Queen's University
Mechanical Engineering

Machine Condition Monitoring

and

Fault Diagnostics

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Current Topic

- Machinery Vibration Trouble Shooting
- Fault Diagnostics Based on Forcing Functions
- Fault Diagnostics Based on Specific Machine Components
- Fault Diagnostics Based on Specific Machine Types
- Automatic Diagnostic Techniques
- Non-Vibration Based Machine Condition Monitoring and Fault Diagnosis Methods

Automatic Diagnostic Techniques

Extraction of meaningful information from data available and linking it automatically to known fault types.

Difficult for many reasons.

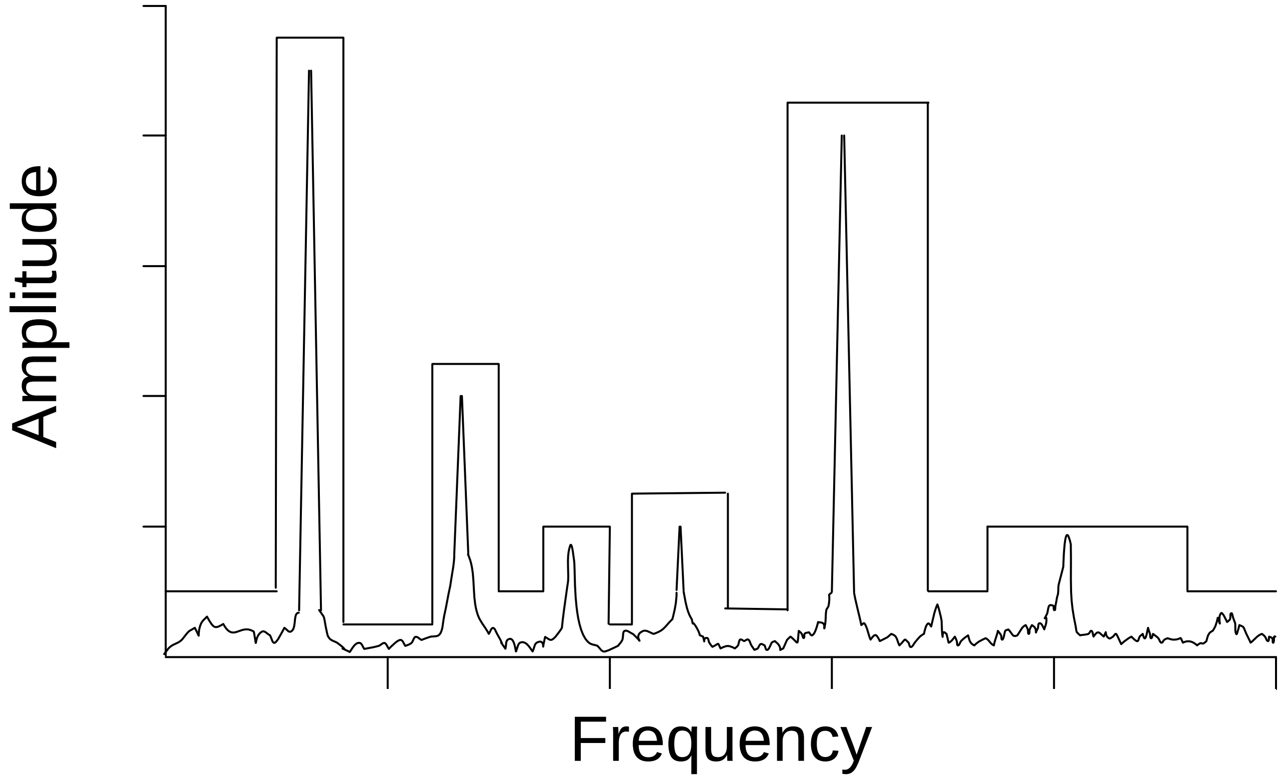
- Diagnosis is often made using a wide array of data/information.
- Diagnosis is not often possible until the fault is well developed.
- A wide range of known fault samples is usually needed to diagnose existing conditions.

Automatic Diagnostic Techniques

Difficult, but not impossible.

Application of amplitude limits on FFT based frequency spectra within different frequency bands (Masks).

Automatic Diagnostic Techniques



Constant Percentage Bandwidth Acceptance Limits.

Model Based Frequency Spectra

Mathematical model provides description of system response.

Changes in the model are sensitive to changes in the system (faults).

- Auto-Regressive (AR) models.
- Auto-Regressive Moving Average (ARMA) models.
- Minimum Variance (MV).
- Prony Models, etc.

Model Based Frequency Spectra

3 steps

1. Selection of an appropriate model type.
2. Calculation of the model parameters and determination of the optimum model order (size).
3. Calculation of the spectral estimate.

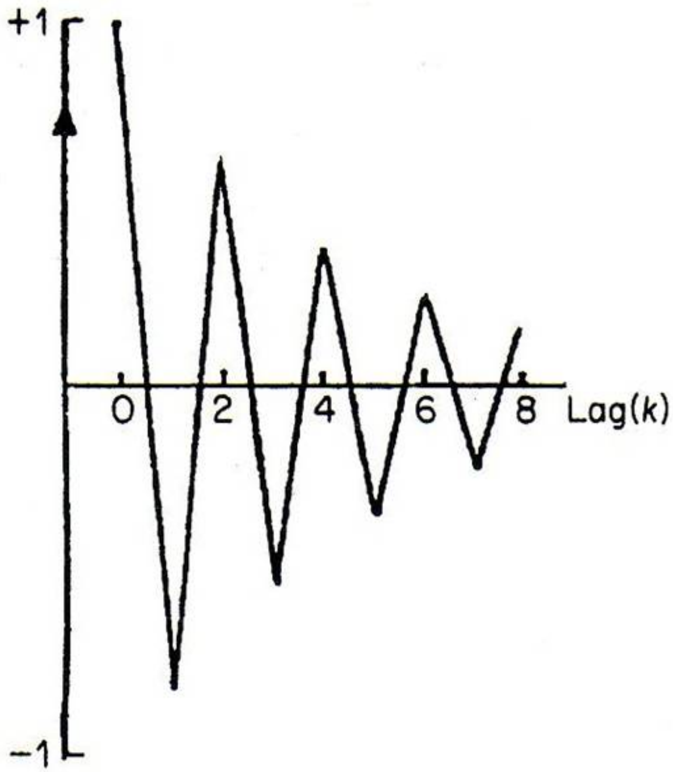
Selection of Appropriate Model Type

TECHNIQUE	COMP. COMPLEXITY (Adds & Mults)	MODEL(S)	ADVANTAGES AND DISADVANTAGES	REMARKS
Periodogram FFT version	$N_d \log_2 N_d$	Sum of harmonically related sinusoids.	Output directly proportional to power. Most computationally efficient. Resolution roughly the reciprocal of the observation interval. Performace poor for short data records. Leakage distorts spectrum and masks weak signals.	Harmonic least squares fit. Requires some type of frequency domain statistical averaging to stabilise spectrum. Windowing can reduce sidelobes at expense of resolution.
Blackman-Tukey (BT)	Lag Ests,: $N_d M$ PSD Est.: MS	Identical to MA with windowing of the lags.	Most computationally efficient if $M \ll N_d$. Resolution roughly the reciprocal of the observation interval. Leakage distorts spectrum and masks weak signals.	Negative PSD values in spectra may result with some window weightings and autocorrelation estimates.
Autoregressive (AR) Yule-Walker version	Lag Ests.: $N_d M$ AR Coeffs.: M^2 PSD Est.: MS	Autoregressive (all pole) process.	Model order must be selected. Better resolution than FFT or BT, but not as good as other AR methods. Spectral line splitting occurs.	Model applicable to seismic, speech, and radar clutter data. Minimum phase linear prediction filter guaranteed if biased lag estimates are computed. AR related to linear prediction analysis and adaptive filtering. Models peaks in the spectrum better than valleys.
Autoregressive (AR) Burg Algorithm version	AR Coeffs.: $N_d M + M^2$ PSD Est.: MS	Autoregressive (all pole) process.	High resolution for low noise levels. Good spectral fidelity for short data records. Spectral line splitting can occur. Bias in the frequency estimates of peaks. No implied windowing. No sidelobes. Must determine order.	Stable linear prediction filter guaranteed. Adaptive filtering applicable. Uses constrained recursive least squares approach.
Autoregressive (AR) Least squares or forward-backward linear prediction version	AR Coeffs.: $N_d M + M^2$ PSD Est.: MS	Autoregressive (all pole) process.	Sharper response for narrow-band processes than other AR estimates. No spectral line splitting observed. No sidelobes. Bias reduced in the frequency estimates. Must determine order.	Stable linear prediction filter not guaranteed, but stable filter results in most instances. Based on exact recursive least squares solution with no constraint.

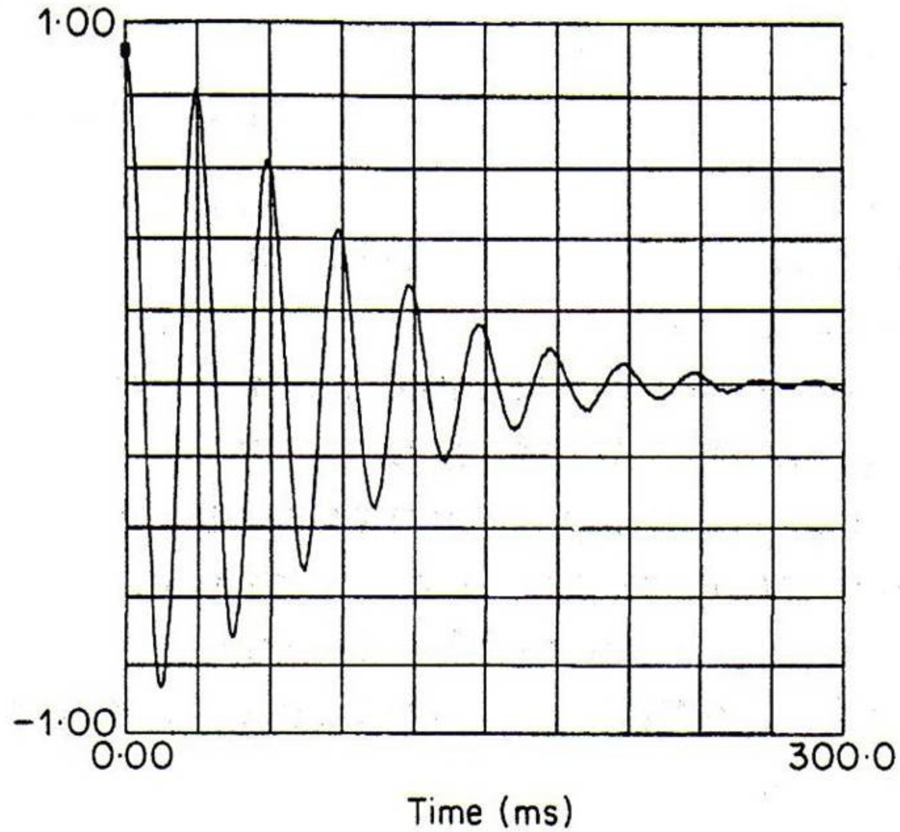
Selection of Appropriate Model Type

TECHNIQUE	COMP. COMPLEXITY (Adds & Mults)	MODEL(S)	ADVANTAGES AND DISADVANTAGES	REMARKS
Moving Average (MA)	MA Coeffs.: Nonlinear Simult. Eqn. Set Lag Ests.: N_dM PSD Est.: MS	Moving Average (all zero) process.	Broad spectral responses (low resolution). Must determine order. Has sidelobes.	General form of BT technique.
ARMA Yule-Walker version	Lag Ests.: N_dM Coeff. Computation: M^3 PSD Est.: MS	ARMA process (Rational Transfer Function) (MA order & AR order).	Must determine AR and MA orders.	Models all rational transfer function processes. Requires accurate lag estimates to obtain good results.
Pisarenko Harmonic Decomposition (PHD)	Lag Ests.: N_dM Eigen Eqn.: M^2 to M^3 Poly. Rooting: Dependent on root algorithm Powers: M^3	Special ARMA with equal MA and AR coefficients. Sum of nonharmonically undamped sinusoids in additive white noise.	Must determine order. Does not work well with high noise levels. Eigen equation and rooting are computationally inefficient.	Requires accurate lag estimates to obtain good results. Spurious spectral lines if order selected too high.
Prony's Method	AR Coeffs.: $M^2 + N_dM$ Poly Rooting: Dependent on root algorithm Amp. Coeffs.: M^3 PSD Est.: MS	Sum of nonharmonically related damped exponentials. ARMA with equal MA and AR coefficients and equal orders.	Must determine order. Output linearly proportional to power. Requires a polynomial rooting. Resolution as good as AR techniques, sometimes better. No sidelobes.	Uses least squares estimates to obtain exponential parameters. First step same as least squares estimation.
Prony Spectral Line Decomposition	Coeffs.: M^3 Rooting: Function of root algorithm used Amp. Coeffs.: M^3	Sum of nonharmonically related sinusoids.	Must determine order. Output linearly proportional to power. Requires a polynomial rooting. Resolution as good as AR techniques, sometimes better. No sidelobes.	Uses least squares estimation.
Capon Maximum Likelihood (MLSE)	Lag Ests.: N_dM Matrix Inversion: M^3 PSD Est.: MS	Forms of optimal bandpass filter for each spectral component.	Resolution better than BT; not as good as AR. Statistically less variability in MLSE spectra than AR spectra.	MLSE is related to AR spectra.

Selection of Appropriate Model Type

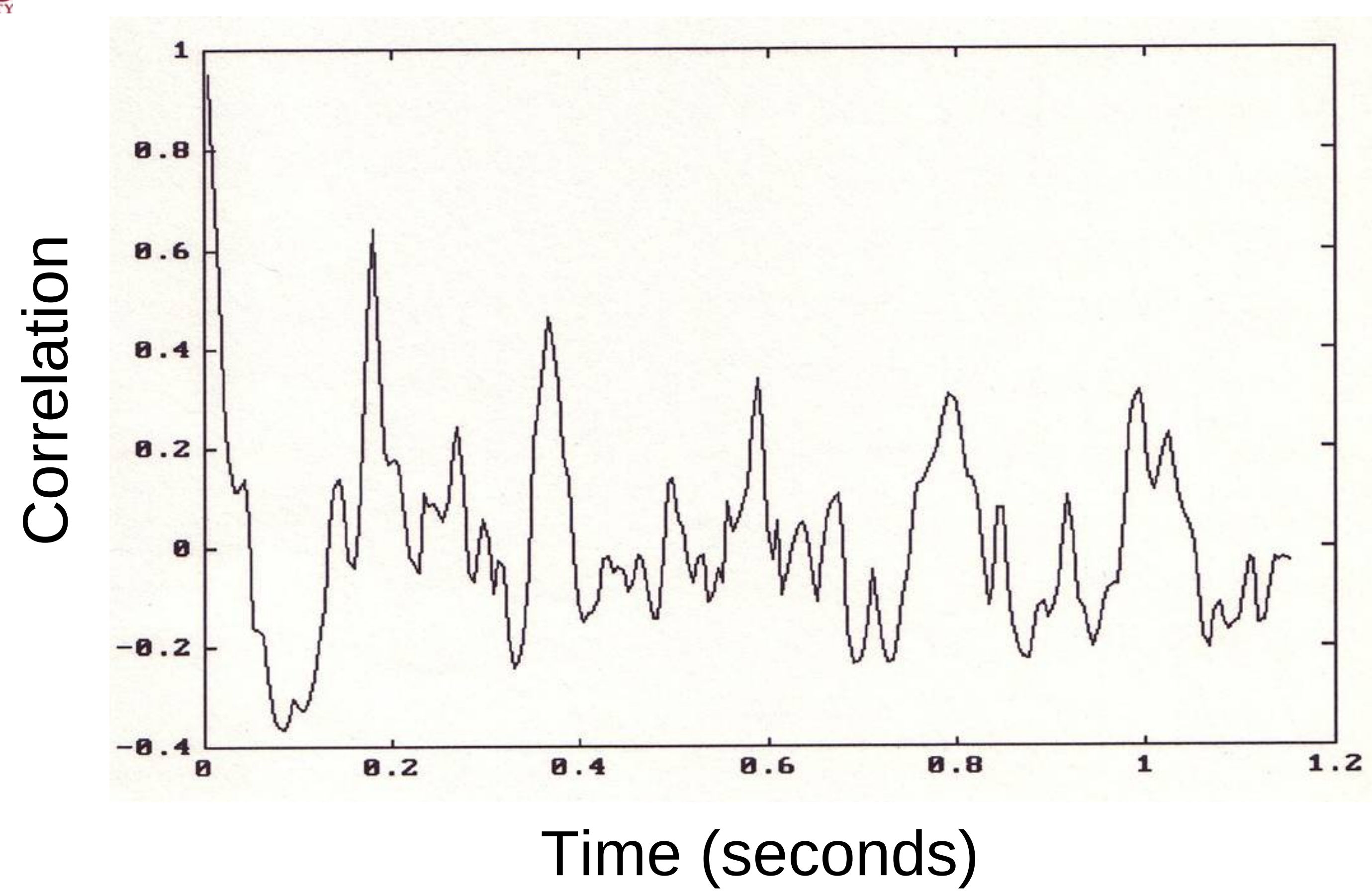


Autocorrelation Function



Function of Sample Data

Selection of Appropriate Model Type



Autocorrelation function from sampled rolling element bearing vibration data.

Selection of Appropriate Model Type

$$X(t) = a_0 X(t-1) + a_1 X(t-2) + a_2 X(t-3) + \cdots + n(t)$$

Model parameters represent a weighted function (series of terms) that, when used as a filter with pure noise (random dynamic data) will generate the original time series used to make the model.

Contain all the valuable information required to reproduce the original signal (data compression).

Contain fault classification information.

Calculation of Model Parameters

Yule – Walker Method

Yule, G.U., "**On a Method of Investigating Periodicities in Distributed Series with Special Reference to Wolfer's Sunspot Numbers**", *Transactions of the Royal Statistical Society of London*, Series A, Vol.226, p267-298, July 1927.

Walker, G., "**On Periodicity in Series of Related Terms**", *Transactions of the Royal Statistical Society of London,* Series A, Vol.231, p518-532, 1931

Levinson – Durbin Algorithm

Levinson, N., "**The Wiener (root mean square) Error Criterion in Filter Design and Prediction**", *Journal of Mathematics and Physics*, Vol.25, p261-278, 1947.

Durbin, J., "**The Fitting of Time Series Models**", *The International Institute of Statistical Review,* Vol.28, p223-244, 1960.

Wiggins, R.A. and E.A. Robinson, "**Recursive Solutionto the Multichannel Filtering Problem**", *Journal of Geophysical Research*, Vol.70, No.8, p1885-1891, 1965.

Calculation of Model Parameters

Forward Linear Prediction

Kay, S.M., "**Modern Septral Estimation: Theory and Application**", *Prentice-Hall*, Englewood Cliffs, New Jersey, USA, 1988.

Kay S.M. and S.L. Marple, "**Spectral Analysis: A Modern Perspective**", *Proceedings of the IEEE,* Vol.69, No.11, p1380-1419, November 1981.

Morf, M., B. Dickinson, T. Kailath and A. Vieira, "**Efficient Solution of Covariance Equations for Linear Prediction**", *IEEE Transactions on Acoustics, Speech and Signal Processing*, Vol.ASSP-25, p429-433, October 1977.

Forward-Backward Linear Prediction

Marple, S.L., "**A New Autoregressive Spectrum Analysis Algorithm**", *IEEE Transactions on Acoustics, Speech and Signal Processing*, Vol.ASSP-28, p441-454, August 1980.

Burg Method

Burg, J.P., "**Maximum Entropy Spectrum Analysis**", *Proceedings of the 37th Meeting of the Society of Exploration Geophysicists*, Oklahoma City, Oklahoma, USA, October 1967.

Calculation of Model Parameters

Basic Procedure

- Use the covariance function derived from a given data set (time series) to generate a set of model parameters.
- Filter some random data with the new model and try to generate the original data set.
- Compare time series data from model to the original.
- Adjust the model parameters in some way to reduce the error between model based time series and original.
- Repeat until the error is suitably small.

Determine the Optimum Model Order

Estimation criteria for optimum AR model order selection

CRITERION	OPTIMUM ORDER ESTIMATE	DEFINITION OF ESTIMATION CRITERION
FPE	$FPE(\hat{p}) = \min\{\mathrm{FPE(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$FPE(p) = \frac{N_d + p}{N_d - p}\hat{\rho}_p$
AIC	$AIC(\hat{p}) = \min\{\mathrm{AIC(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$AIC(p) = N_d \ln(\hat{\rho}_p) + 2p$
RIS	$RIS(\hat{p}) = \min\{\mathrm{RIS(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$RIS(p) = N_d \ln(\hat{\rho}_p) + 2\ln p$
CAT	$CAT(\hat{p}) = \min\{\mathrm{CAT(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$CAT(p) = \frac{i}{N_d} \sum_{i=1}^{p} \left(\frac{N_d}{N_d - i}\hat{\rho}_i\right)^{-1} - \left(\frac{N_d}{N_d - i}\hat{\rho}_p\right)^{-1}$
Schwartz	$BIC(\hat{p}) = \min\{\mathrm{BIC(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$BIC(p) = N_d \ln(\hat{\rho}_p) + \frac{p\ln(N_d)}{N_d}$
Hannan-Quinn	$HQ(\hat{p}) = \min\{\mathrm{HQ(p)} \mid \mathrm{p} = 1,2,\ldots,\mathrm{m}\}$	$HQ(p) = N_d \ln(\hat{\rho}_p) + \frac{p\ln(\ln(N_d))}{N_d}$

p is the model order

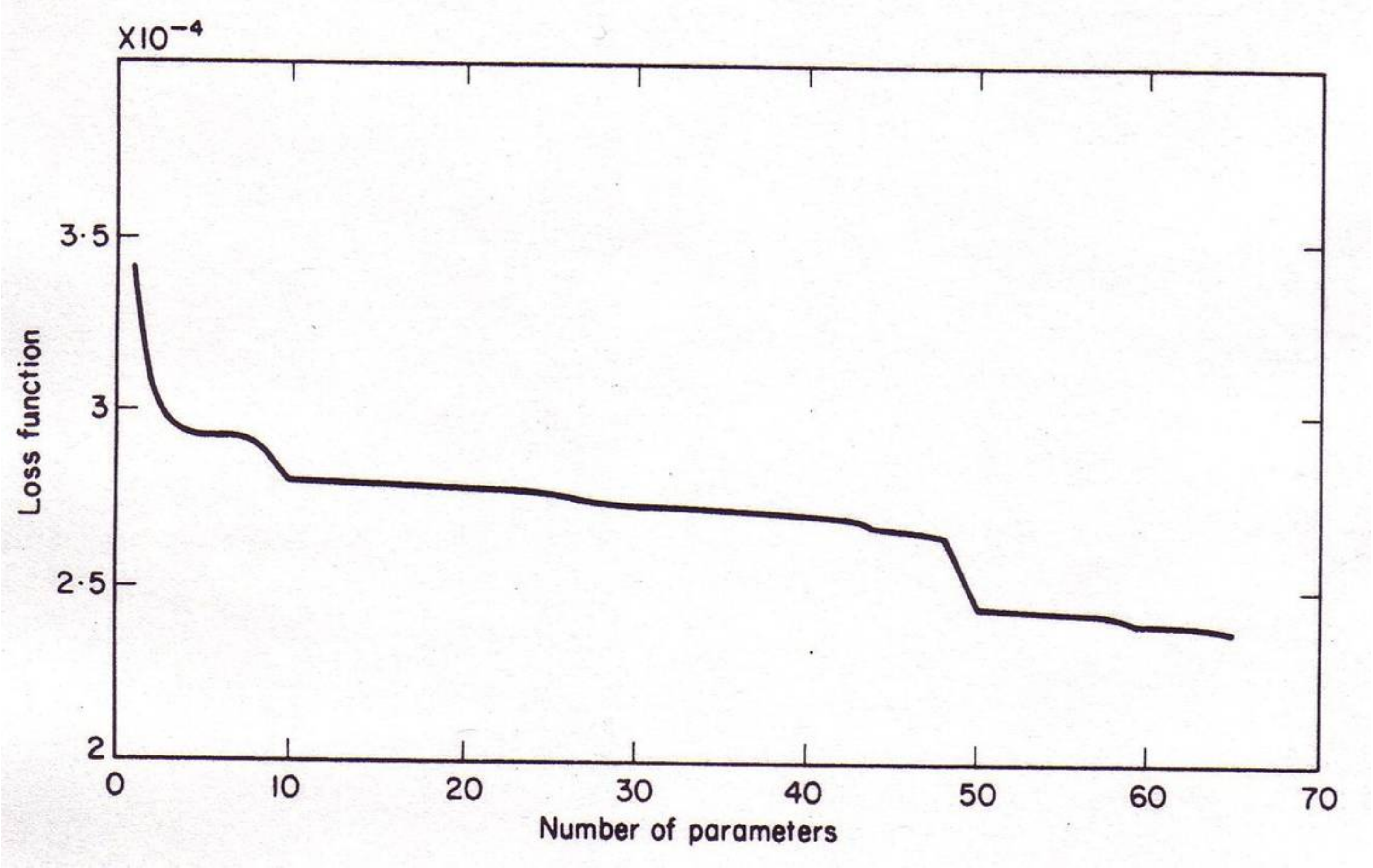
$\hat{p}$ is the optimum model order

N_d is the sample size

m is half the sample size

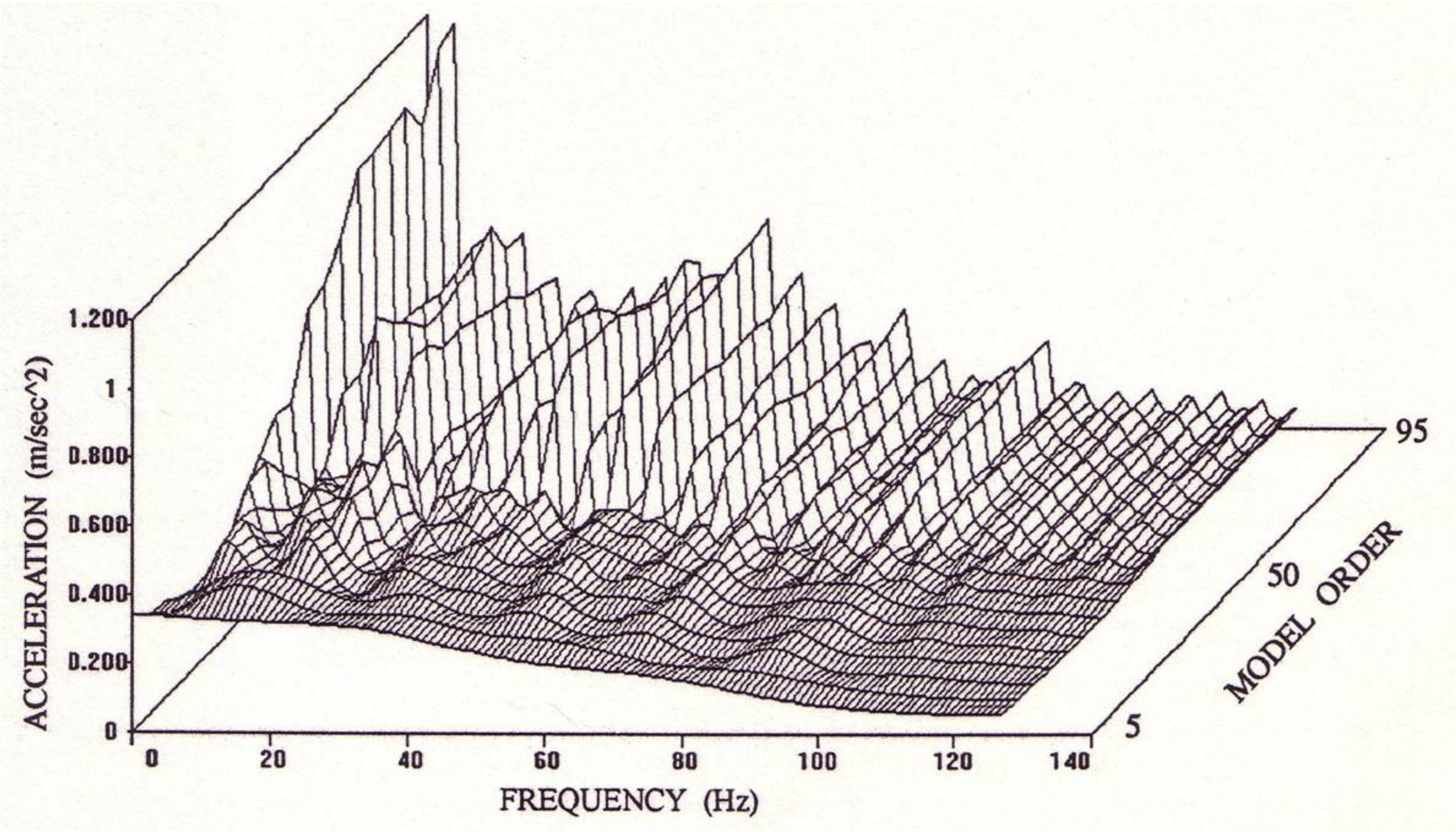
$\hat{\rho}_p$ is the prediction error power

Determine the Optimum Model Order



Final Prediction Error (FPE) Loss Function
for Rolling Element Bearing Data

Determine the Optimum Model Order



Rolling Element Bearing Outer Race Fault AR Spectra
Increasing Model Orders

Calculation of Spectral Estimate

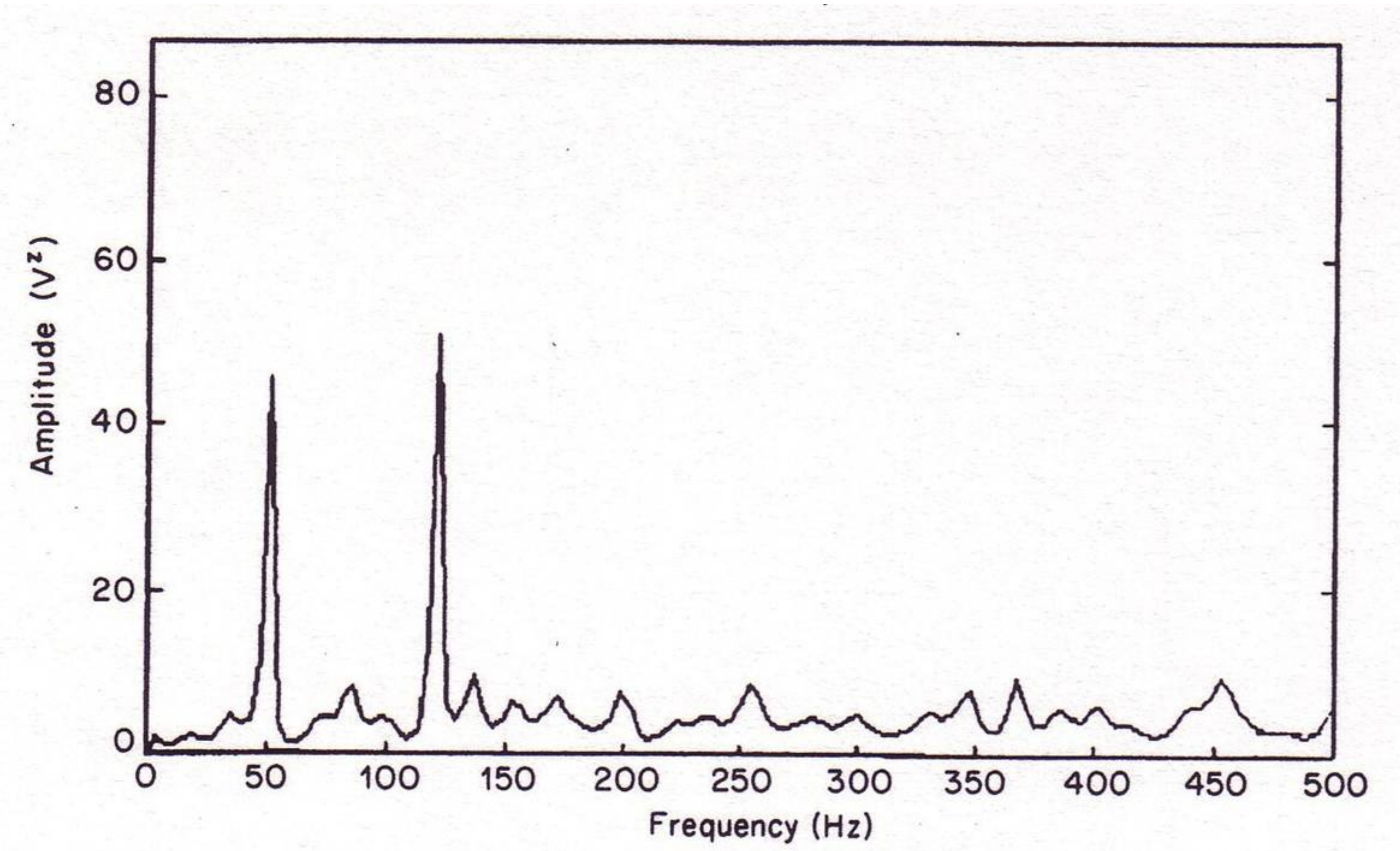
$$F_{AR}(f) = \frac{\sigma^2 \Delta t}{\left| 1 + \sum_{k=0}^{p} a_k \exp(-j2\pi f k \Delta t) \right|^2}$$

$F_{AR}(f)$ is the AR power spectral density estimation,

a_k are the AR coefficients,

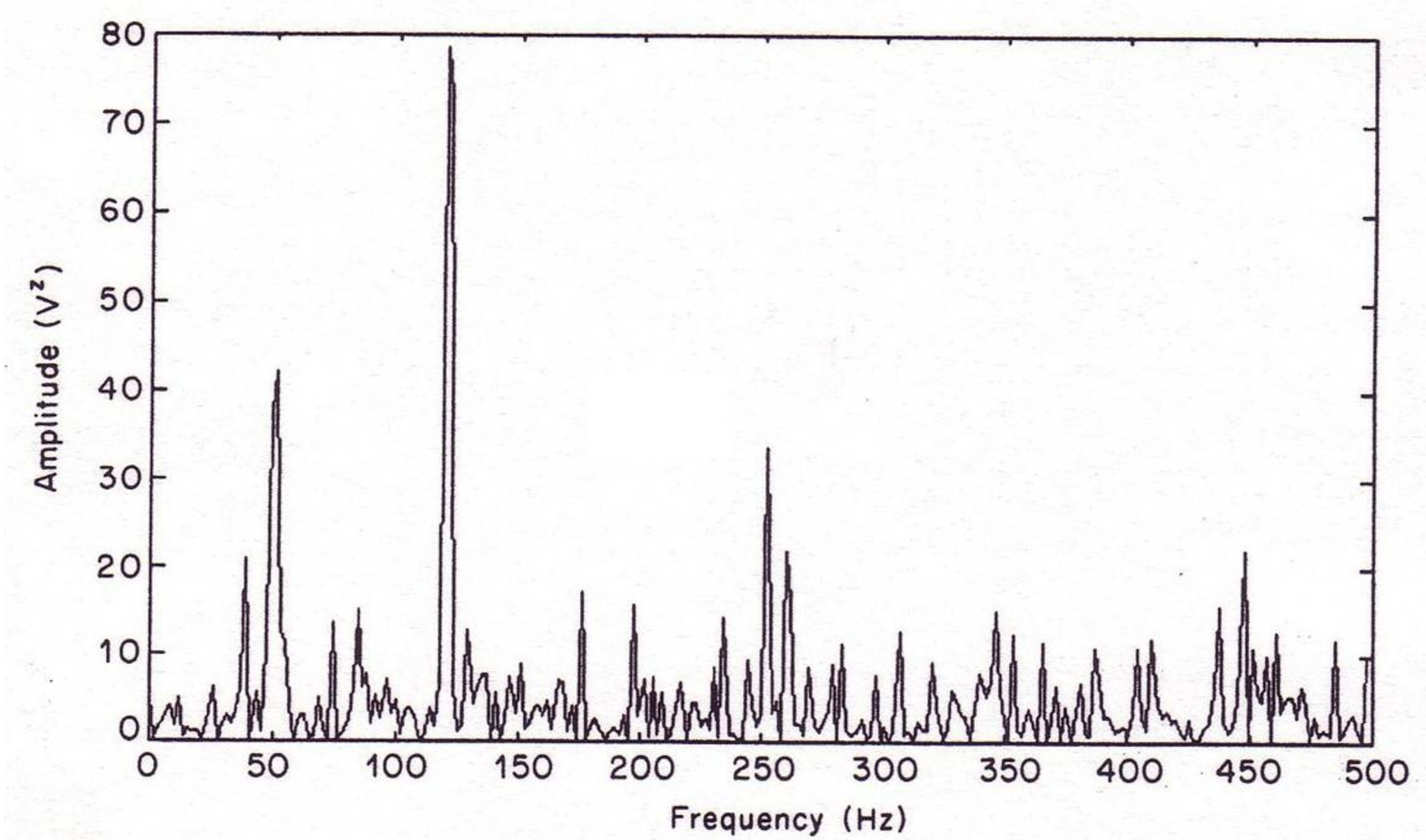
σ^2 is the variance.

Calculation of Spectral Estimate



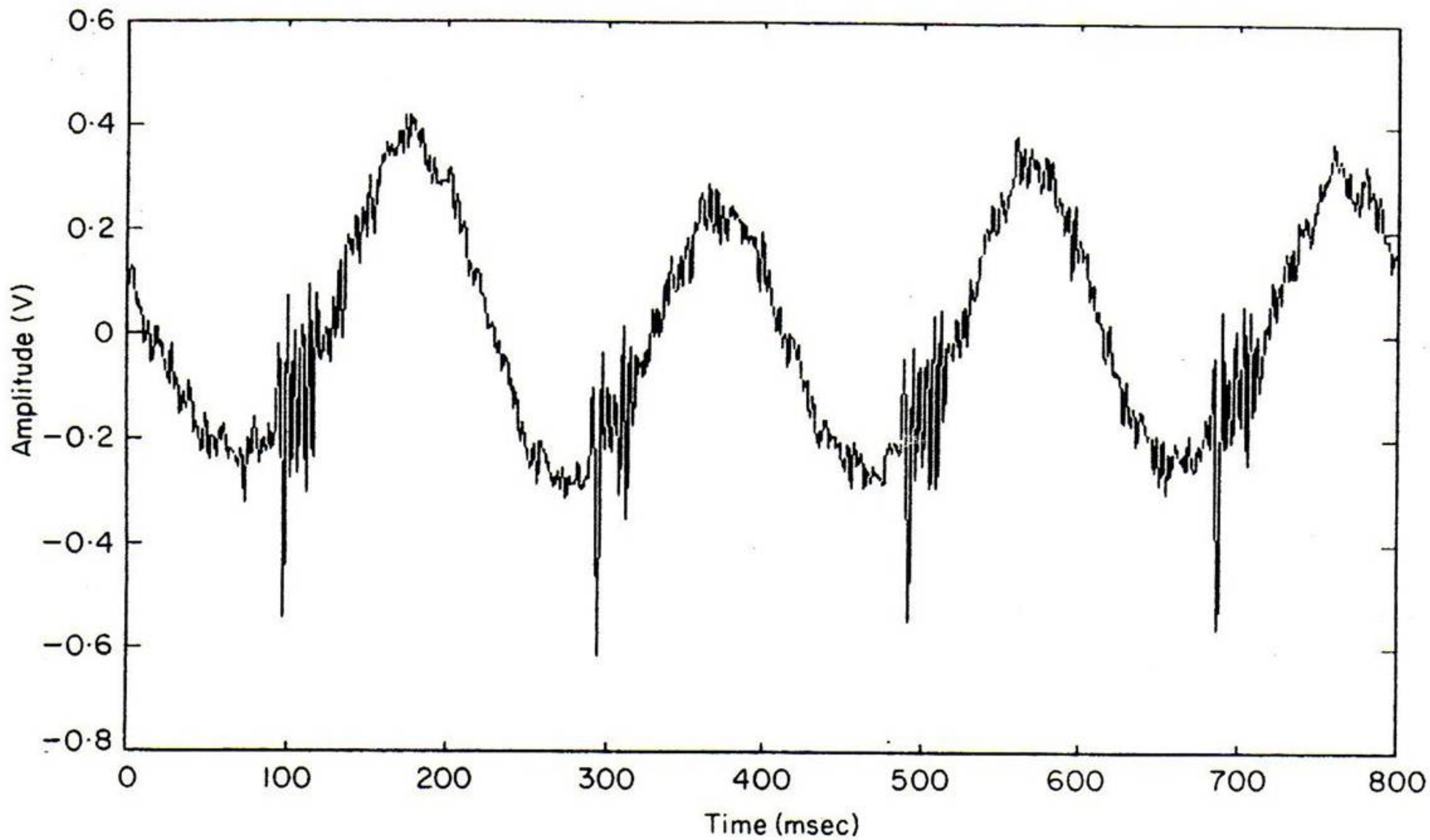
AR model-based spectral estimate
Sine waves in noise

Calculation of Spectral Estimate



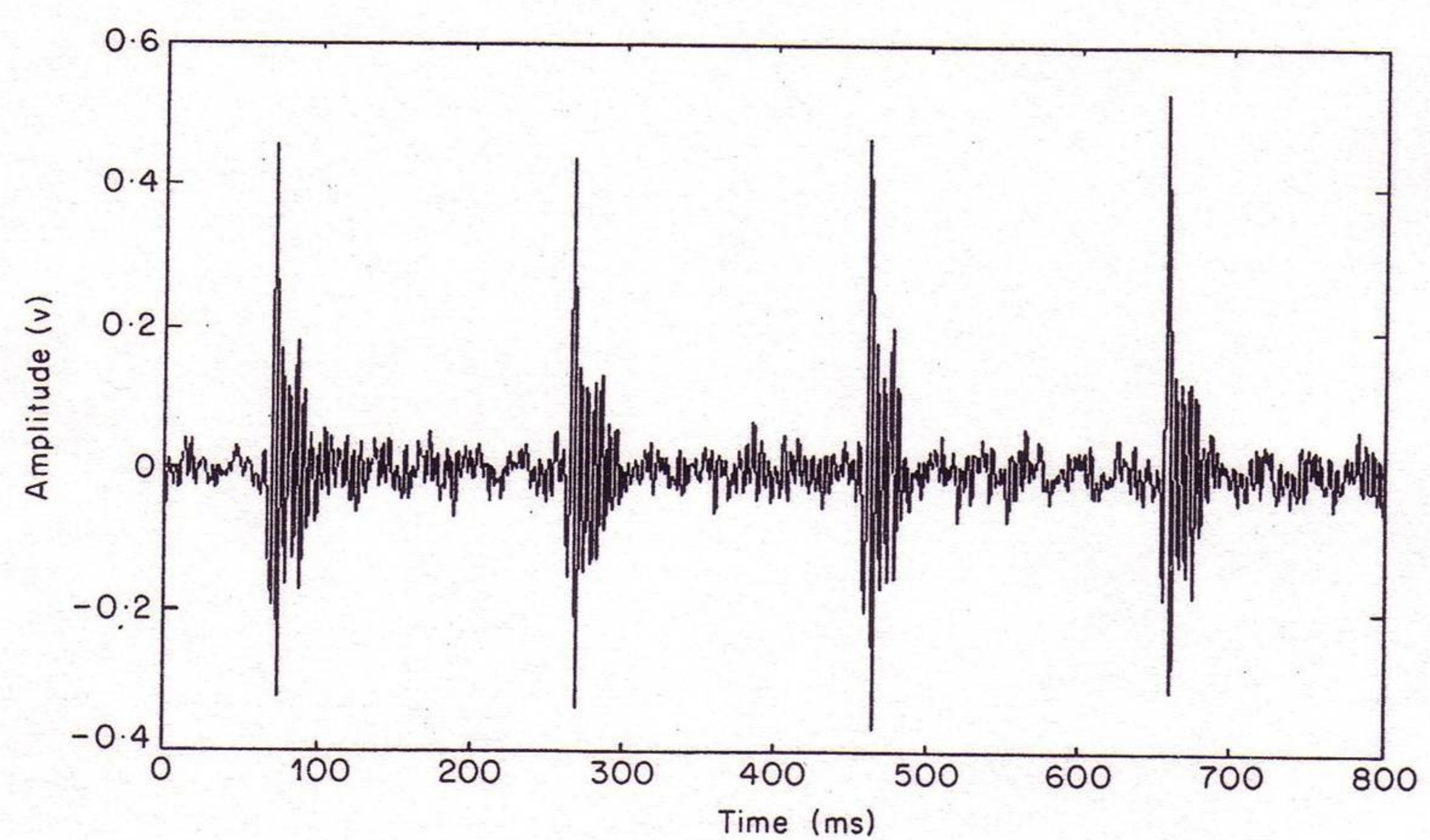
FFT-based spectral estimate
Sine waves in noise

Example



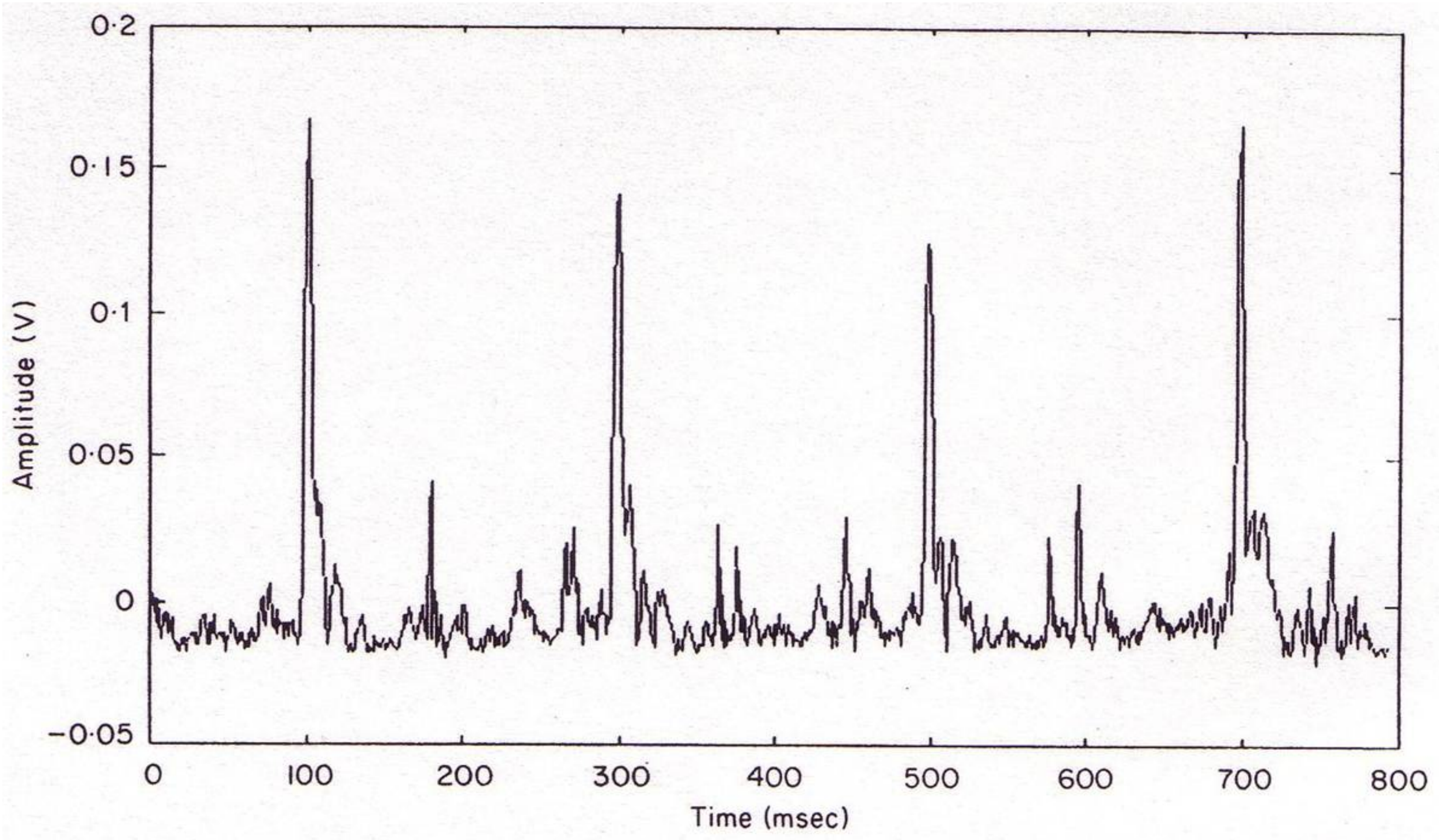
Vibration Signal
Outer Race Fault on a rolling Element Bearing

Example



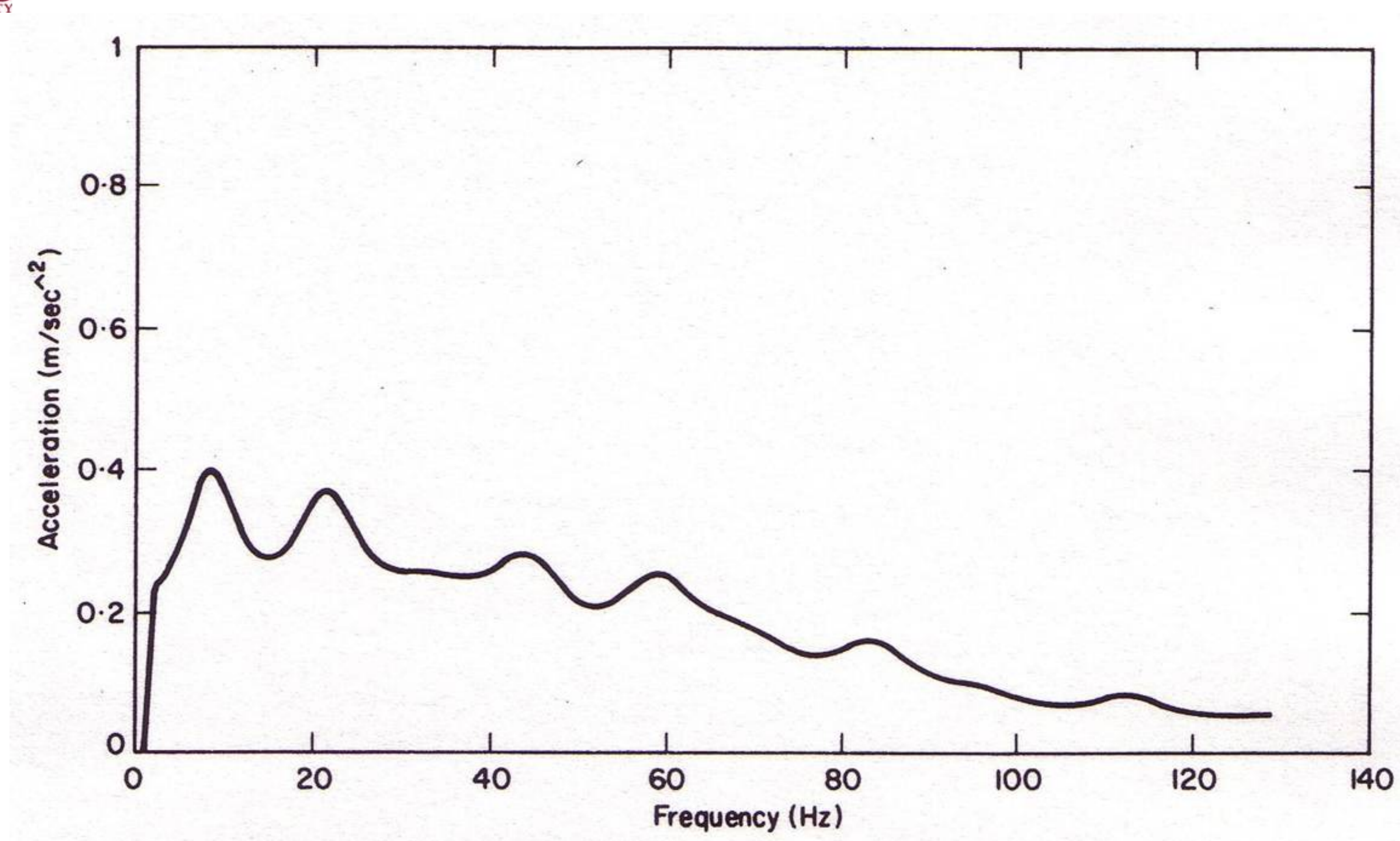
Vibration Signal
After High Pass Filtering

Example



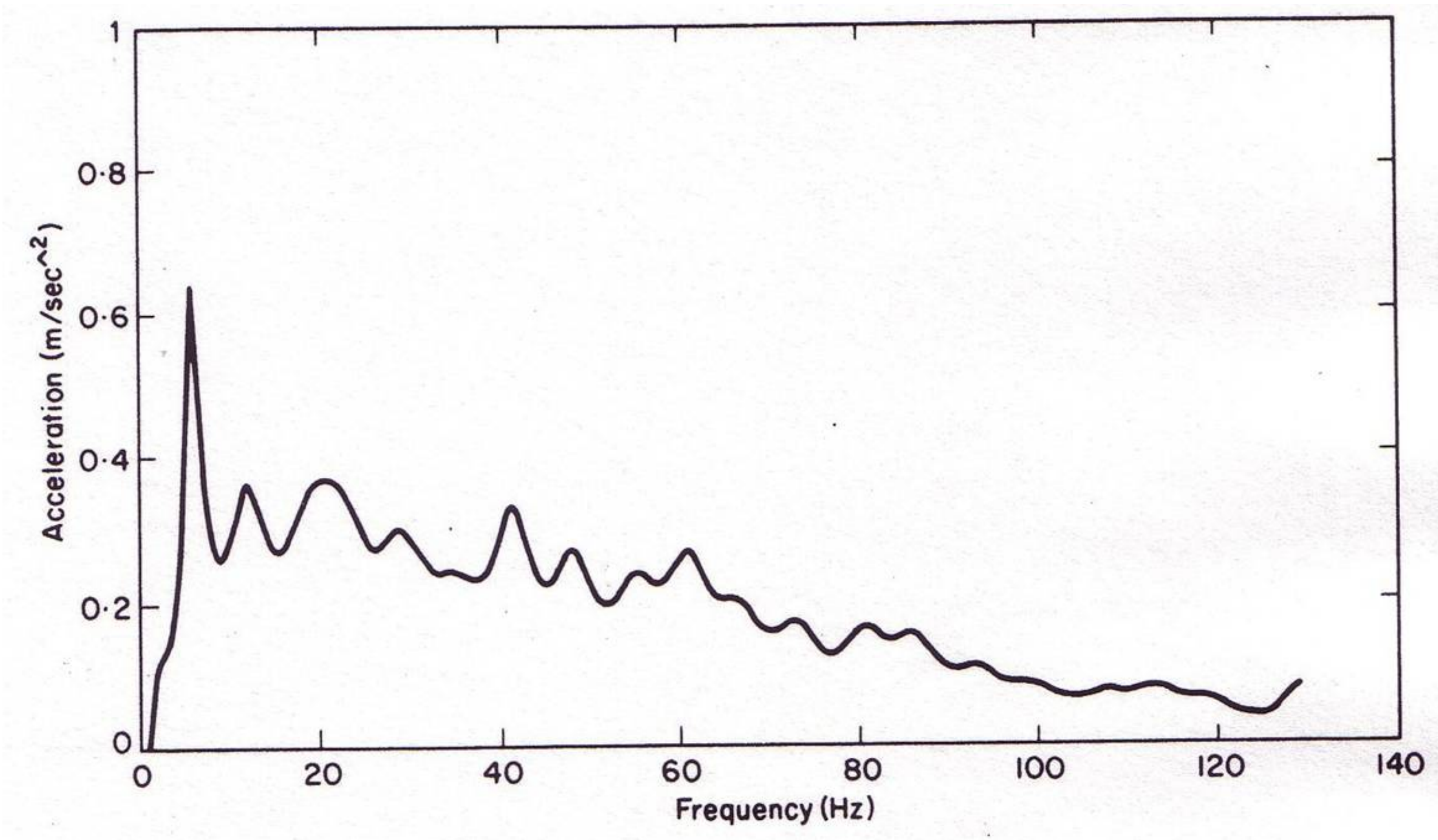
Vibration Signal
After Rectification

Example



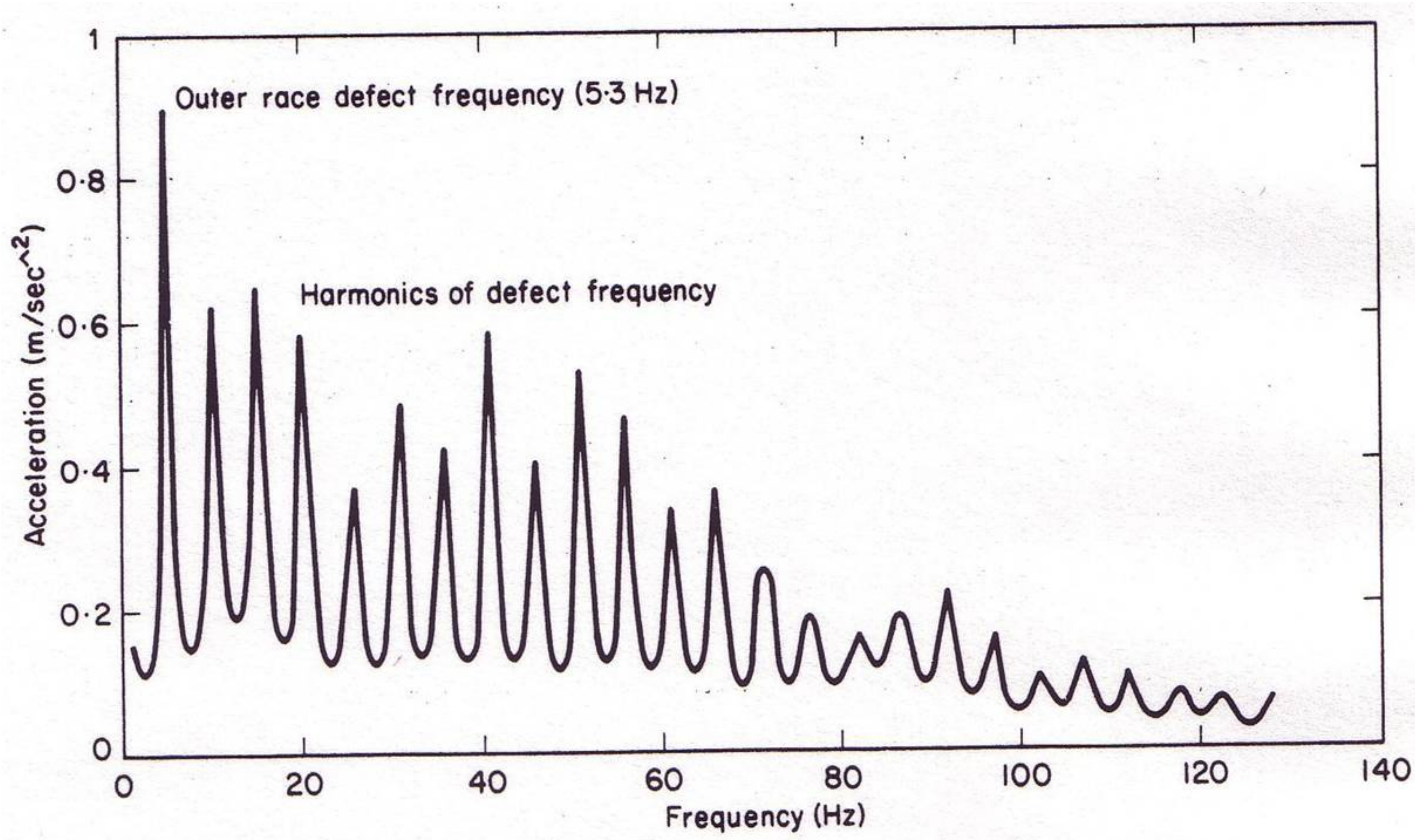
AR Frequency Spectrum of Outer Race Fault
(Model Order 20)

Example



AR Frequency Spectrum of Outer Race Fault
(Model Order 40)

Example



AR Frequency Spectrum of Outer Race Fault
(Model Order 60)

Example

Index	Parameter	Index	Parameter	Index	Parameter
1	−0·7480	8	0·1201	15	0·0142
2	0·5111	9	−0·0691	16	0·0256
3	−0·3039	10	0·0529	17	−0·0473
4	0·1839	11	−0·0273	18	0·0330
5	−0·1023	12	0·0315	19	−0·0200
6	0·0989	13	0·0175	20	0·0428
7	−0·0701	14	0·0030		

AR Model Parameters
(Model Order 20)

Example

Index	Parameter	Index	Parameter	Index	Parameter
1	−0·7332	15	0·0224	29	0·0165
2	0·5079	16	0·0249	30	0·0370
3	−0·2921	17	−0·0391	31	0·0410
4	0·1847	18	0·0335	32	0·0099
5	−0·1042	19	−0·0109	33	0·0166
6	0·1115	20	0·0448	34	0·0323
7	−0·0730	21	−0·0027	35	−0·0481
8	0·1184	22	0·0256	36	−0·0756
9	−0·0616	23	0·0132	37	0·0635
10	0·0544	24	−0·0178	38	0·0144
11	−0·0239	25	0·0710	39	0·0120
12	0·0405	26	0·0049	40	0·0013
13	0·0217	27	0·0455		
14	0·0067	28	0·0257		

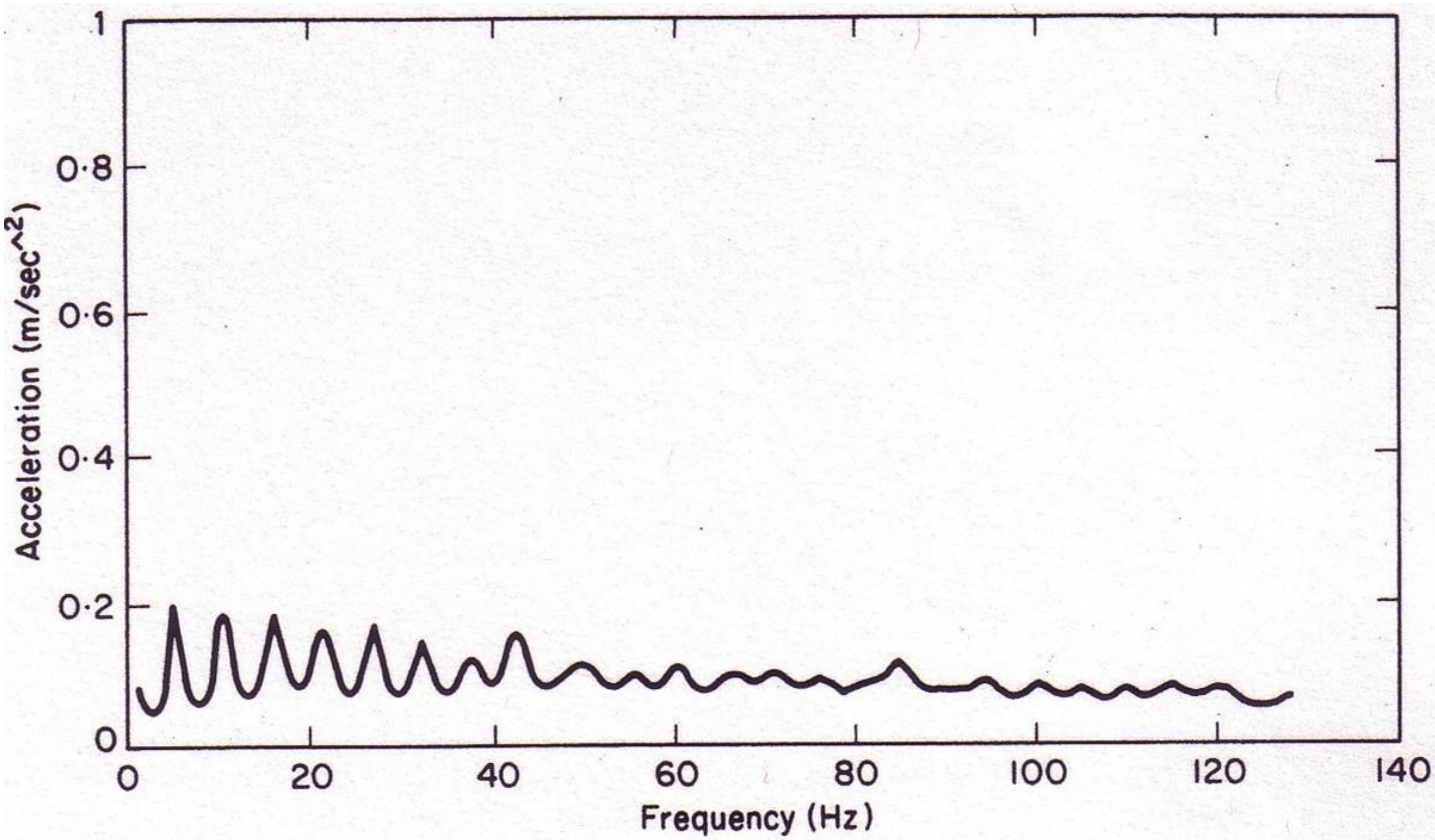
AR Model Parameters
(Model Order 40)

Example

Index	Parameter	Index	Parameter	Index	Parameter
1	−0·6770	21	−0·0046	41	−0·0042
2	0·4546	22	0·0074	42	0·0510
3	−0·2877	23	0·0004	43	−0·0825
4	0·1674	24	−0·0275	44	0·1024
5	−0·0987	25	0·0576	45	−0·0362
6	0·0911	26	0·0156	46	0·0305
7	−0·0568	27	0·0371	47	0·0159
8	0·0839	28	0·0246	48	0·0201
9	−0·0345	29	0·0070	49	−0·0879
10	0·0590	30	−0·0435	50	−0·2415
11	−0·0377	31	0·0420	51	0·0458
12	0·0338	32	0·0120	52	0·0107
13	0·0208	33	−0·0276	53	0·0403
14	0·0129	34	0·0011	54	0·0122
15	0·0142	35	0·0380	55	−0·0471
16	0·0344	36	−0·0703	56	0·0485
17	−0·0336	37	0·0467	57	−0·0223
18	0·0190	38	0·0168	58	0·0224
19	0·0097	39	0·0189	59	−0·0129
20	0·0393	40	−0·0085	60	−0·0460

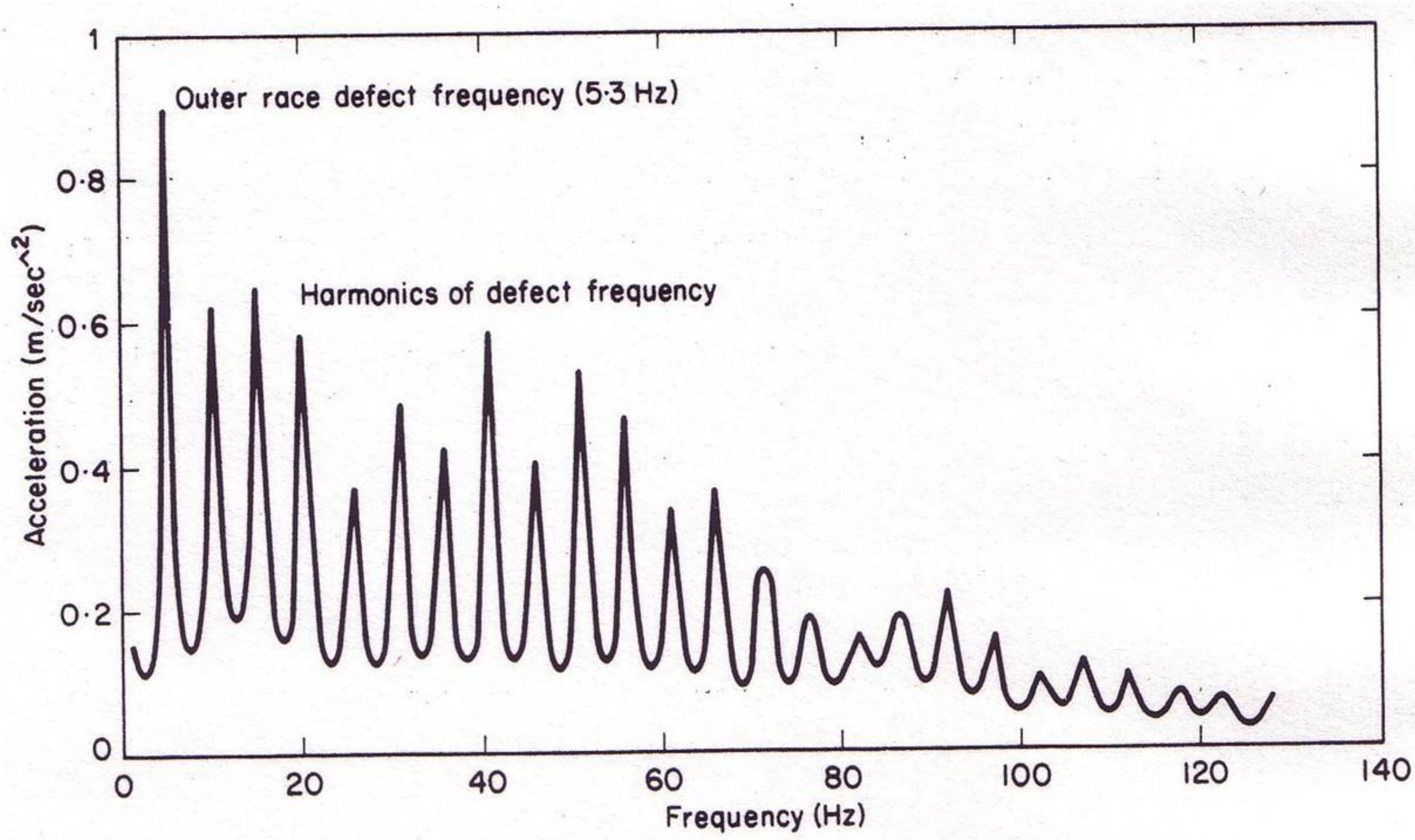
AR Model Parameters
(Model Order 60)

Example



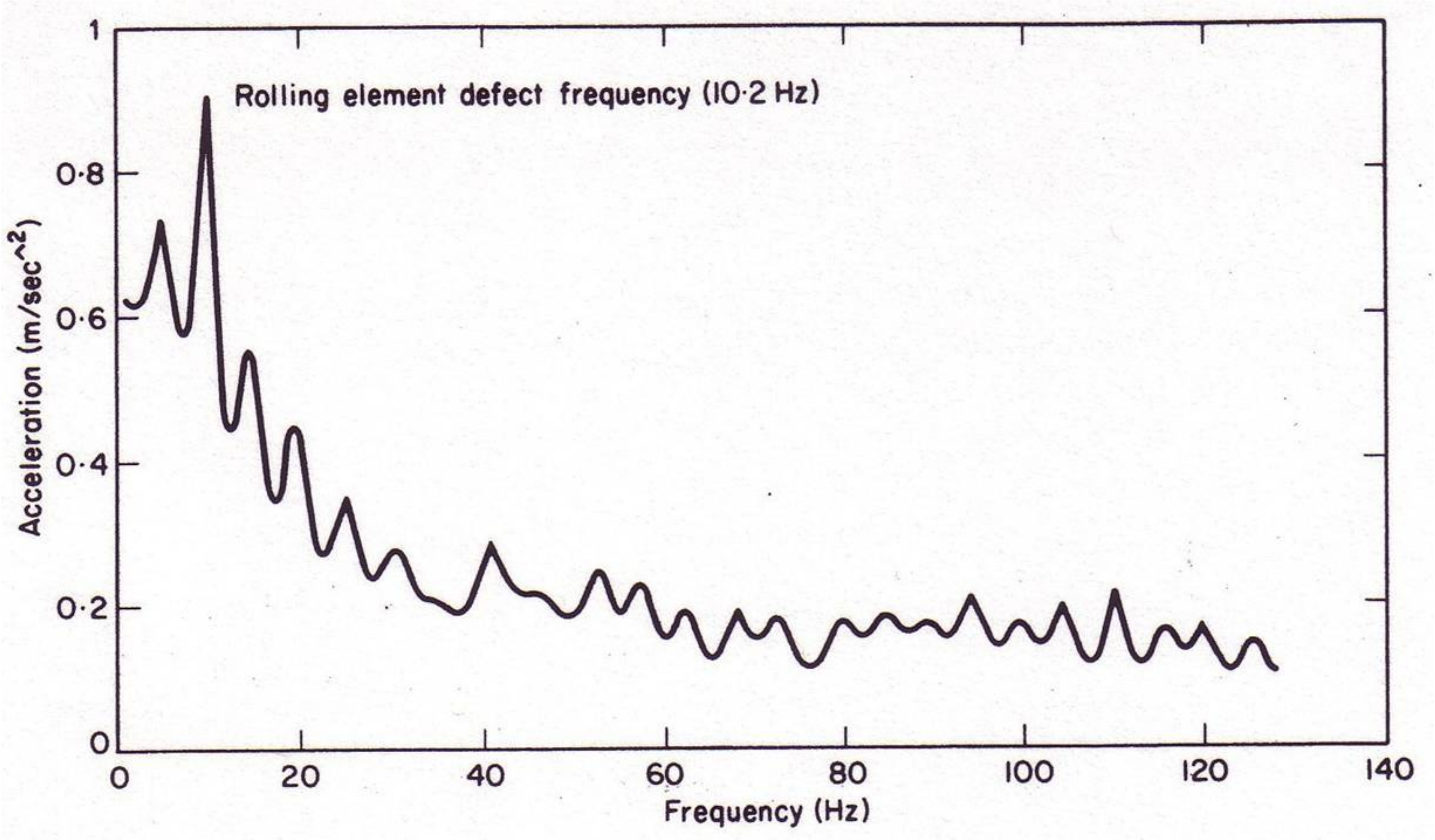
AR Frequency Spectrum – No Fault

Example



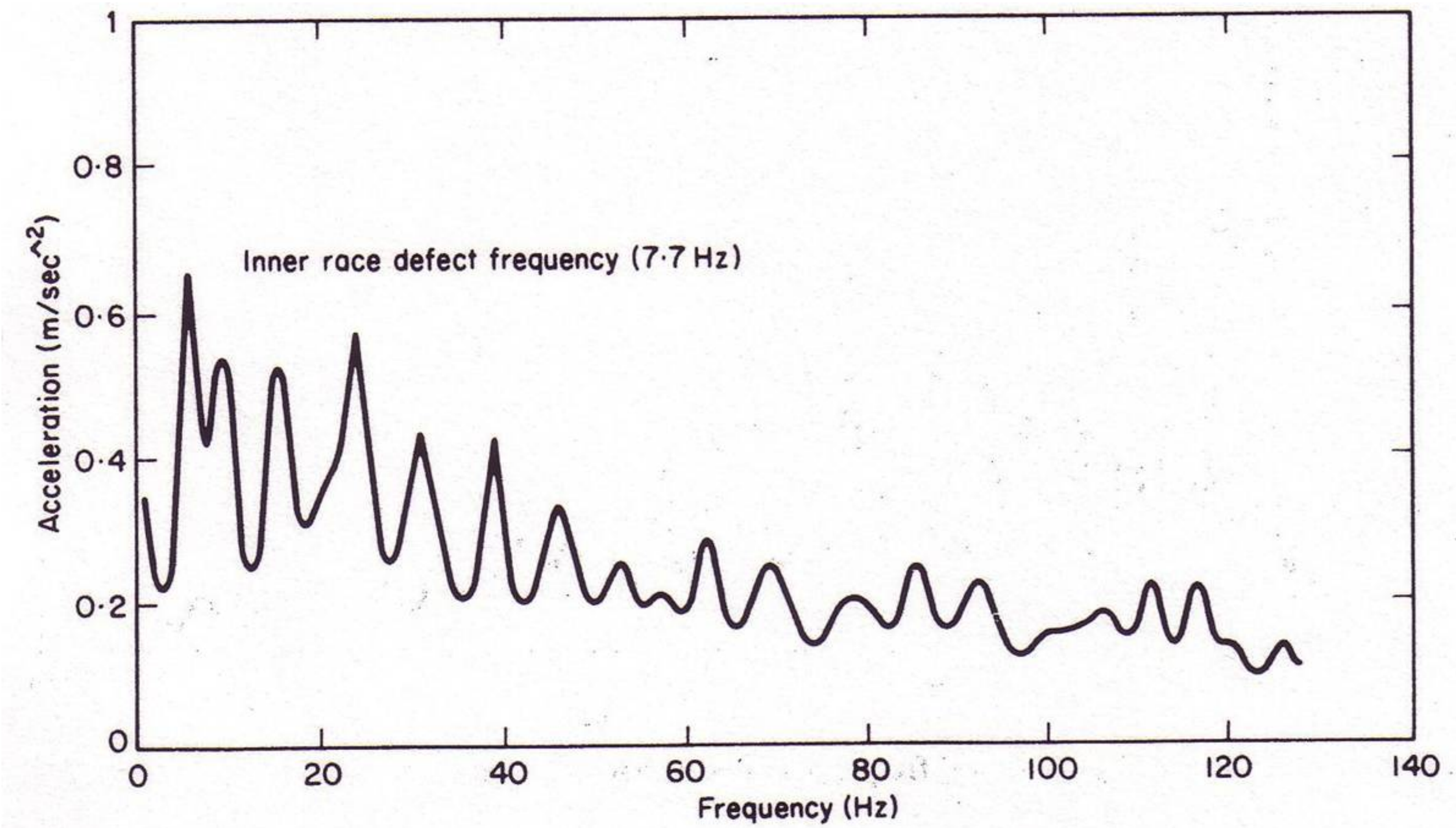
AR Frequency Spectrum – Outer Race Fault

Example



AR Frequency Spectrum – Rolling Element Fault

Example



AR Frequency Spectrum – Inner Race Fault

Using Parametric Models as Diagnostics Tools

Nearest Neighbour Classification

Different time series (vibration signals) can represent different conditions (faults), but these are often difficult to distinguish.

When converted to models they become easier to distinguish or group into sets with similar characteristics.

Nearest Neighbour Classification

The difference between two sets can be defined as

$$I(f_0, f_m) = \int f_0(x) \log \frac{f_0(x)}{f_m(x)} \, dx$$

Where f_o and f_m are the probability density functions of two different variables.

Nearest Neighbour Classification

When x_o and x_m are multidimensional, normally distributed variables, with mean values μ_o and μ_m and the covariance matrices Σ_o and Σ_m, then,

$$2I(f_0, f_m) = \log \frac{|\Sigma_m|}{|\Sigma_0|} + \mathrm{tr}\,\{\Sigma_m^{-1}\Sigma_0\} + \mathrm{tr}\,\{\Sigma_m^{-1}(\mu_0 - \mu_m)(\mu_0 - \mu_m)'\} - n$$

Where: |A| is the determinant of matrix A,
tr(A) is the trace of matrix A,
A^{-1} is the inverse of matrix A,
and A' is the transpose of matrix A.

Nearest Neighbour Classification

If only a sample of data is available, (exact probability density functions are not known) then an approximation can be made using

$$2d(x^{(0)}, x^{(m)}) = \log \frac{|\hat{\Sigma}_m|}{|\hat{\Sigma}_0|} + \mathrm{tr}\{\hat{\Sigma}_m^{-1}\hat{\Sigma}_o\} + \mathrm{tr}\{\hat{\Sigma}_m^{-1}(\hat{\mu}_0 - \hat{\mu}_m)(\hat{\mu}_0 - \hat{\mu}_m)'\} - n$$

Where the ^ represents estimated values based on the sample data.

Nearest Neighbour Classification

Given that each sample time series has a corresponding AR model, a dissimilarity number can be determined.

$$2d(x^{(0)}, x^{(m)}) = \frac{\log \hat{\sigma}_m^2}{\hat{\sigma}_0^2} + \frac{1}{\hat{\sigma}_m^2} \sum_{i=0}^{p_0} \sum_{k=0}^{p_m} a_0(i) a_m(k) C_0(k-i) - 1$$

Where: $\hat{\sigma}_j^2$ – sample covariance,

a_j – AR model parameter,

p_j – AR model order,

and C_o – estimated covariance function.

Nearest Neighbour Classification

$$C_j(k) = \frac{1}{n} \sum_{t=1}^{n-k} (x^{(j)}(t+k) - \hat{x})(x^{(j)}(t) - \hat{x})$$

$$\hat{x} = \frac{1}{n} \sum_{t=1}^{n} x^{(j)}(t); \, k = 0, 1, \ldots, p_j$$

Knowing $2d(x^{(o)}, x^{(m)})$ (the dissimilarity between $x^{(o)}$ and $x^{(m)}$) we can determine the probability of misclassification of a sample as

$$P_e = \exp\{-d(x^{(0)}, x^{(m)})\}$$

Nearest Neighbour Classification

Or, the probability of fault existence (the likelihood of a fault being present when comparing new samples with samples known to represent fault-free conditions.

$$P_{fe} = 100 \times (1 - P_e).$$

Experimental Results (using the same data as above)

Statistical distance measure between signals

Known faults	Samples: NOF	ORF	REF	IRF
NOF	**0·0115**	0·7374	0·5366	1·5494
ORF	0·3590	**0·0059**	1·2104	0·8434
REF	1·0450	1·3321	**0·0042**	0·1598
IRF	0·3062	0·2722	0·2782	**0·0065**

Experimental Results (using the same data as above)

Probability of fault existence (P_{fe}) *measure between signals*

	Samples			
Known faults	NOF	ORF	REF	IRF
NOF	**1·2**	52·2	41·5	78·8
ORF	30·2	**0·6**	70·2	57·0
REF	64·8	73·6	**0·4**	18·0
IRF	26·4	23·8	31·5	**0·7**

Experimental Results (using the same data as above)

Probability of fault existence (P_{fe})

	Sample signals			
Known condition	NOF	ORF	REF	IRF
NOF1	**1·2**	52·2	41·5	78·8
NOF2	**6·5**	54·2	74·3	78.0
NOF3	**4·9**	62·6	52·6	70·1

Nearest Neighbour Classification

Good example of a trending and classification parameter that can distinguish between fault-free conditions and various types of faults, as well as distinguish between each fault type.

However, this procedure needs known fault data.

And, what happens if faults are poorly distinguishable (early stages) or if the data is noisy.

Nearest Neighbour Classification

Note:

This is an example of supervised classification.

The user defines the specifics of classification (# of classes, etc.).

Some prior knowledge of the system and signals is required.

Inductive Inference Classification

Reducing the data to a common form removes redundant/unneeded data.

Classification based on the length of description of a data set is then possible.

Example: classify people using as few parameters as possible.

Physical atributes
- sex
- height/weight
- hair colour
- eye colour, etc.

Inductive Inference Classification

By randomly dividing the sample into groups, then shifting members between groups we can zero in on the shortest (optimum encoded) description of all the groups (spectra).

Descriptions based on sample statistics.

This is an example of unsupervised classification.

Mechefske, C.K. and D. Plummer, **"Gradual Deterioration Trending and Fault Diagnosis in Cutting Tools Using Inductive Inference Classification",** *Int. Journal of Machine Tools Manufacture, Design, Research and Application*, Vol.34, No.4, p591-601, 1994.

Inductive Inference Classification

Example

Class A		Class B		Class C	
Thing serial number	Attribute value	Thing serial number	Attribute value	Thing serial number	Attribute value
1	72.86	11	815.30	21	25817.0
2	−137.75	12	985.90	22	17286.1
3	−27.38	13	1029.58	23	24142.2
4	−132.29	14	888.58	24	10222.9
5	31.80	15	932.66	25	9785.0
6	−51.12	16	1083.05	26	23177.3
7	20.10	17	1311.56	27	35161.2
8	160.65	18	511.14	28	27494.2
9	84.76	19	780.36	29	14923.9
10	26.81	20	1224.53	30	28853.5
Mean	4.84	Mean	956.27	Mean	21686.33
standard deviation	94.30	standard deviation	229.64	standard deviation	8367.48

Data to be Classified – Shown in True Classes.

Inductive Inference Classification

Example

Parameter described	Description length estimation equation (Units: Nits)
Relative abundance of a class	$-\log_2\left(\frac{n}{t}\right)$
Distribution parameter for each class (Mean)	$\log_2\left(\frac{\sigma}{\sqrt{n/12}}\right)$
Distribution parameter for each class (standard deviation)	$\log_2(\sigma\sqrt{n(n-1)}\sqrt{6/(n-1)})$
Attribute values for each thing	$-\log_2\left(\frac{1}{2\pi\sigma}\,(e^{-(x-m^2/2\sigma^2)})\right)$

n is the number of things in a class; x is the attribute value of any particular thing; m is a class mean; σ is a class standard deviation.

Data Description Length Estimation Equations

Inductive Inference Classification

Example

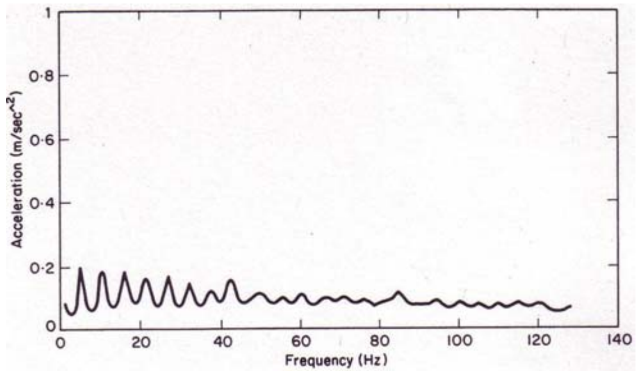
Classification	Estimated data description length (Nits)		
	Class definition	Attribute values	Total
One class	25.13	464.20	489.33
Three random classes	84.71	460.31	545.02
Two classes (A and C combined)	43.83	410.65	454.49
Three true classes	59.37	333.58	392.95

Estimated Data Description Lengths for Various Classifications.

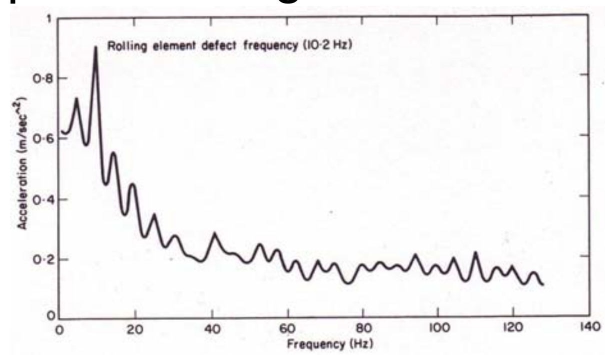
Inductive Inference Classification

Experimental Results – Low Speed Rolling Element Bearings

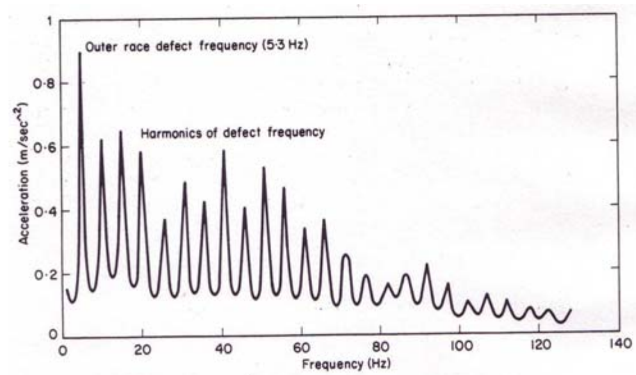
NOF



REF

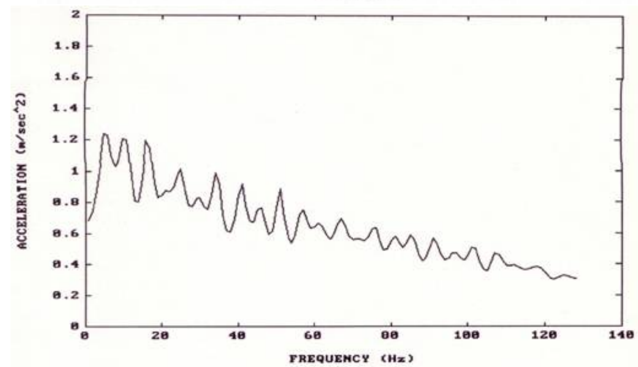


ORF

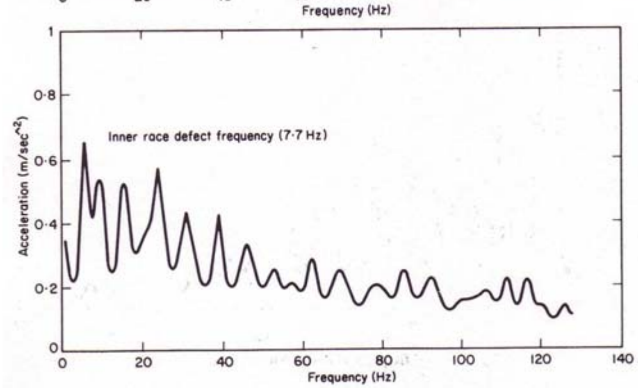


COM1

ORF & REF



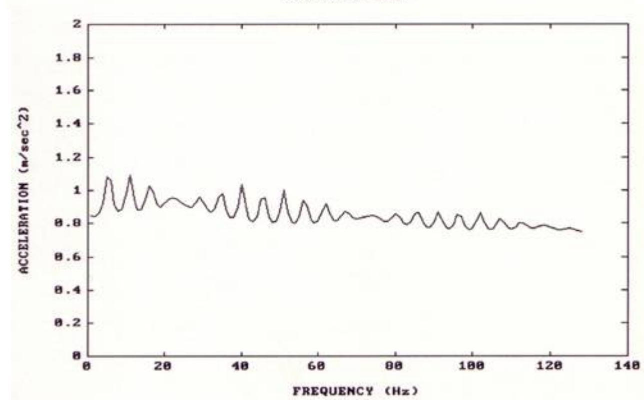
IRF



COM2

ORF, REF

& IRF



Inductive Inference Classification

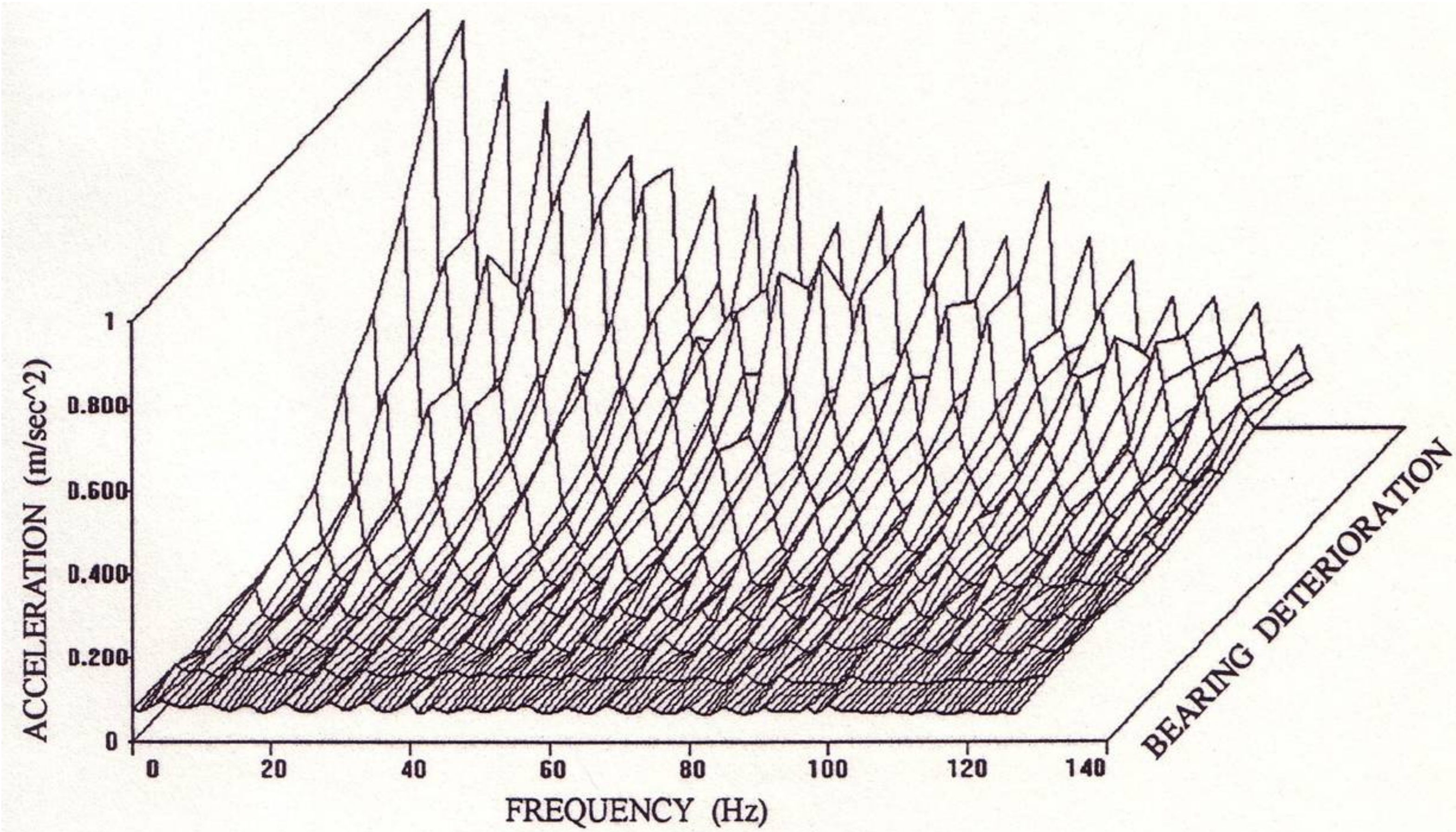
Experimental Results – Low Speed Rolling Element Bearings

True class	Thing serial number—Snob class serial				
No fault	1–01	1–02	1–03	1–04	1–05
	1–06	1–07	1–08	1–09	1–10
	1–11	1–12	1–13	1–14	1–15
Outer Race Fault	2–16	2–17	2–18	2–19	2–20
	2–21	2–22	2–23	2–24	2–25
	2–26	2–27	2–28	2–29	2–30
Inner Race Fault	3–31	3–32	3–33	3–34	3–35
	3–36	3–37	3–38	3–39	3–40
	3–41	3–42	3–43	3–44	3–45
Rolling Element Fault	4–46	4–47	4–48	4–49	4–50
	4–51	4–52	4–53	4–54	4–55
	4–56	4–57	4–58	4–59	4–60
Fault Combination 1	5–61	5–62	5–63	5–64	5–65
	5–66	5–67	5–68	5–69	5–70
	5–71	5–72	5–73	5–74	5–75
Fault Combination 2	6–76	6–77	6–78	6–79	6–80
	6–81	6–82	6–83	6–84	6–85
	6–86	6–87	6–88	6–89	6–90

Classification results for all fault types.

Inductive Inference Classification

Experimental Results – Low Speed Rolling Element Bearings



AR model based frequency spectra from low speed rolling element bearing gradually deepening outer race fault.

Inductive Inference Classification

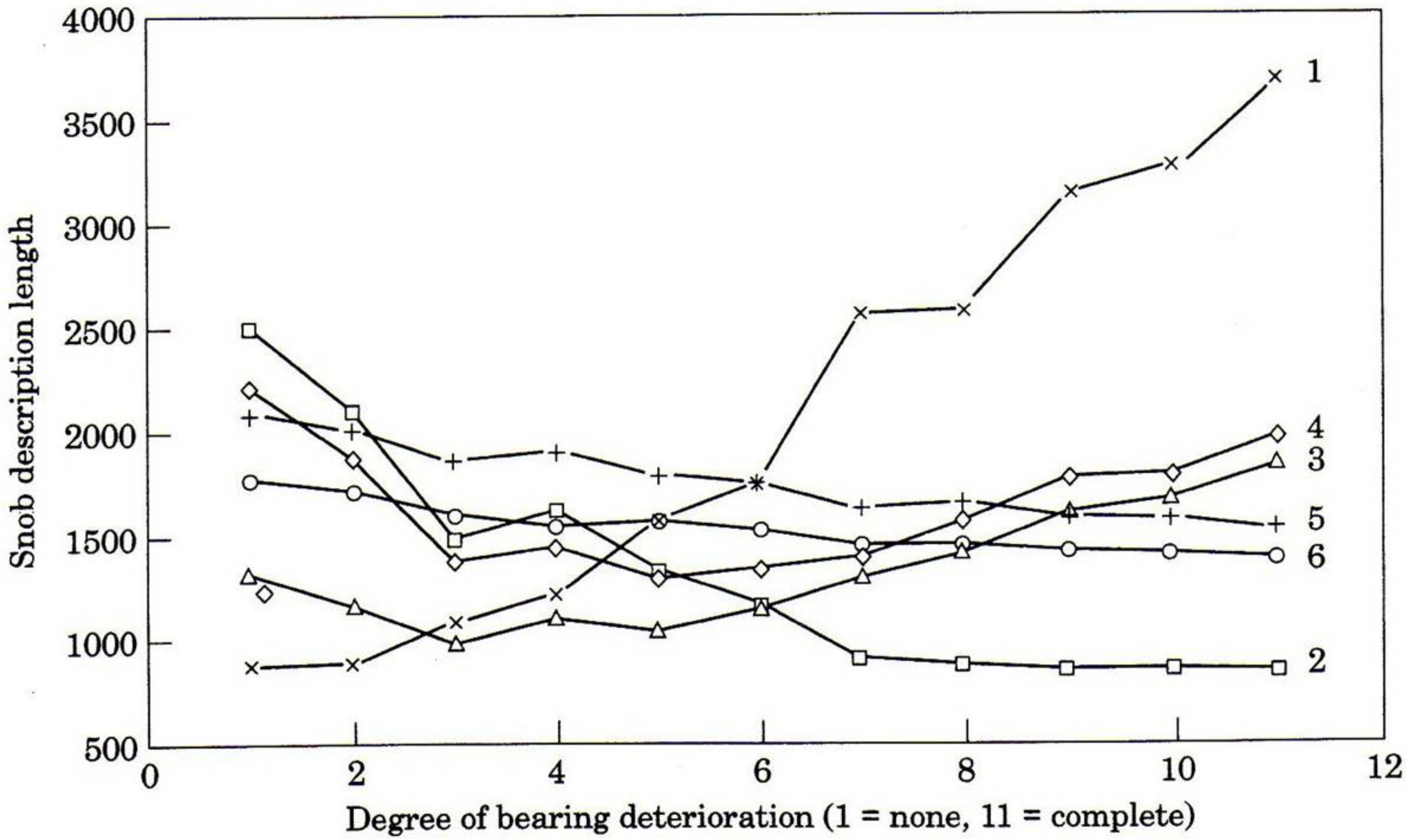
Experimental Results – Low Speed Rolling Element Bearings

	Known Reference Spectra Description Length (Nits)					
Test No.	No. fault	Outer race fault	Rolling element fault	Inner race fault	Fault combination 1	Fault combination 2
1	881.7	2507.0	1325.3	2217.4	2102.1	1774.0
2	876.2	2105.4	1161.7	1884.3	2026.8	1725.1
3	1086.9	1495.9	988.4	1377.3	1862.2	1611.2
4	1223.8	1632.4	1111.8	1457.6	1915.9	1552.2
5	1593.7	1349.3	1048.8	1307.5	1815.9	1583.8
6	1771.2	1183.9	1131.7	1341.0	1766.0	1549.5
7	2572.6	910.4	1309.9	1405.8	1645.8	1463.3
8	2596.8	883.8	1426.2	1587.3	1667.2	1477.4
9	3156.8	863.6	1628.2	1781.8	1609.2	1434.3
10	3293.2	871.3	1703.6	1810.6	1598.7	1429.6
11	3713.8	855.6	1878.0	1993.4	1563.8	1403.5
True Fault Average	752	886	867	919	1060	975

Estimated data description lengths vs. gradual development of an outer race fault.

Inductive Inference Classification

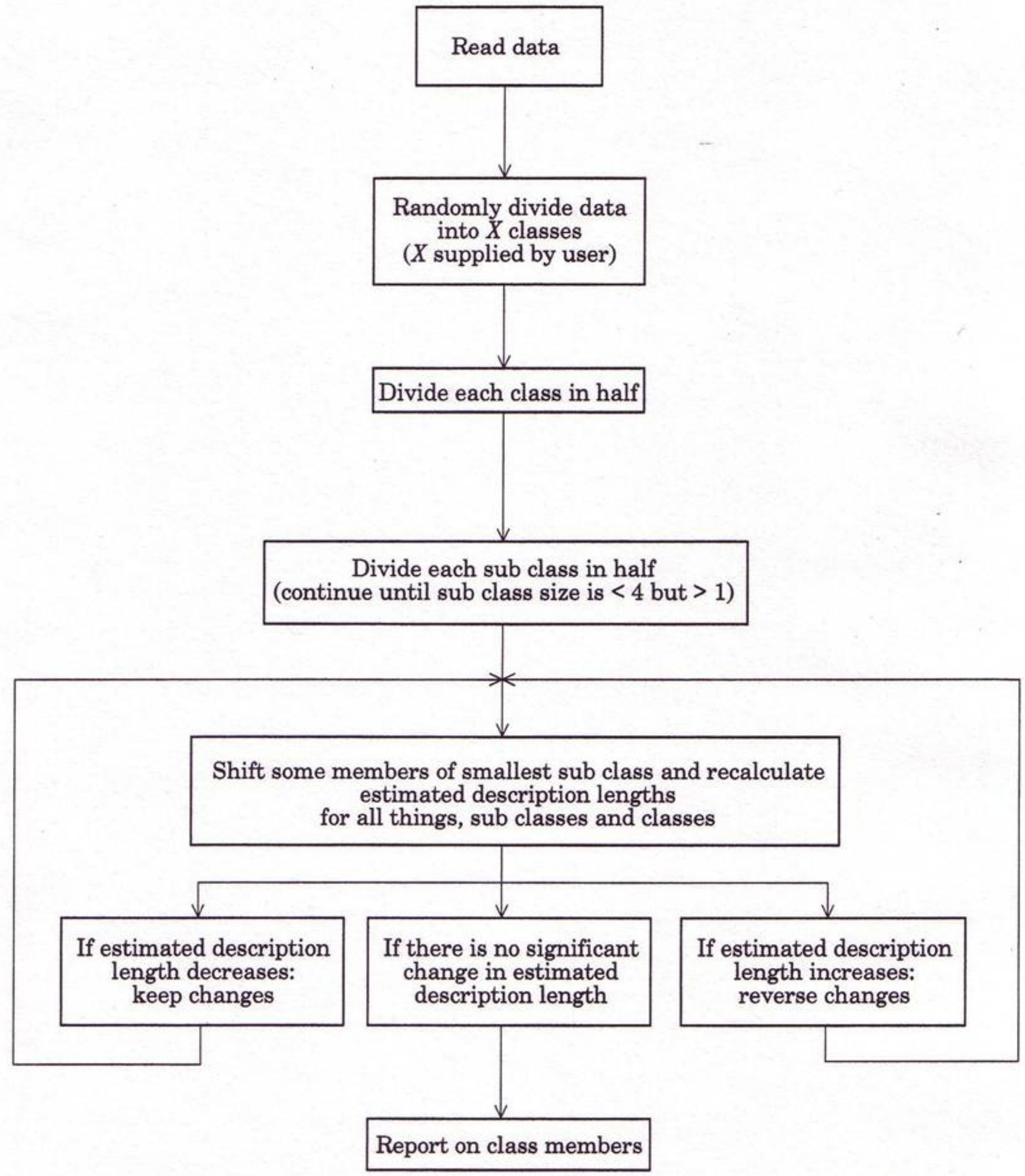
Experimental Results – Low Speed Rolling Element Bearings



Estimated data description lengths vs. gradual development of an outer race fault. (1 – NOF, 2 – ORF, 3 – REF, 4 – IRF, 5 – COM1, 6 – COM2)

Inductive Inference Classification

Flowchart of procedural steps.



Inductive Inference Classification

Experimental Results – Cutting Tool Deterioration

Accelerated wear rate tests 1 – 4

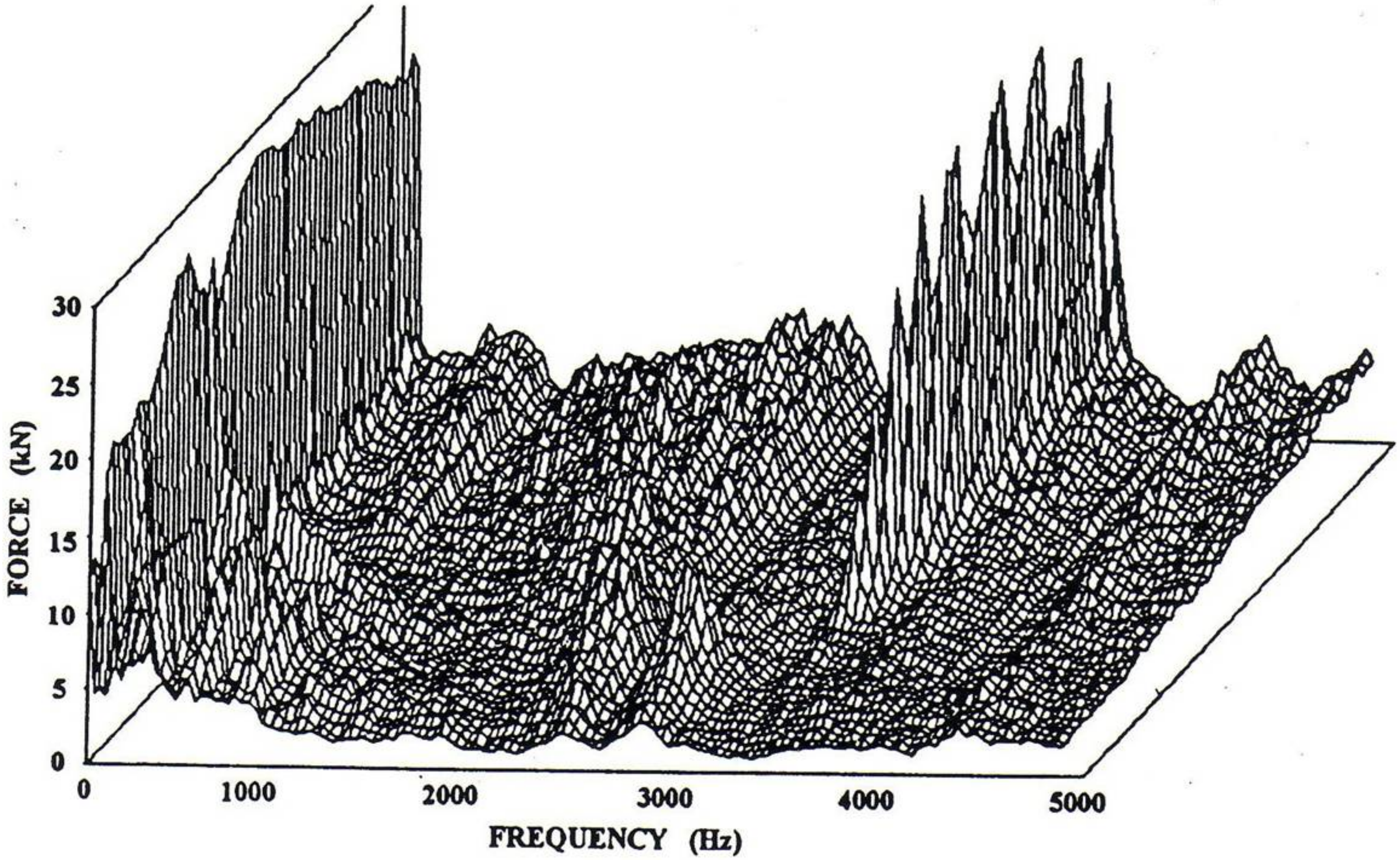
Regular wear rate test – 5

Test No.	Depth of cut (mm)	Feed rate (mm/rev)	Cut speed (m/min)	RPM	Cut length (min:s)
1	2.15	0.20	150	397	3:52
2	2.15	0.20	150	400	4:41
3	2.15	0.20	150	404	4:16
4	2.15	0.20	150	410	4:38
5	1.52	0.25	70	200	44:24

Feed rate and speed conditions

Inductive Inference Classification

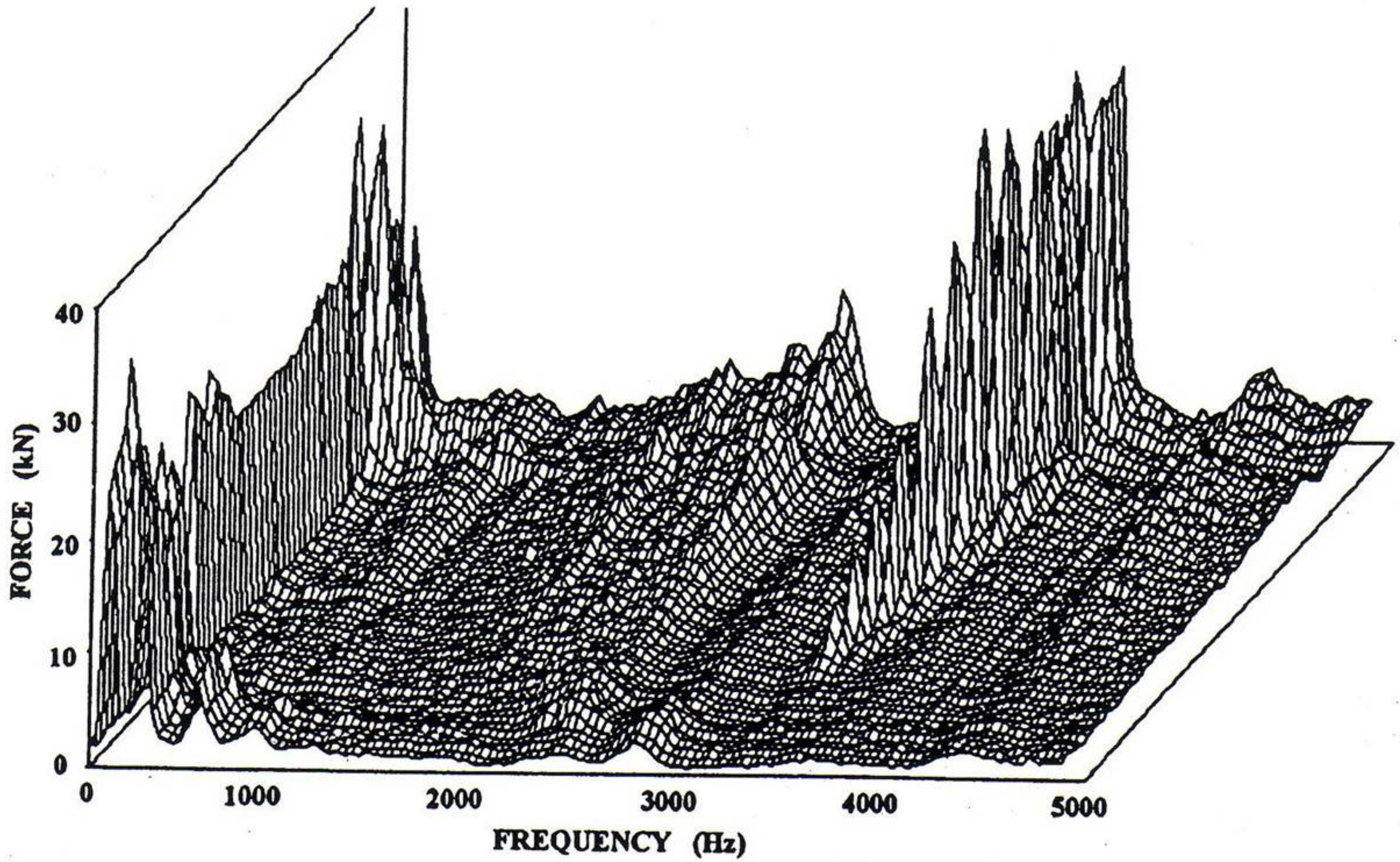
Experimental Results – Cutting Tool Deterioration



AR frequency spectra for test # 1.

Inductive Inference Classification

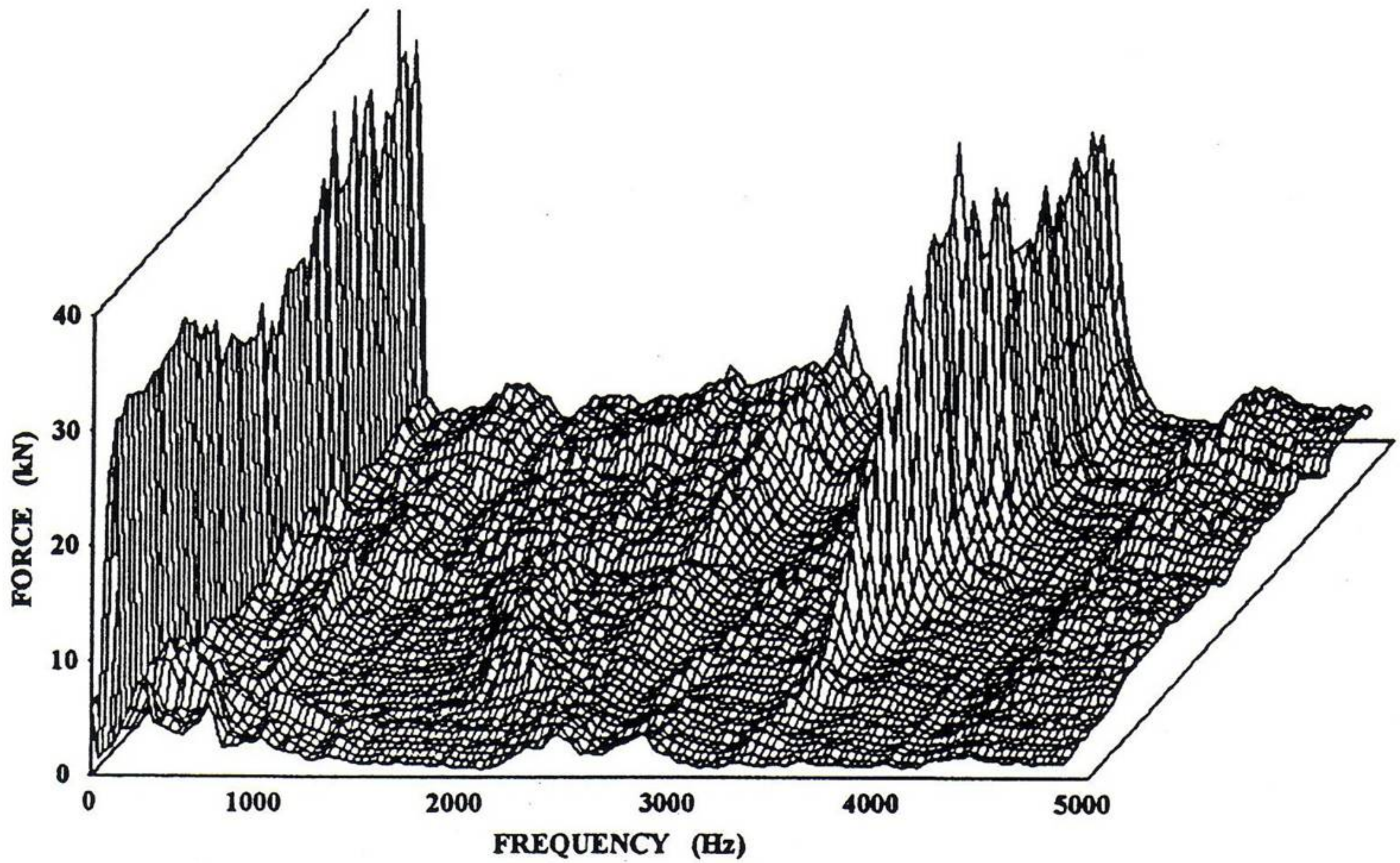
Experimental Results – Cutting Tool Deterioration



AR frequency spectra for test # 2.

Inductive Inference Classification

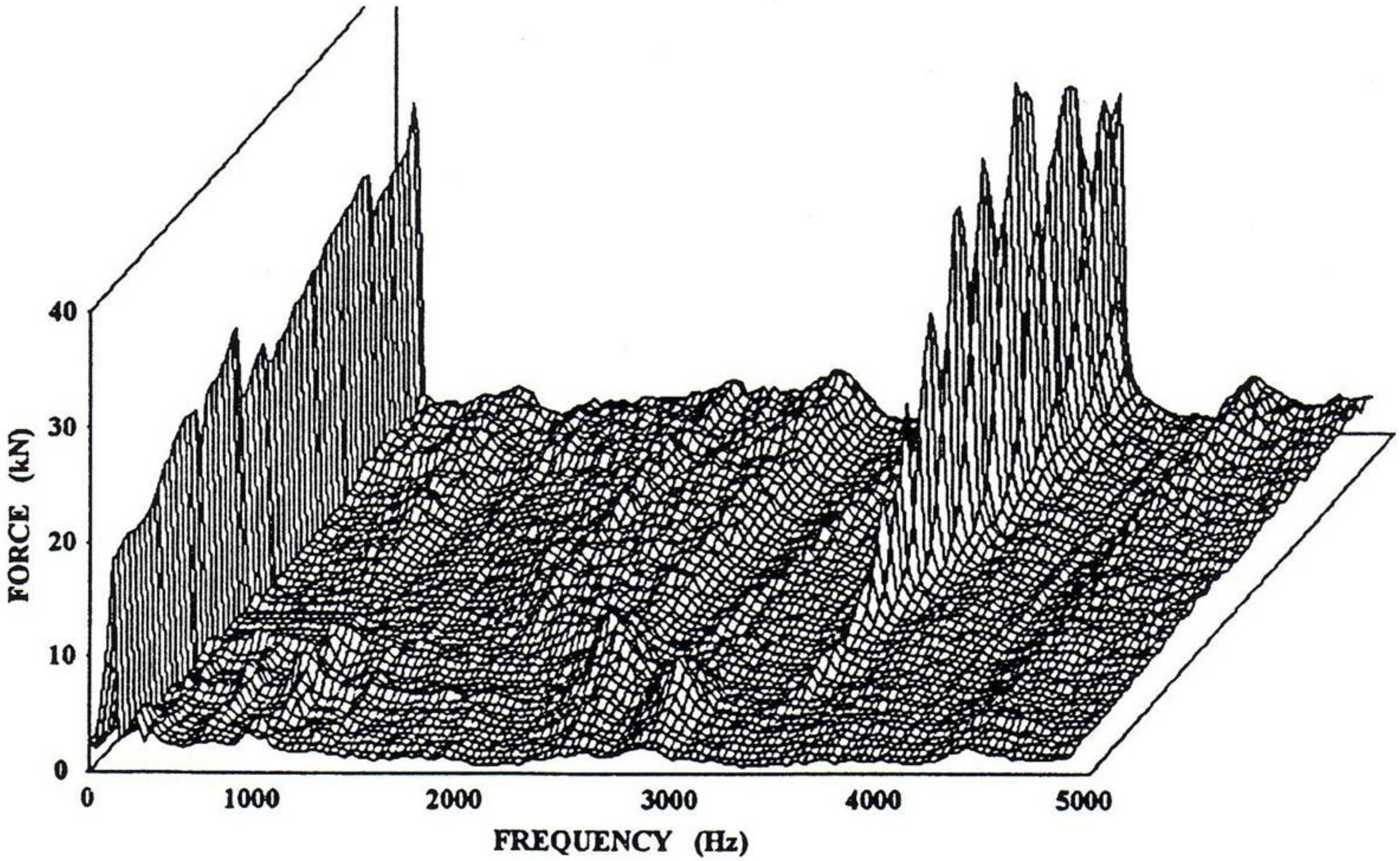
Experimental Results – Cutting Tool Deterioration



AR frequency spectra for test # 3.

Inductive Inference Classification

Experimental Results – Cutting Tool Deterioration



AR frequency spectra for test # 4.

Inductive Inference Classification

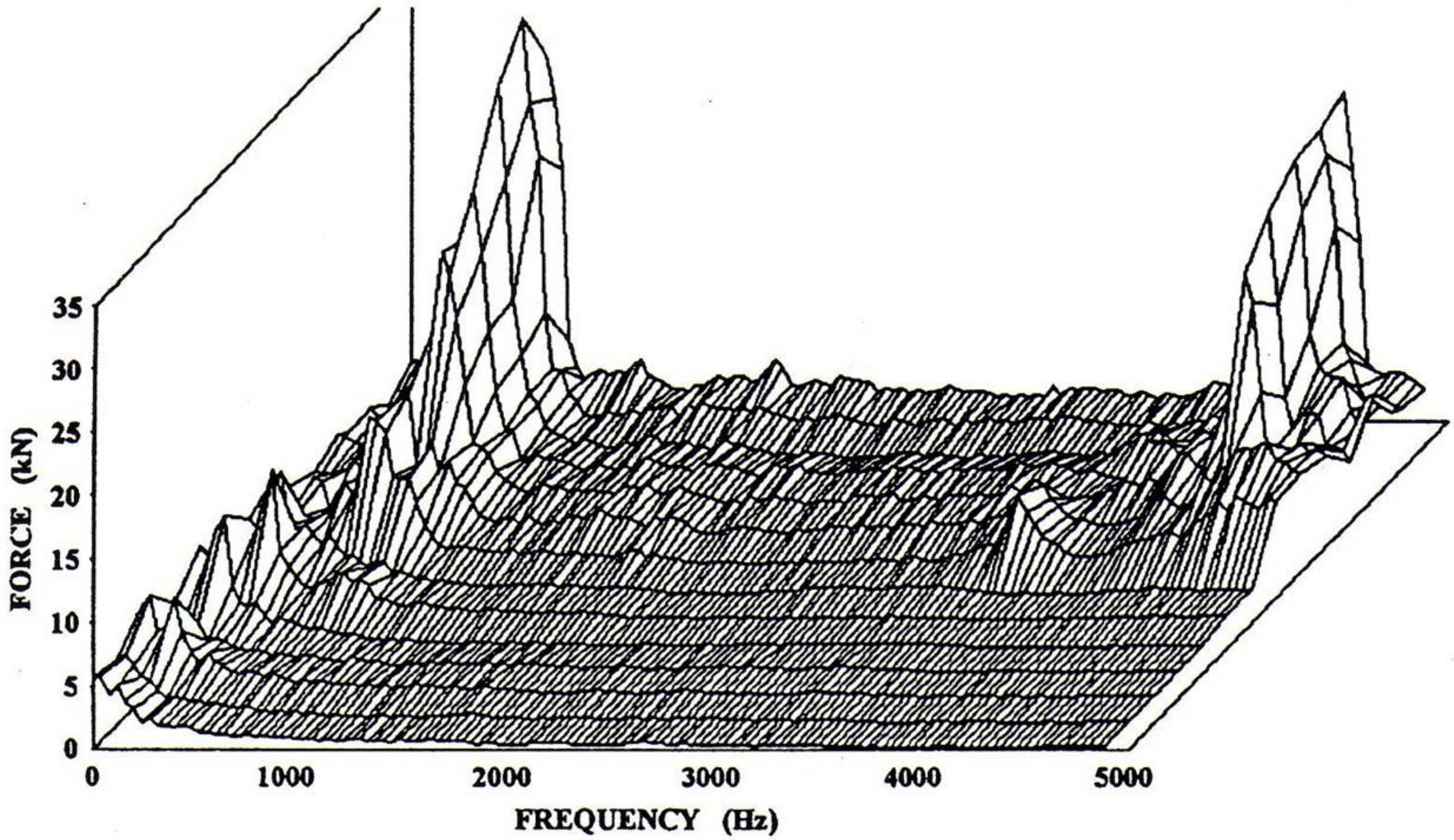
Experimental Results – Cutting Tool Deterioration

True class	Thing serial number	Snob class serial number
Minimal wear	1–01 → 1–20 2–01 → 2–20 3–01 → 3–16 4–01 → 4–22	1
Moderate wear	1–21 → 1–30 2–21 → 2–28 3–17 → 3–27 4–23 → 4–33	2
Advanced wear	1–28 → 1–60 2–29 → 2–60 3–30 → 3–60 4–34 → 4–60	3

Classification results – accelerated wear rate test data.

Inductive Inference Classification

Experimental Results – Cutting Tool Deterioration



AR frequency spectra for test # 5 (normal wear rate).

Inductive Inference Classification

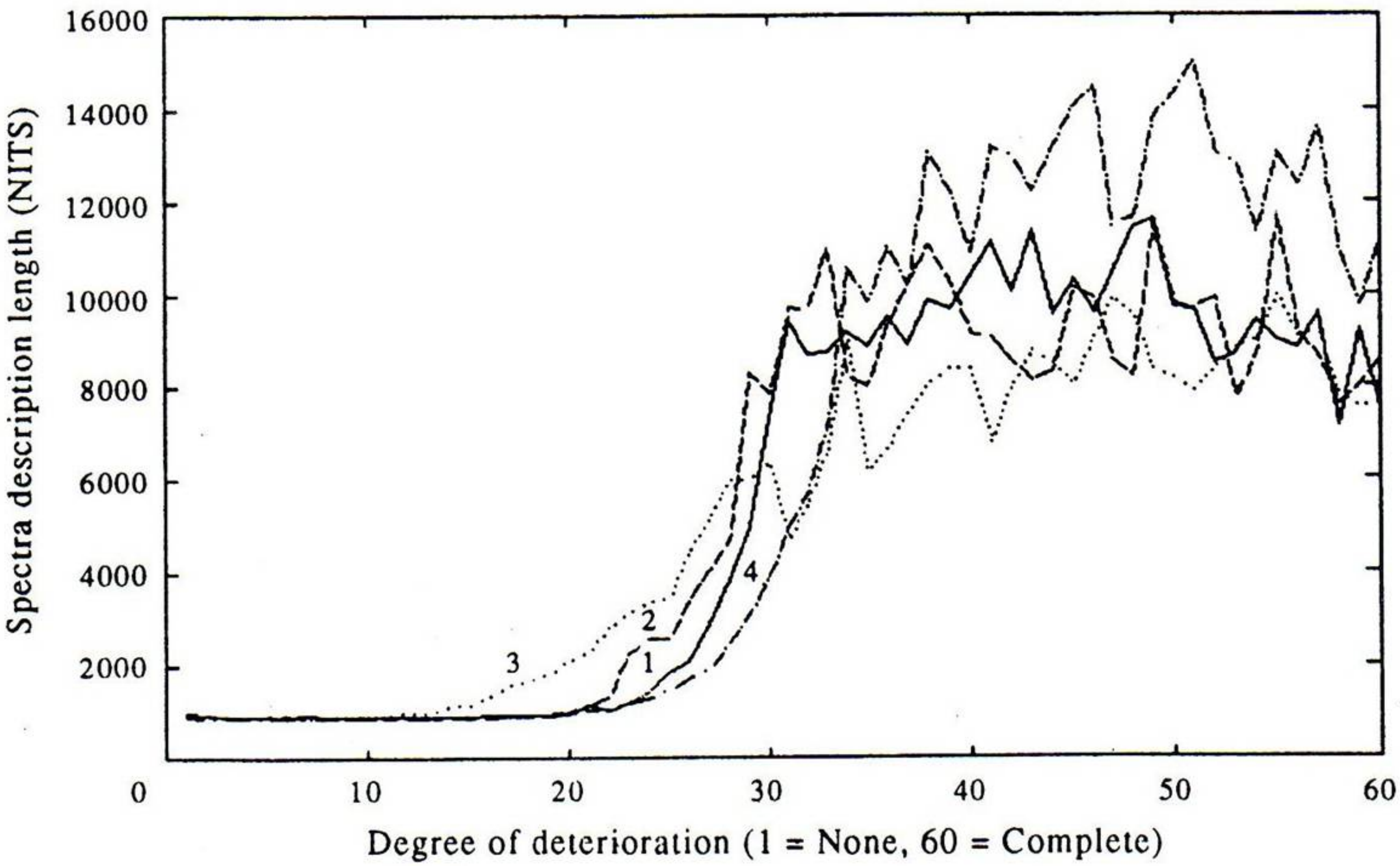
Experimental Results – Cutting Tool Deterioration

True class	Thing serial number	Snob class serial number
Minimal wear	1–1 → 1–7	1
Moderate wear	1–8 → 1–10	2
Advanced wear	1–11 → 1–14	3

Classification results – normal wear rate test data.

Inductive Inference Classification

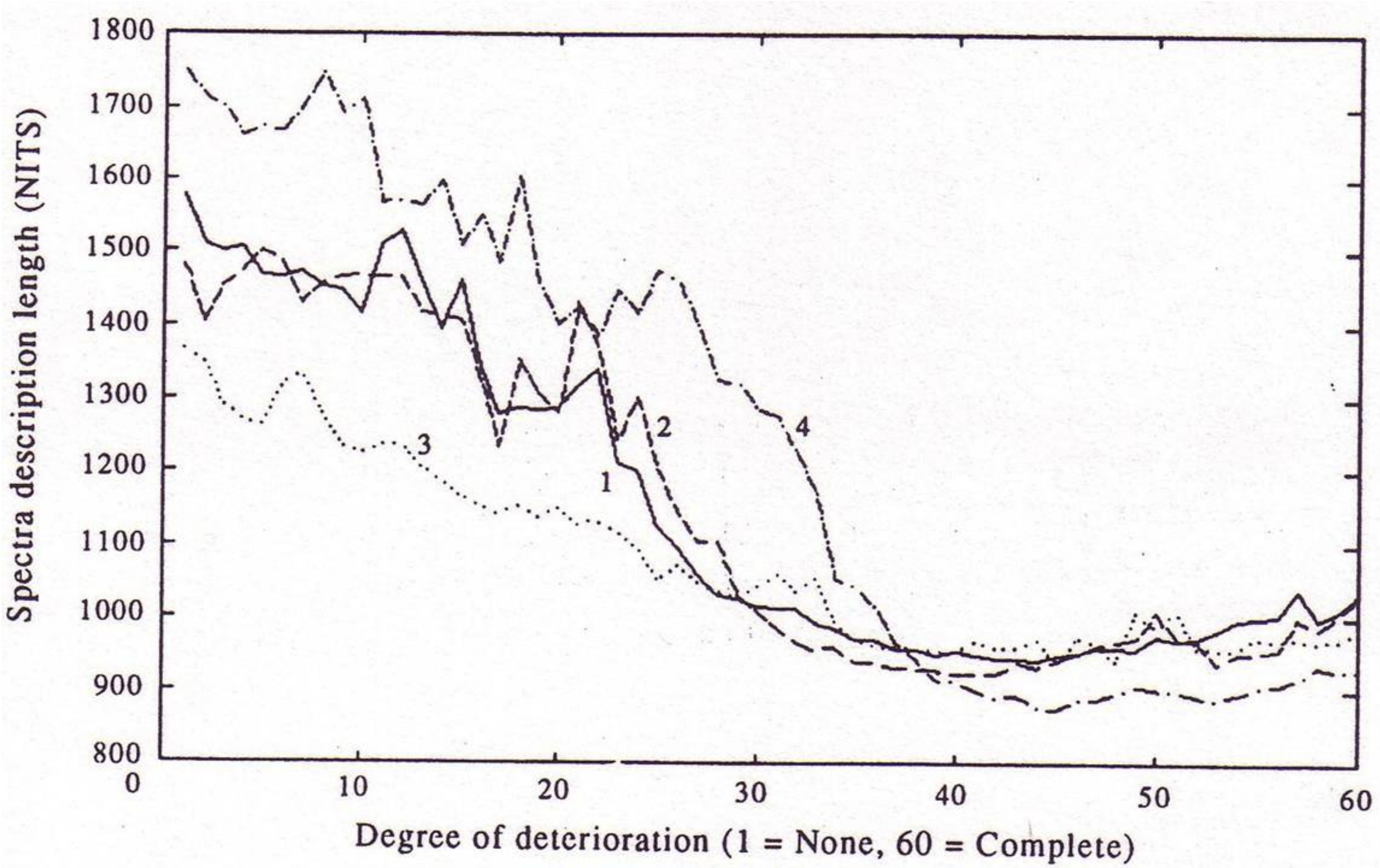
Experimental Results – Cutting Tool Deterioration



Estimated data description lengths vs. gradual deterioration. Baseline – minimal wear. (1 – test #1, 2 – test #2, 3 – test #3, 4 – test #4)

Inductive Inference Classification

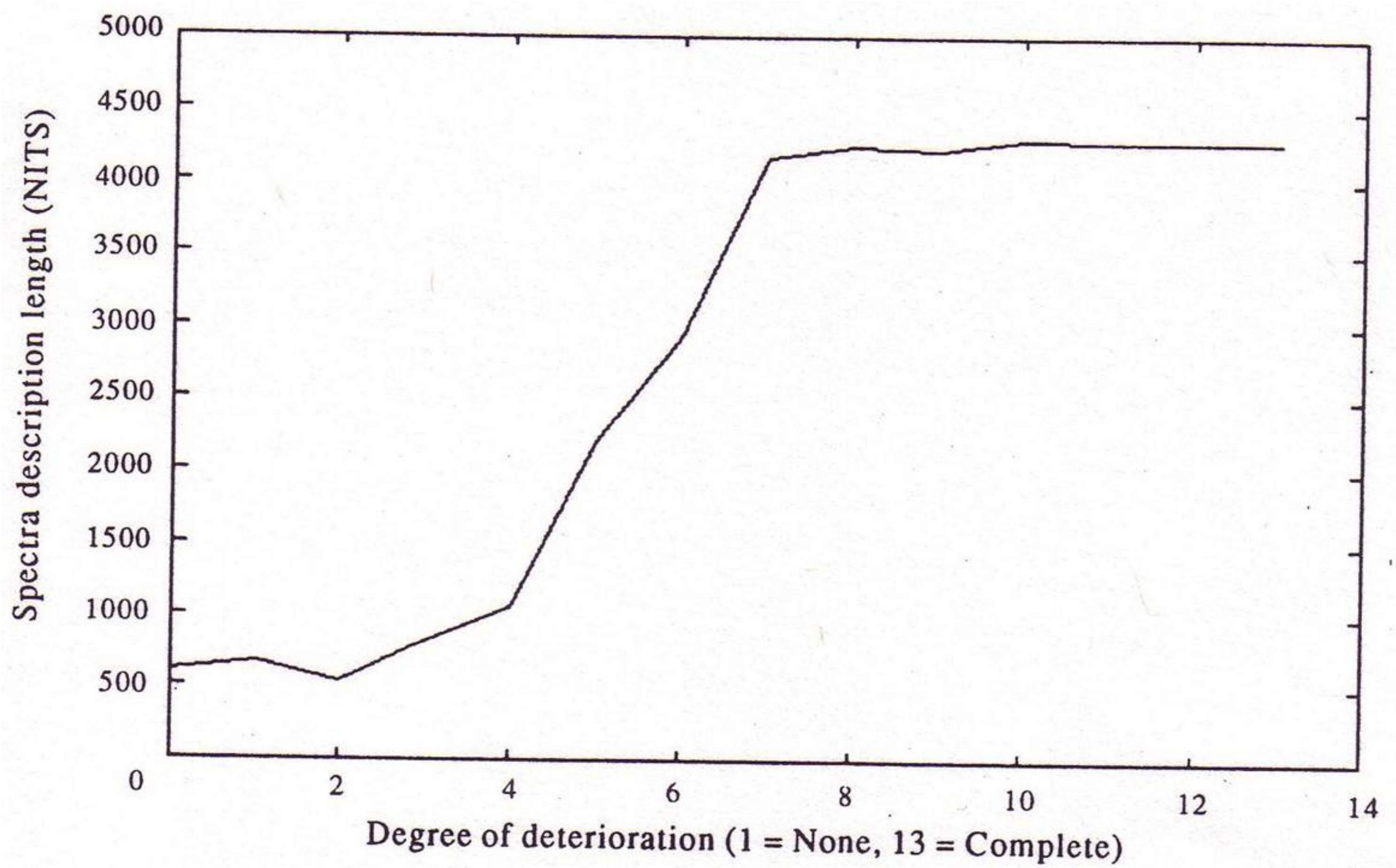
Experimental Results – Cutting Tool Deterioration



Estimated data description lengths vs. gradual deterioration. Baseline – advanced wear. (1 – test #1, 2 – test #2, 3 – test #3, 4 – test #4)

Inductive Inference Classification

Experimental Results – Cutting Tool Deterioration



Estimated data description lengths vs. gradual deterioration.
Baseline – minimal wear. (test #5 - normal wear rate)

End