 1/BPFI, BPFI = 118.875
Acceleration (g)
Envelope signal
Acceleration (g)
Time (s)

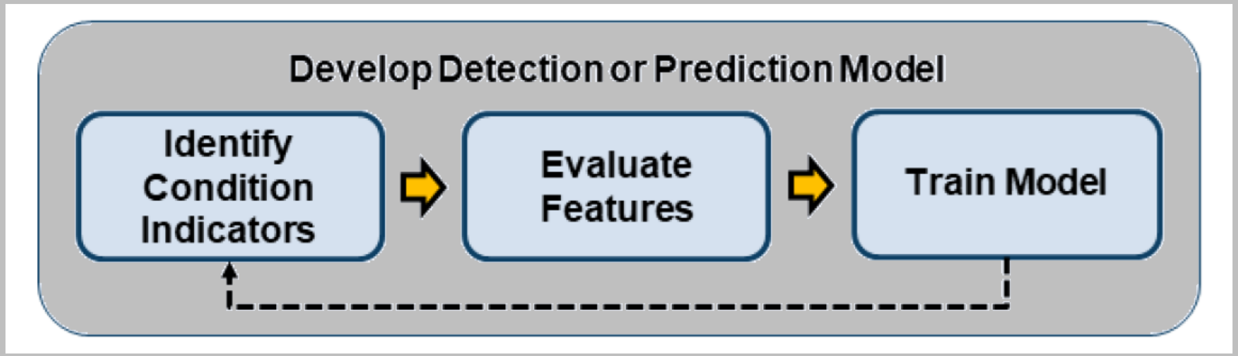

Envelope Spectrum: Inner Race Fault
Envelope Spectrum
BPFI Harmonics
Peak Amplitude
Frequency (Hz)



The histogram shows a clear separation among the three different bearing conditions. The log ratio between the BPFI and BPFO amplitudes is a valid feature to classify bearing faults. To simplify th example, a very simple classifier is derived:

- If log (BPFI Amplitude/BPFO Amplitude) ≤ -1.5, the bearing has an outer race fault.
- If $-1.5 <$ (log BPFI Amplitude/BPFO Amplitude) ≤ 0.5, the bearing is normal.
- If (log BPFI Amplitude/BPFO Amplitude) > 0.5, the bearing has an inner race fault.

Predict Remaining Useful Life

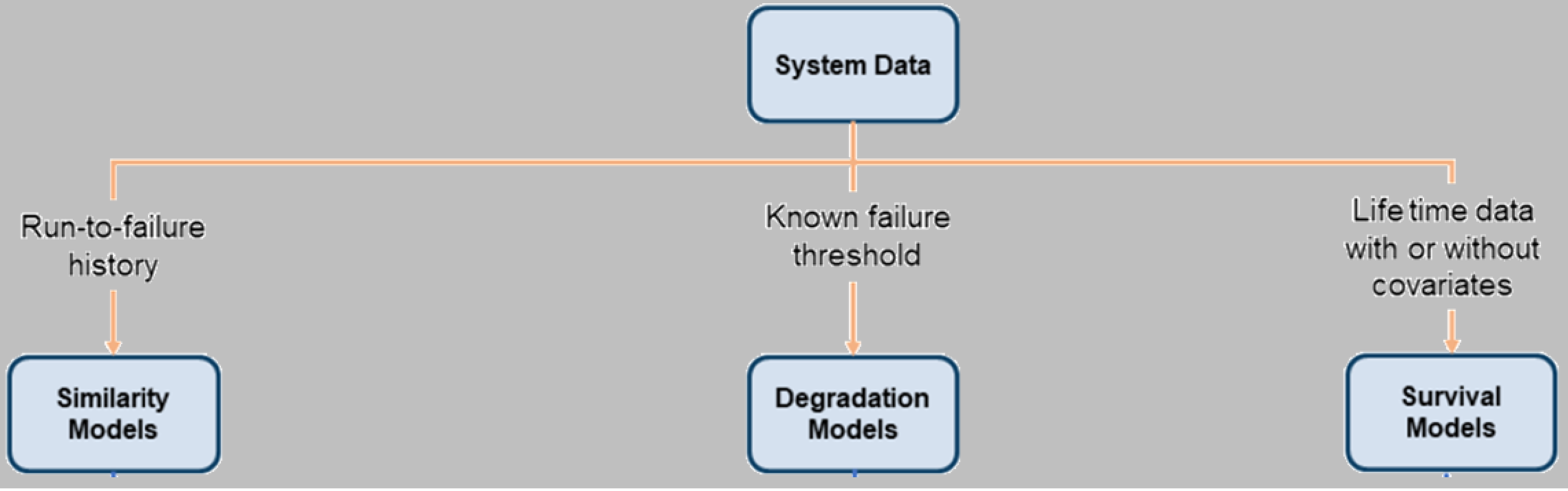


- **Monotonicity** characterizes the trend of a feature as the system evolves toward failure. As a system gets progressively closer to failure, a suitable condition indicator has a monotonic positive or negative trend.
- **Prognosability** is a measure of the variability of a feature at failure relative to the range between its initial and final values. A more prognosable feature has less variation at failure relative to the range between its initial and final values.
- **Trendability** provides a measure of similarity between the trajectories of a feature measured in multiple run-to-failure experiments. Trendability of a candidate condition indicator is defined as the smallest absolute correlation between measurements.

Models for Predicting Remaining Useful Life

- A model that fits the time evolution of a condition indicator and predicts how long it will be before the condition indicator crosses some threshold value indicative of a fault condition.
- A model that compares the time evolution of a condition indicator to measured or simulated time series from systems that ran to failure. Such a model can compute the most likely time-to-failure of the current system.

- Run-to-failure histories of machines similar to the one you want to diagnose
- A known threshold value of some condition indicator that indicates failure
- Data about how much time or how much usage it took for similar machines to reach failure (lifetime)



Similarity models:

- You have run-to-failure data from similar systems (components). Run-to-failure data is data that starts during healthy operation and ends when the machine is in a state close to failure or maintenance.
- The run-to-failure data shows similar degradation behaviors. That is, the data changes in some characteristic way as the system degrades

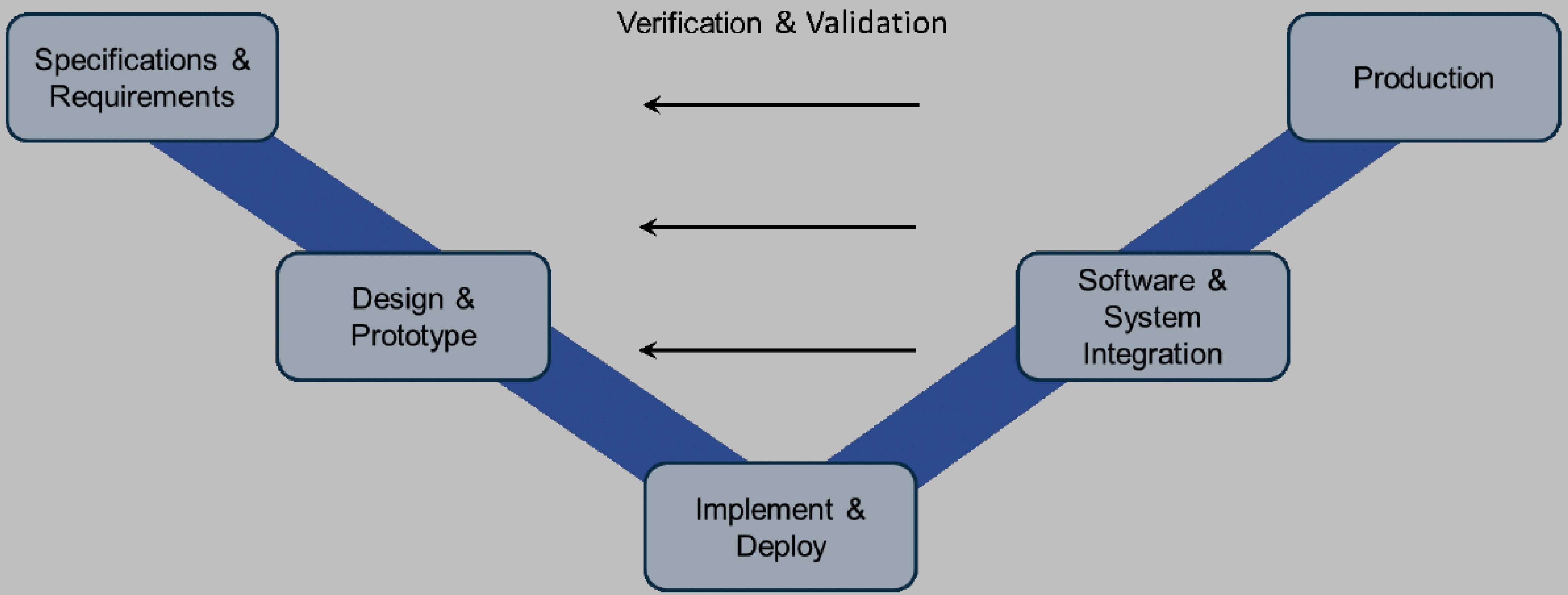
Degradation Models:

- Linear degradation model: Describes the degradation behavior as a linear stochastic process with an offset term. Linear degradation models are useful when your system does not experience cumulative degradation.
- Exponential degradation model: Describes the degradation behavior as an exponential stochastic process with an offset term. Exponential degradation models are useful when the test component experiences cumulative degradation.

Survival Models:

- Only data about the life span of similar components. Given the historical information on failure times of a fleet of similar components, this model estimates the probability distribution of the failure times. The distribution is used to estimate the RUL of the test component.
- Both life spans and some other variable data (covariates) that correlates with the RUL. Covariates, also called environmental variables or explanatory variables, comprise information such as the component provider, regimes in which the component was used, or manufacturing batch.

Deploy Predictive Maintenance Algorithms



Deploy Predictive Maintenance Algorithms

- Memory and computational power
- Operating mode. For instance, the algorithm might be a batch process that runs at some fixed time interval such as once a day. Or, it might be a streaming process that runs every time new data is available.
- Maintenance or update of the algorithm. For example, the deployed algorithm might be fixed, changing only changes through occasional updates. Or, you might develop an algorithm that adapts and automatically updates as new data is available.
- Where the algorithm runs, such as whether the algorithm must run in a cloud, or be offered as a web service.

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