Fault diagnosis and prognosis using wavelet packet decomposition, Fourier transform and artificial neural network

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Outline

- Motivation
- Data acquisition experiment
  - Setup
  - Procedure
- Method Explanation
  - Wavelet Transformation
    - Continuous wavelet transform
    - Discrete wavelet transform
    - Wavelet packet decomposition

Outline

- Method Explanation
  - Fast fourier transform
  - Back-propagation
- Case Study
  - Experiment
  - Results
- Discussions & Feature Work

Motivation

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- Maintenance improvement
  - 80% of downtime is spent to locate the source of fault
  - 1 min downtime may cause ~20.000$
  - Early fault diagnosis is important to prevent major malfunctions
- No Literature combine and integrating the three techniques: WPD, FFT and ANN(BP)

Experiment Hardware

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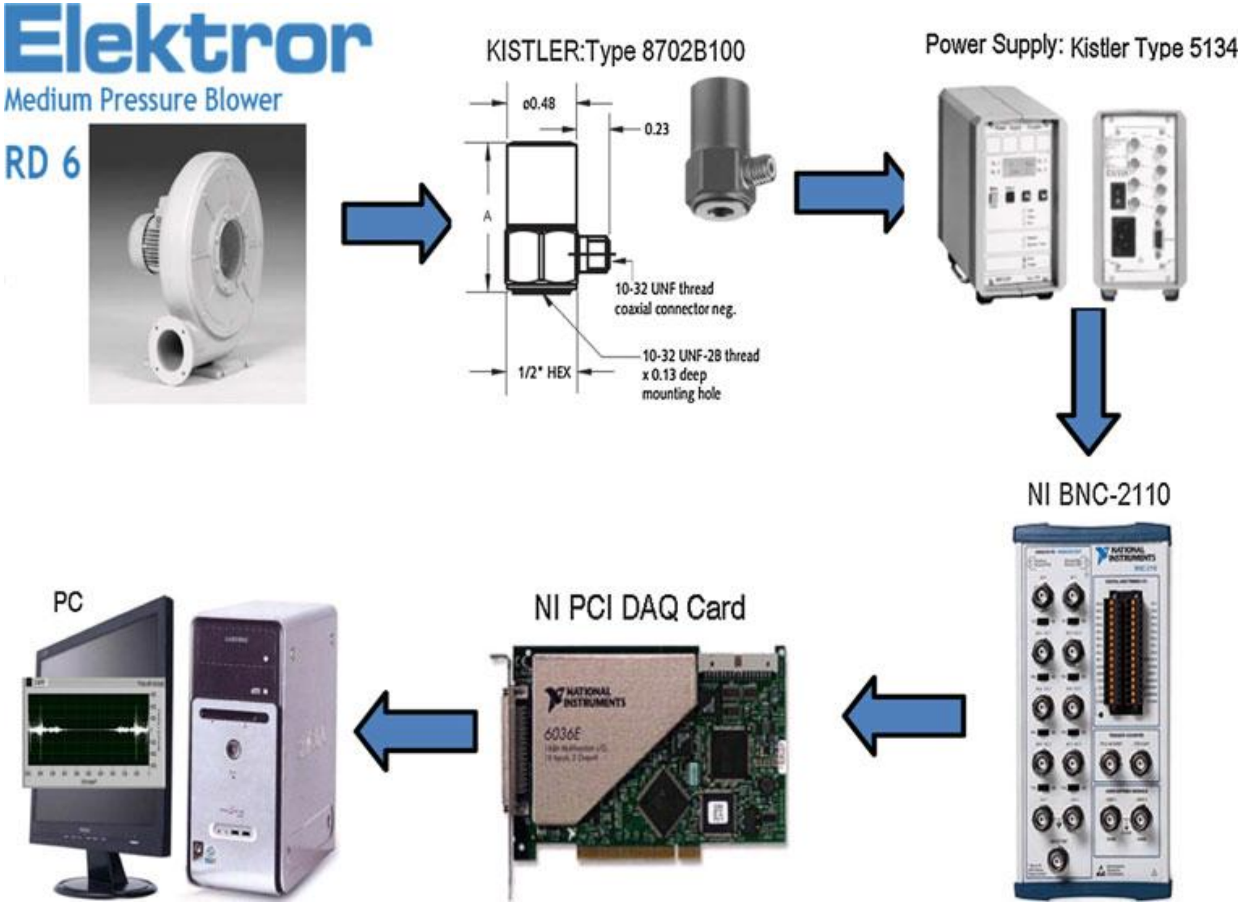
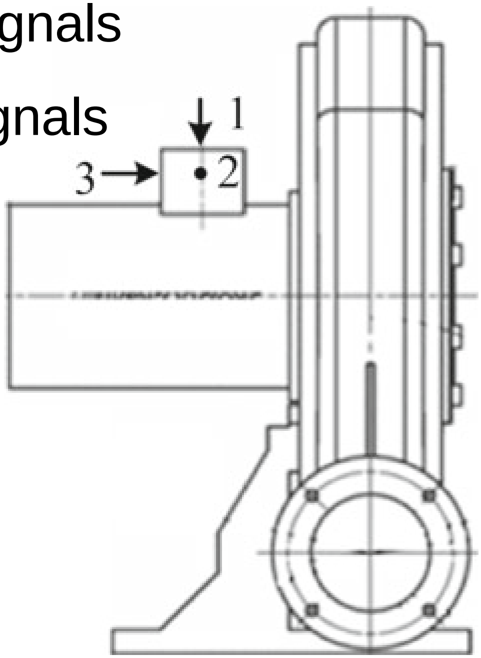
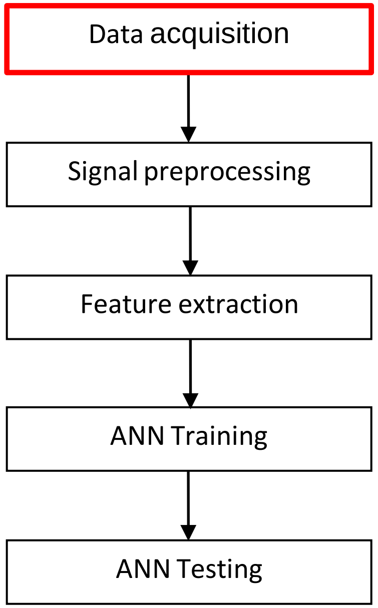


Data acquisition
↓
Signal preprocessing
↓
Feature extraction
↓
ANN Training
↓
ANN Testing

Experiment – The Setup

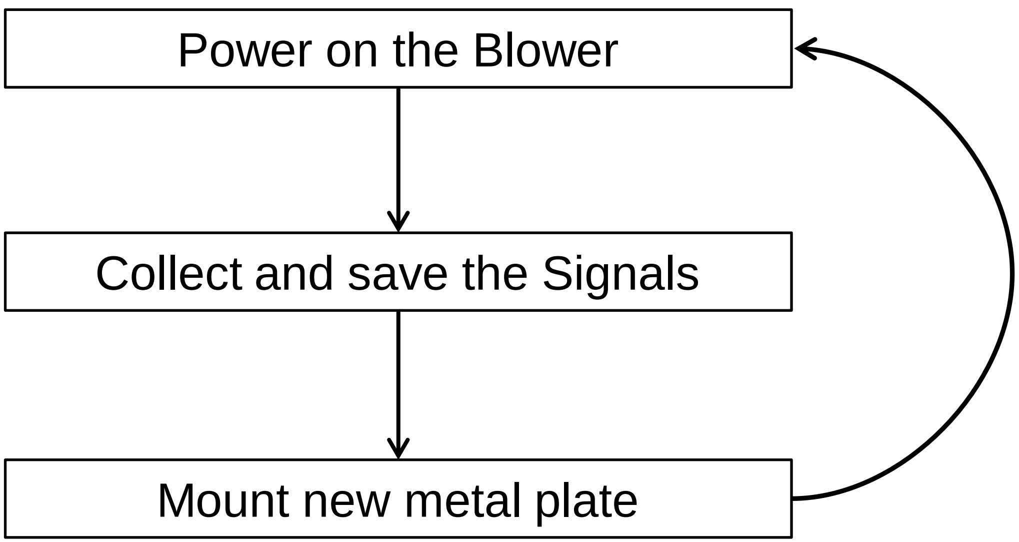
- One Blower
- Three Vibration Sensor
- Mounted on three Directions
- Sensors collect the Vibrations Signals
- Extract the Features from the Signals

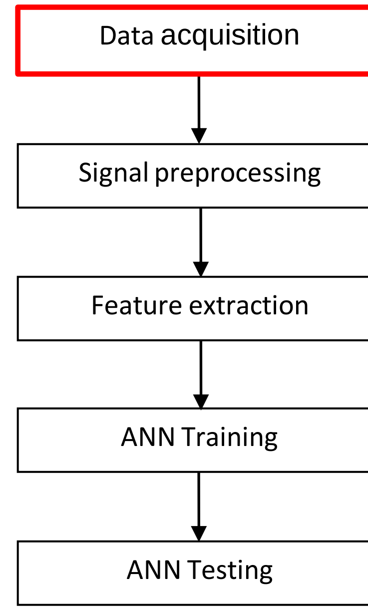




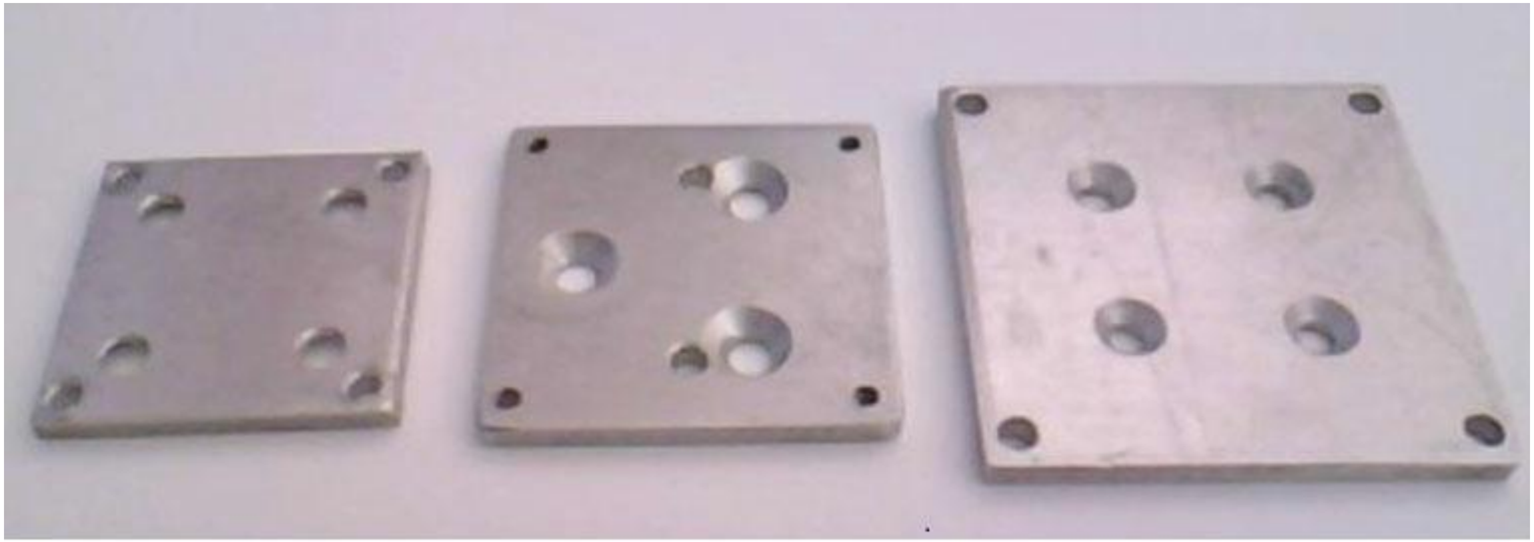
Experiment – Data acquisition

- Four different degradation simulated
- Simulated from the metal plates
- Grades from 0, 0.3, 0.6, 1





Metal plates



Vibration Signal Example

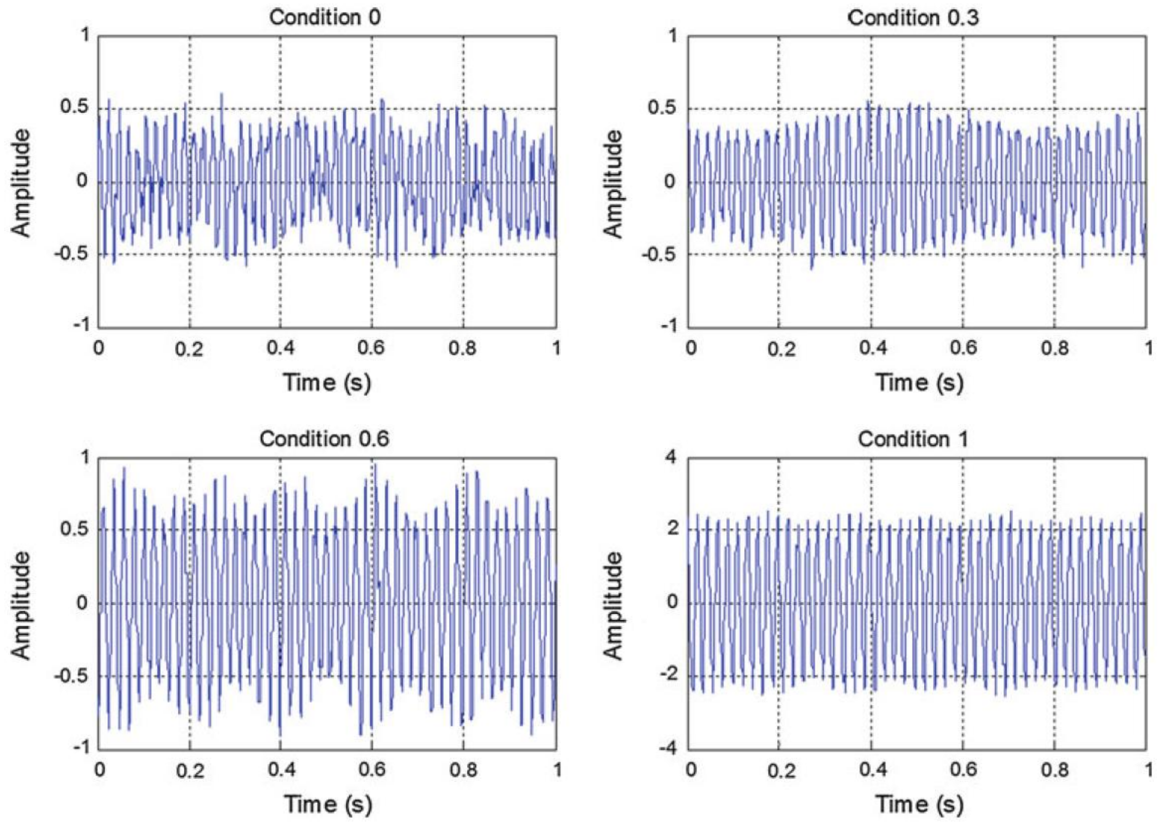
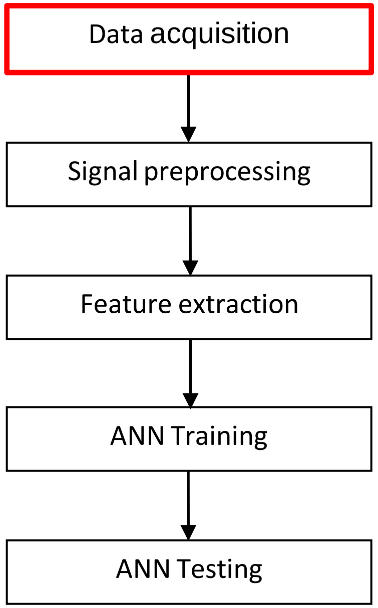


Fig. 4 Raw signals with different degradations



CWT & DWT

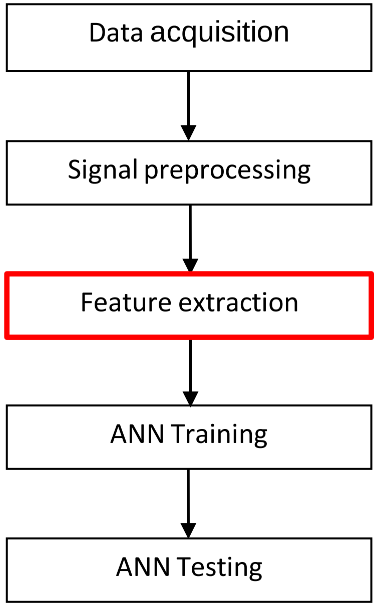
- Divide a continuous-time function into wavelets
- Very good time and frequency location
- A is the scale value and B is the translational value

$$CT(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{(a,b)}(t)dt \qquad \psi^{*}_{(a,b)}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right)$$

- Complex Conjugate is discretely sampled

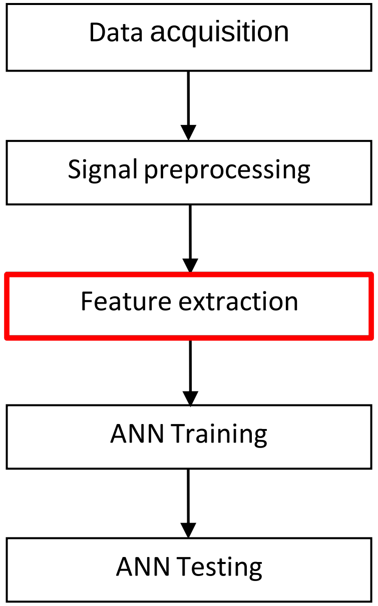
$$DT(a,b) = \int_{-\infty}^{\infty} x(t)\psi^{*}_{(j,k)}(t)dt \qquad \psi^{*}_{(j,k)}(t) = \frac{1}{\sqrt{2^{j}}}\,\psi\left(\frac{t-2^{j}k}{2^{j}}\right)$$

- Two filters one for low frequencies(Approximation)
- One for high frequencies(Details)



Wavelet packet decomposition

- Differences to DWT:
  - DWT only breaks up as approximation versions
  - Frequency bandwidth is in each resolution the same
- Decomposition don´t lose or increase information
- Good in decomposing, denoising, signal analysis
- Analysis from non stationary signals
- The lost information from the low frequency
- Was captured by the high frequency



Wavelet packet decomposition

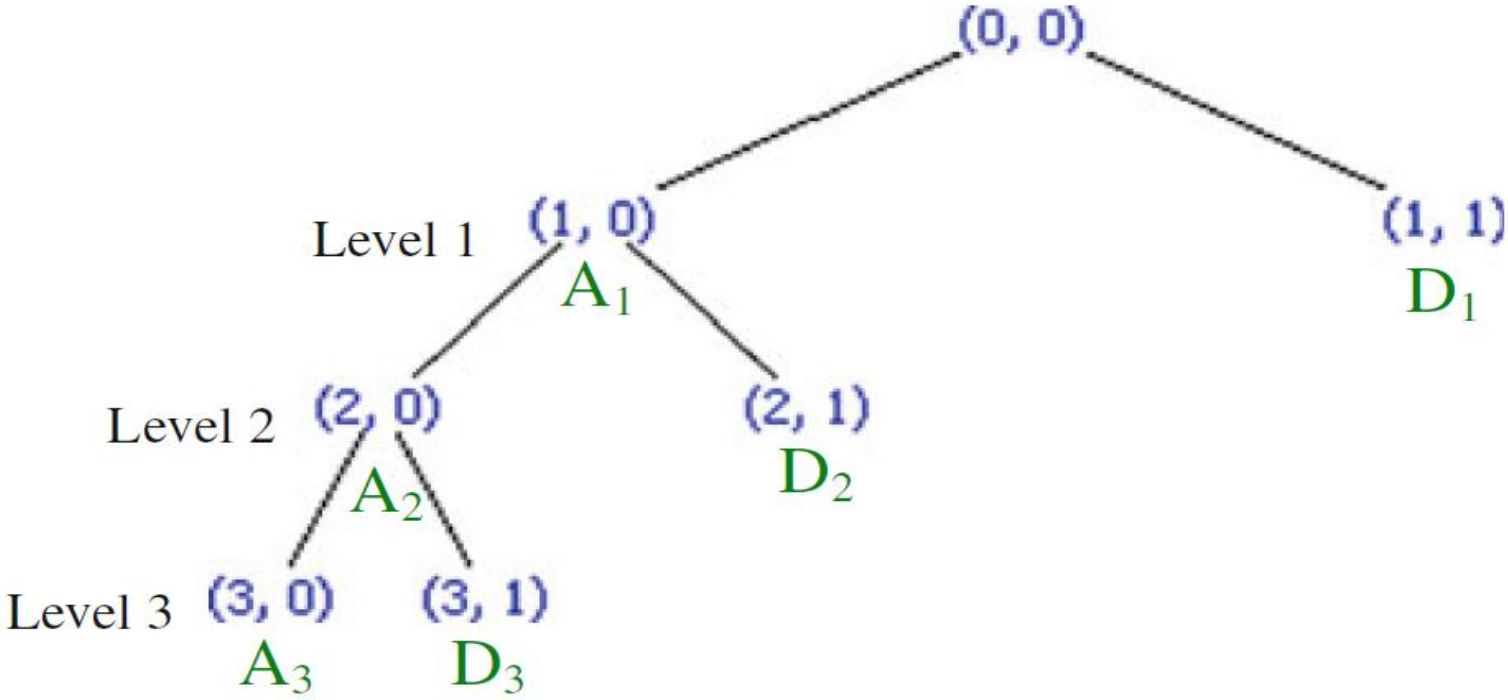


Fig. 5 3-Layer structure of wavelet packet decomposition

WPD Example

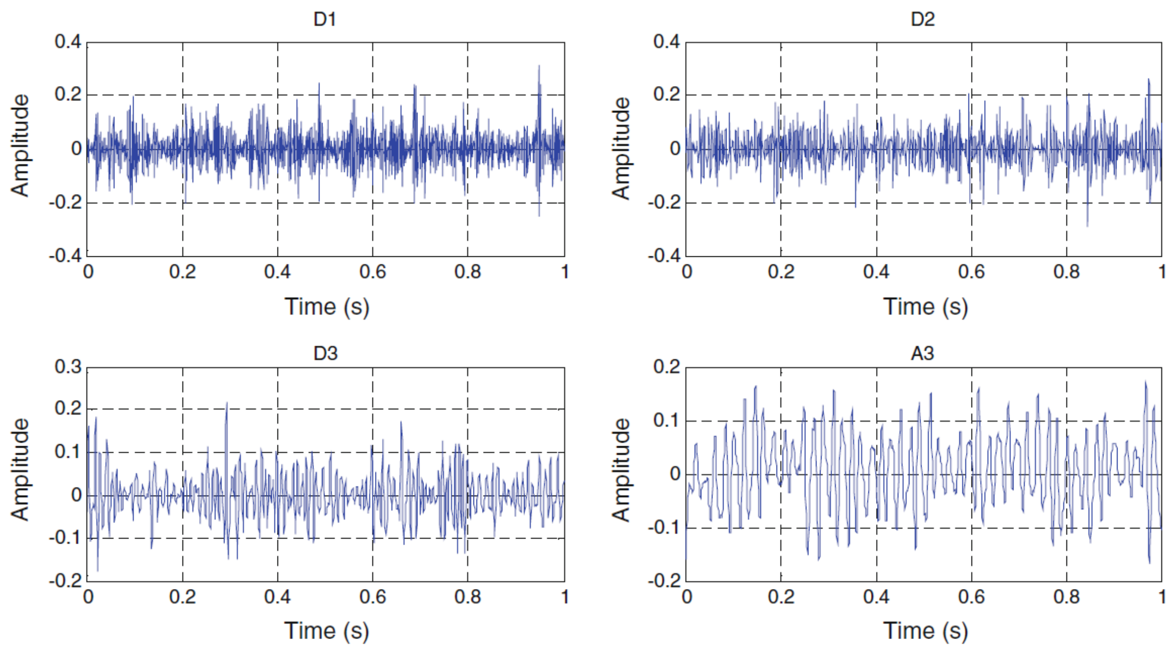
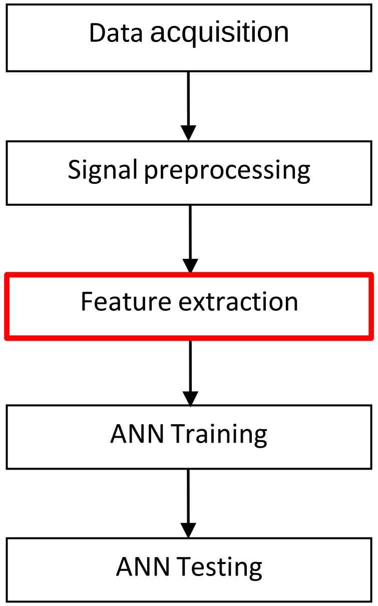


Fig. 6 Decomposed signal of condition 0



WPD Example

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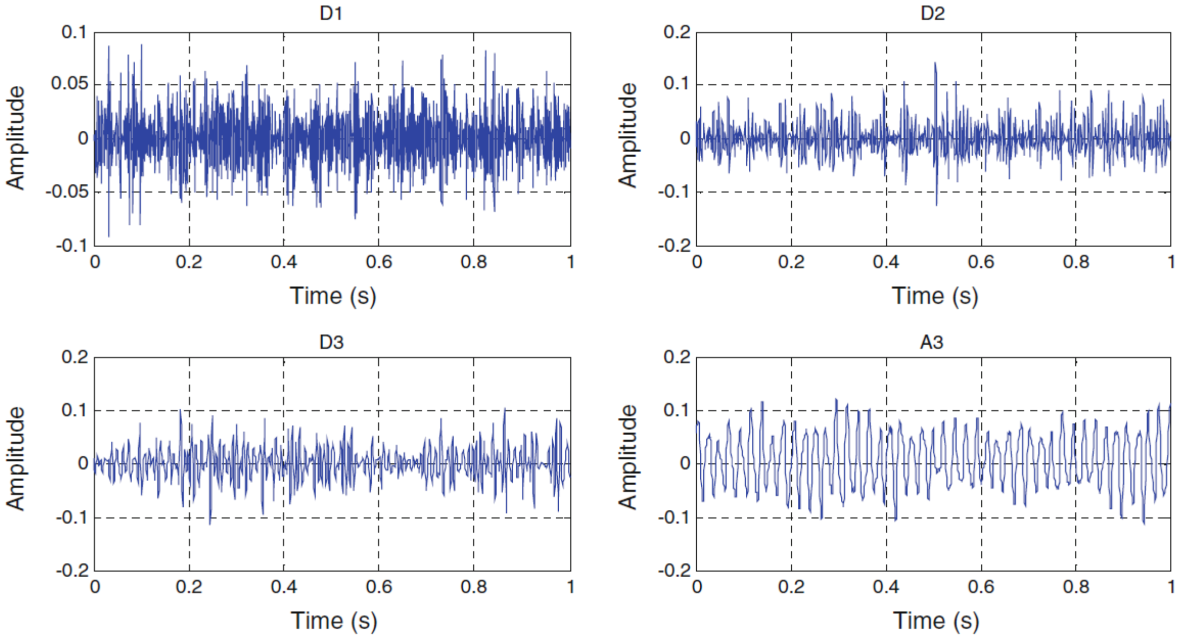
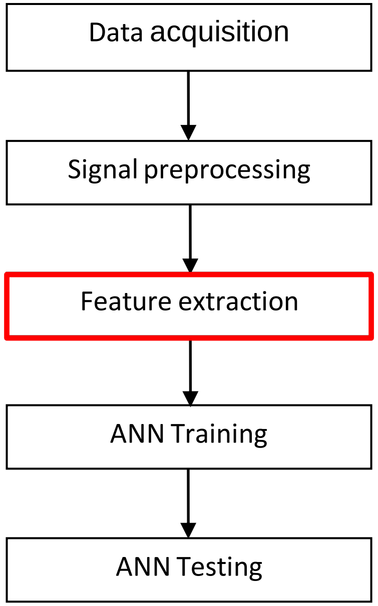


Fig. 7 Decomposed signal of condition 0.3



WPD Example

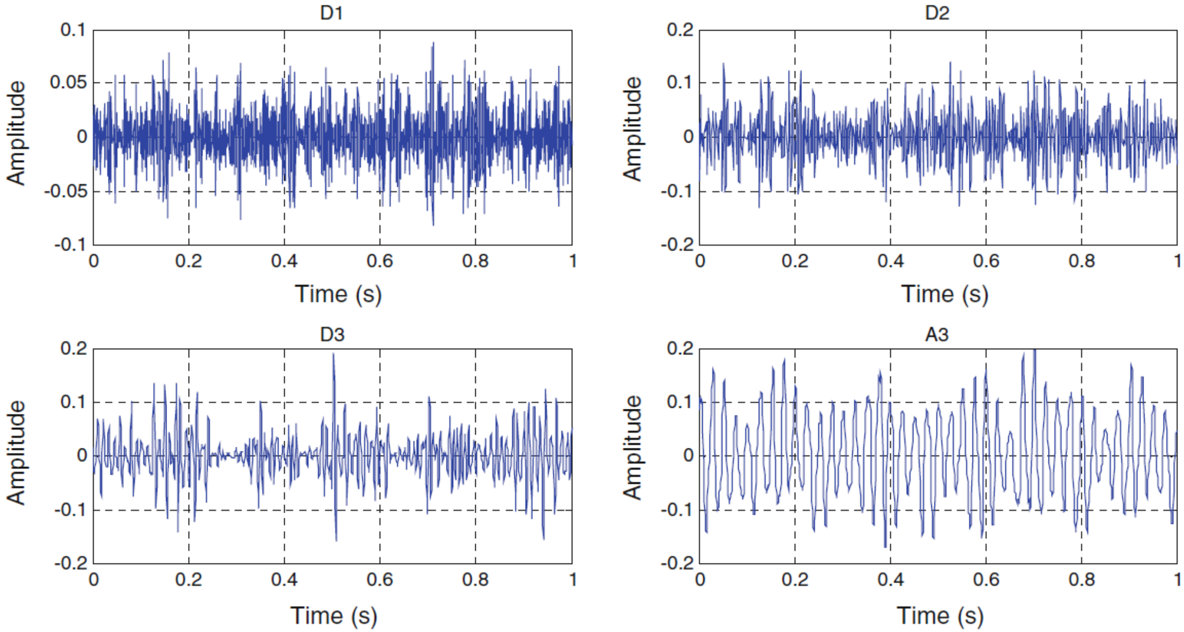
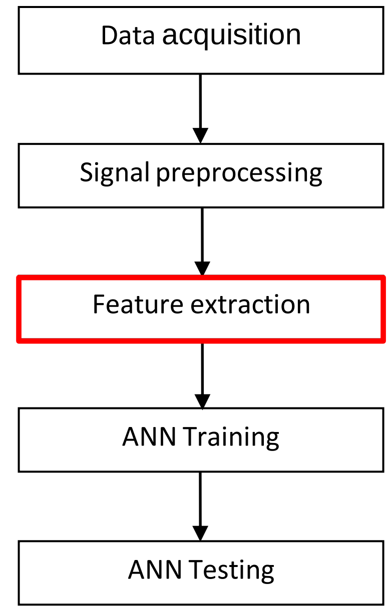


Fig. 8 Decomposed signal of condition 0.6



WPD Example

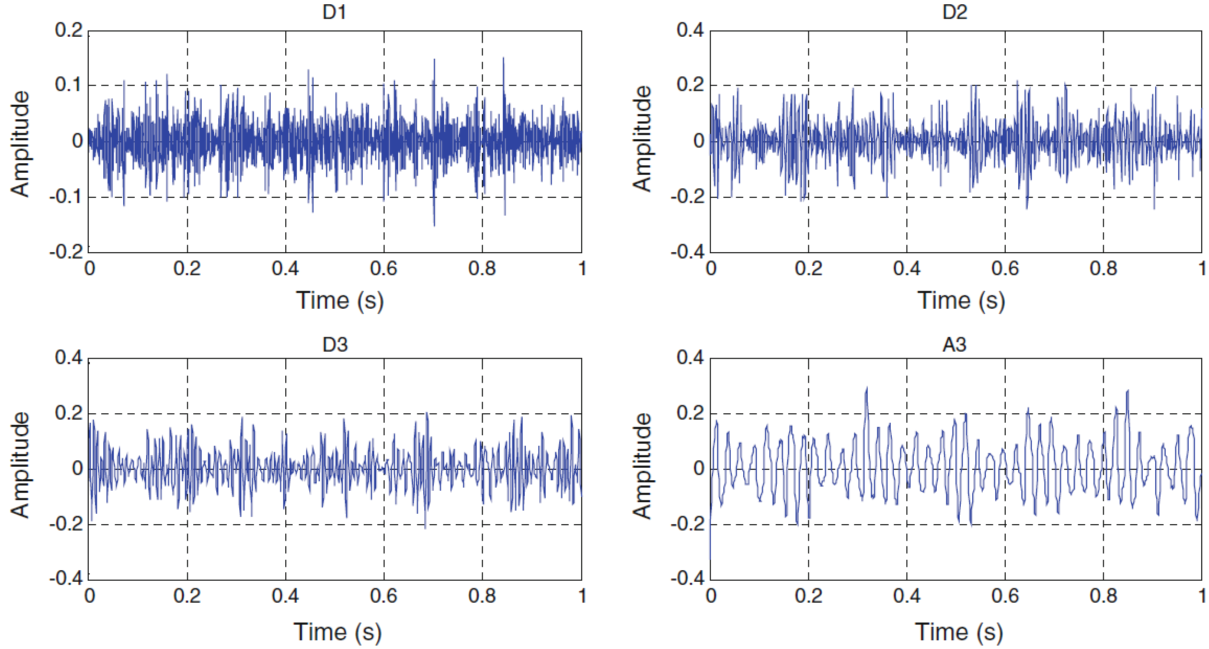
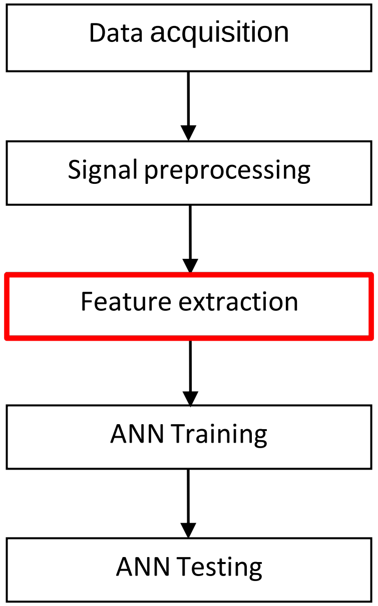


Fig. 9 Decomposed signal of condition 1

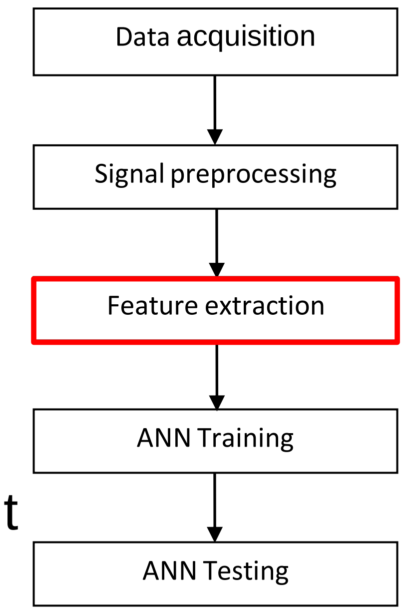


FFT

- Decomposed a signal into constituent frequencies
- Transform Time Domain Signal into Frequency Domain

$$FFT(k) = \sum_{n=1}^{N} x(j)\,\omega_N^{(n-1)(k-1)} \qquad \omega_N = e^{\frac{(-2\pi i)}{N}}$$

- Get the approximation and detail signal from WPD as input



FFT Example

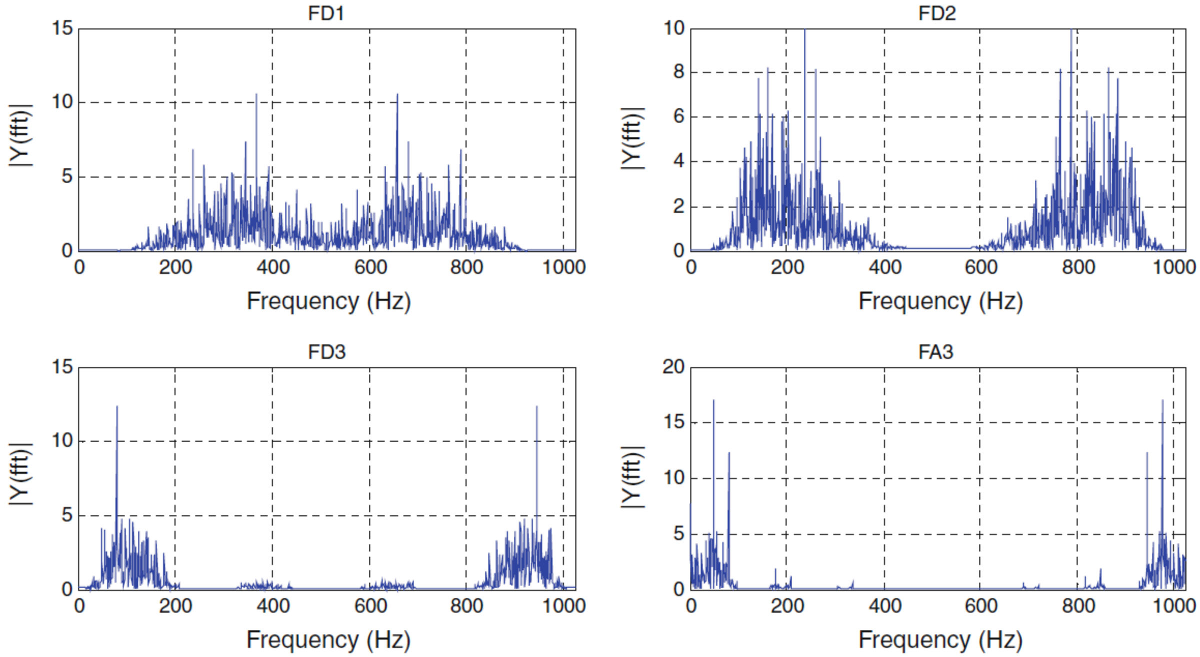
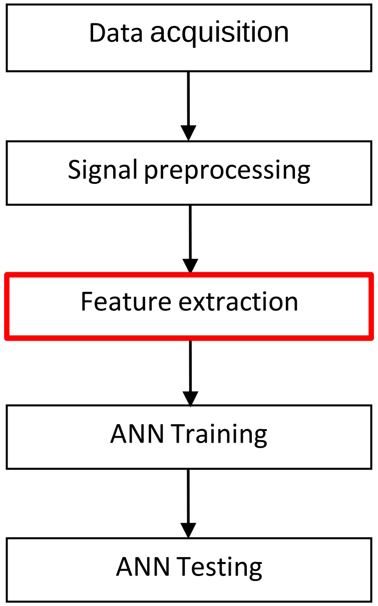


Fig. 10 FFT for each version signal of condition 0



FFT Example

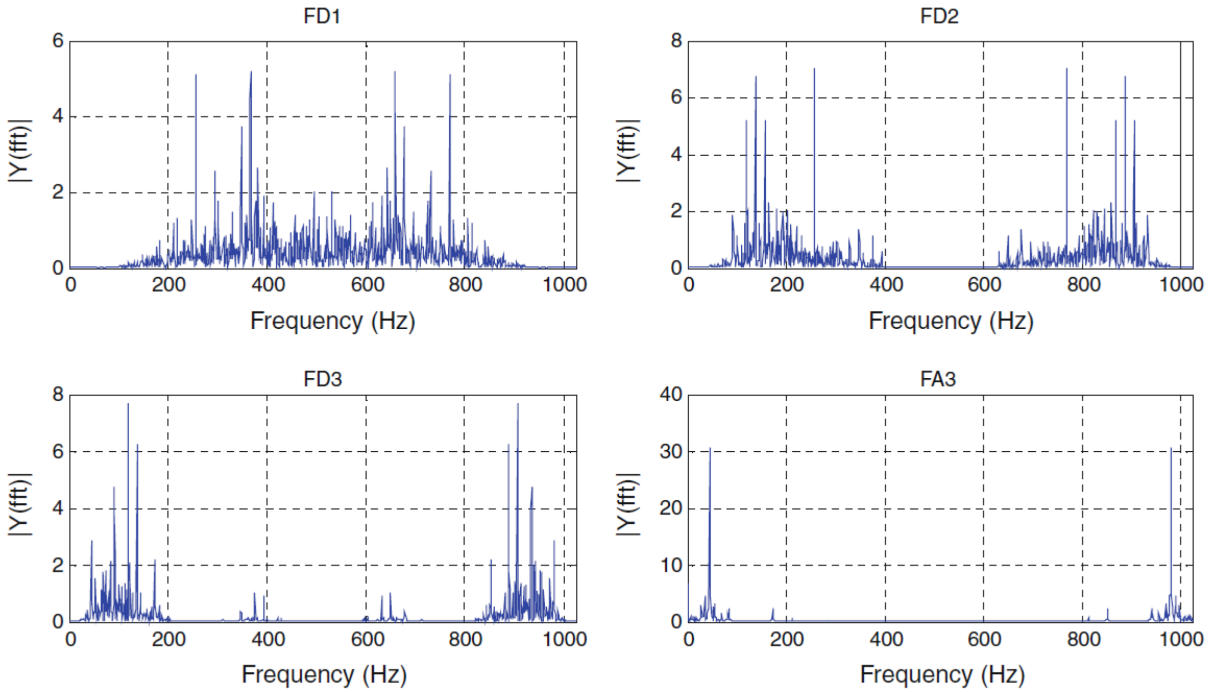
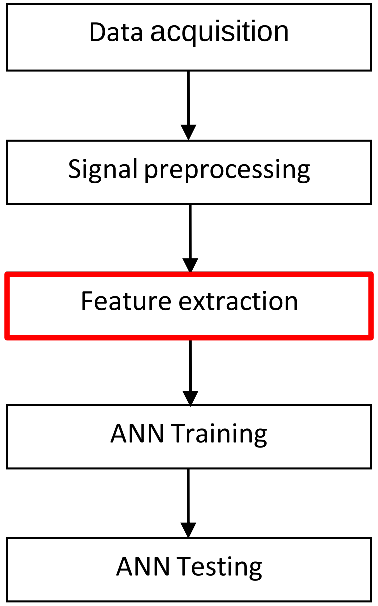


Fig. 11 FFT for each version signal of condition 0.3



FFT Example

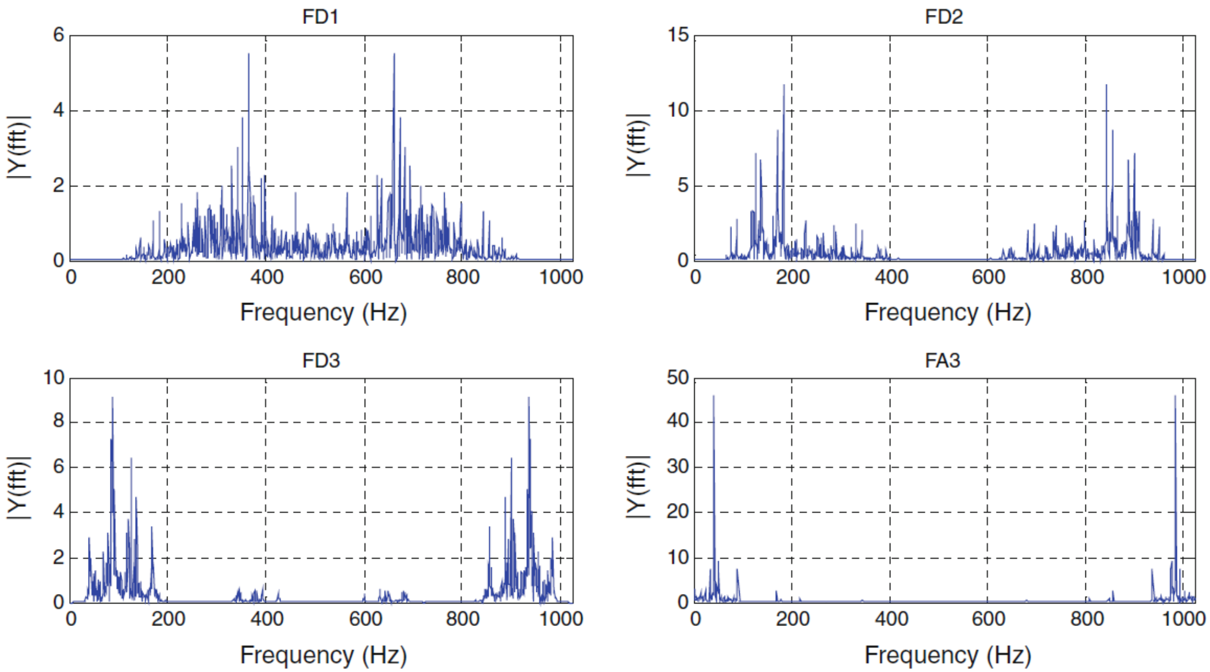
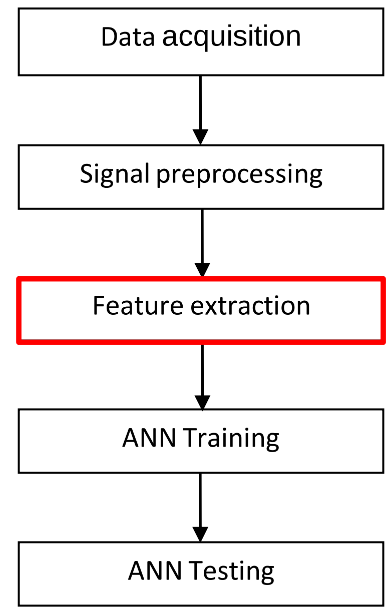


Fig. 12 FFT for each version signal of condition 0.6



FFT Example

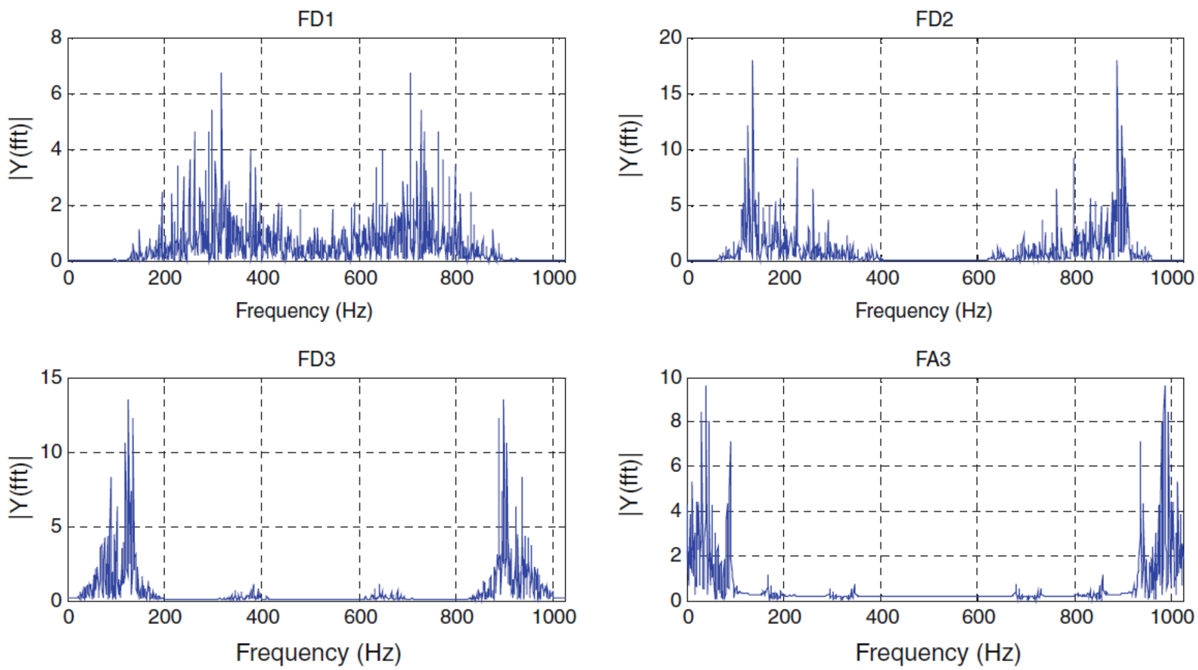
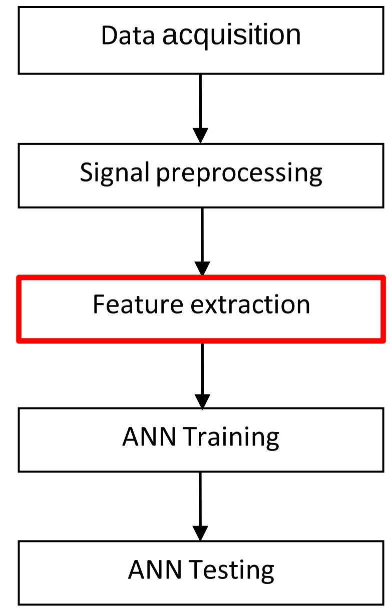


Fig. 13 FFT for each version signal of condition 1



BP Network Explanation

$\vec{x}$	Input
$\vec{t}$	Target
v_{ji}	Weight between Input and Hidden
w_{kj}	Weight between hidden and actual output
z_k	Actual output
y_i	Hidden layer Output

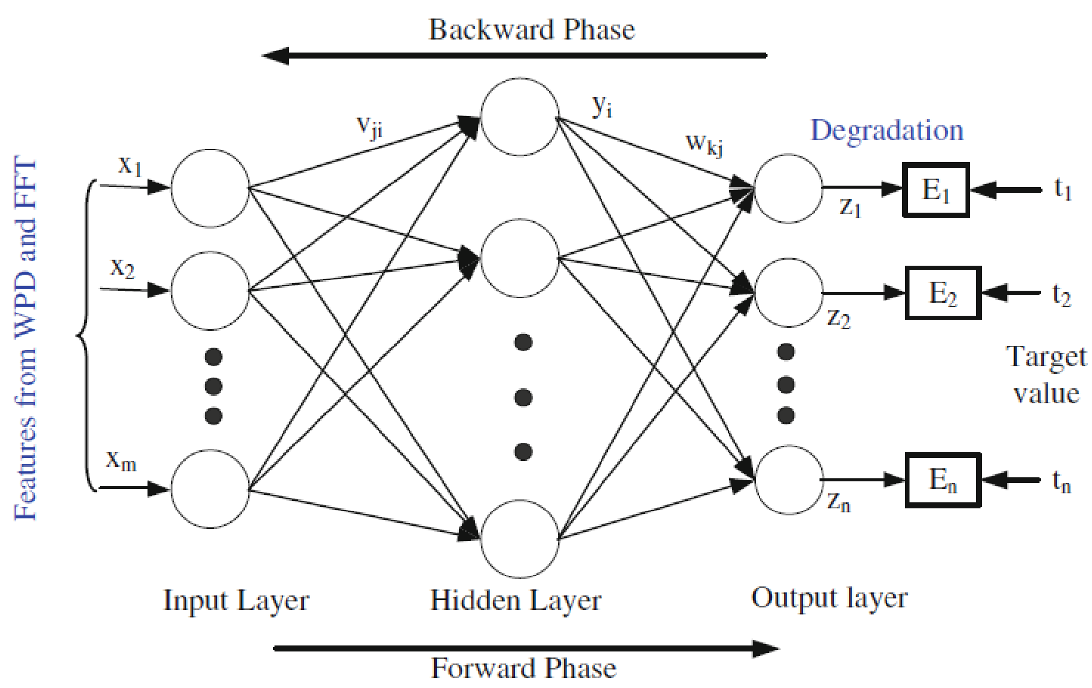
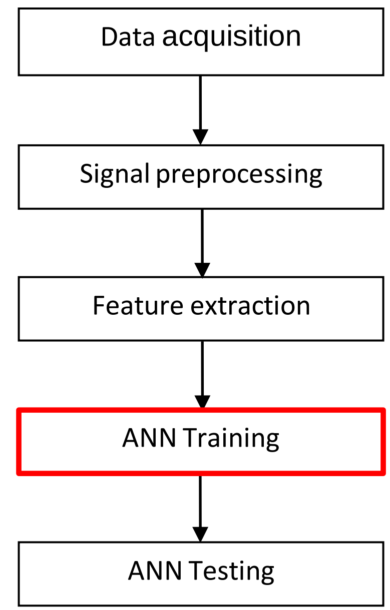


Fig. 14 A BP neural network with single hidden layer

BP Procedure

1. Initialize weight to small random Values (1,-1)
2. Select a training Vector pair (input and the corresponding desired output) from the training set and present the input vector to the vector to the inputs layer of the ANN
3. Calculate the actual outputs
4. Adjust the weights wji to reduce the difference between actual output and target (backward phase)
5. Return to step 2 and repeat for each pattern p until the error has reached an acceptable Level
6. Stop



Case Study

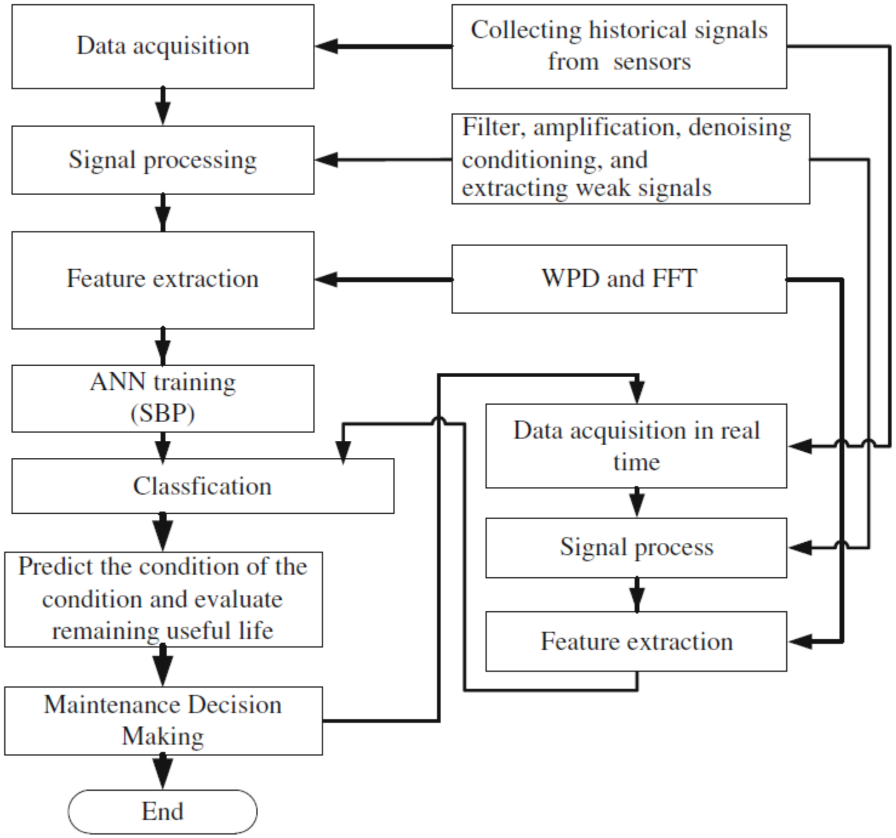
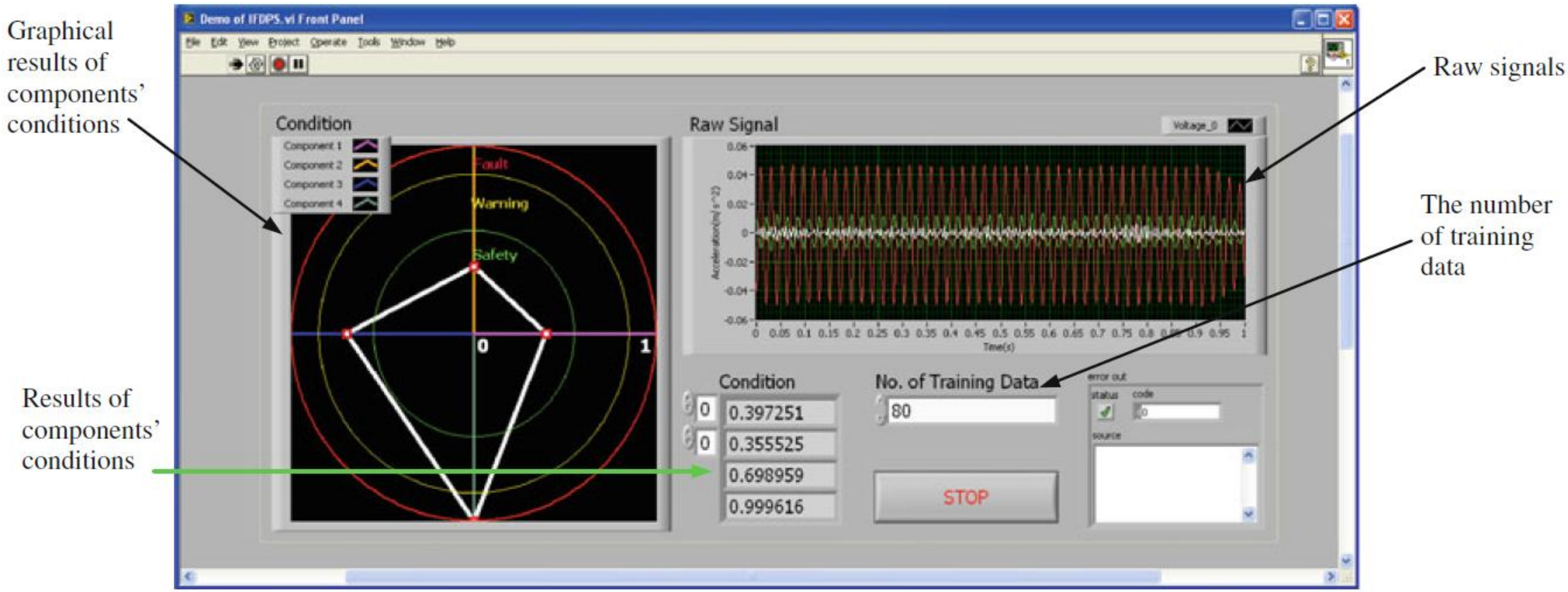


Fig. 15 The procedure of diagnosis and prognosis

Case Study

- Intelligent Blower Fault Diagnosis as Framework
- Validate the correctness of proposed techniques
- Part of SFI-Norman project called condition based maintenance
- Certify the correctness robustness and precision of methods

Case Study



16 The interface of the system

Experiment

- 200 Training Results for each condition
- 3 Sensors á 4 Frequency Parts = 12 Parameters
- 20 Hidden Layer
- One Output Layer Condition
- Max training epoch 5000
- 80 training sets used for training for each condition
- 20 sets of features are chosen to test 5 from each condition

Experiments Training Data

Table 1 Part of training data

Sensor 1				Sensor 2				Sensor 3				C
PFD1	PFD2	PFD3	PFA3	PFD1	PFD2	PFD3	PFA3	PFD1	PFD2	PFD3	PFA3	
4.20	3.18	3.768	49.05	4.07	3.756	3.26	95.17	4.325	4.323	2.816	101.08	0
4.46	2.965	2.788	20.38	4.54	3.404	3.346	102.0	3.891	4.108	3.248	107.36	0
4.58	4.039	3.874	317.6	6.15	3.603	3.704	4,170	4.663	3.55	5.447	1,094.9	0.3
3.42	3.802	3.227	314.3	3.46	3.765	3.659	4,220	4.261	3.42	4.659	1,132.5	0.3
4.87	4.238	5.951	482.2	5.19	4.184	4.617	6,975	3.523	3.845	2.723	1,889.8	0.6
4.49	3.745	4.178	395.6	4.03	4.412	4.289	6,828	4.781	3.705	3.022	1,861.4	0.6
6.41	3.007	18.46	1,933	4.94	3.053	5.048	2,035	5.095	2.919	5.601	6,189.9	1
4.54	4.304	18.43	1,936	4.72	4.23	4.73	2,103	4	4.506	6.062	6,391.8	1
…	…	…	…	…	…	…	…	…	…	…	…	…

DEMO

Experiment Test Data

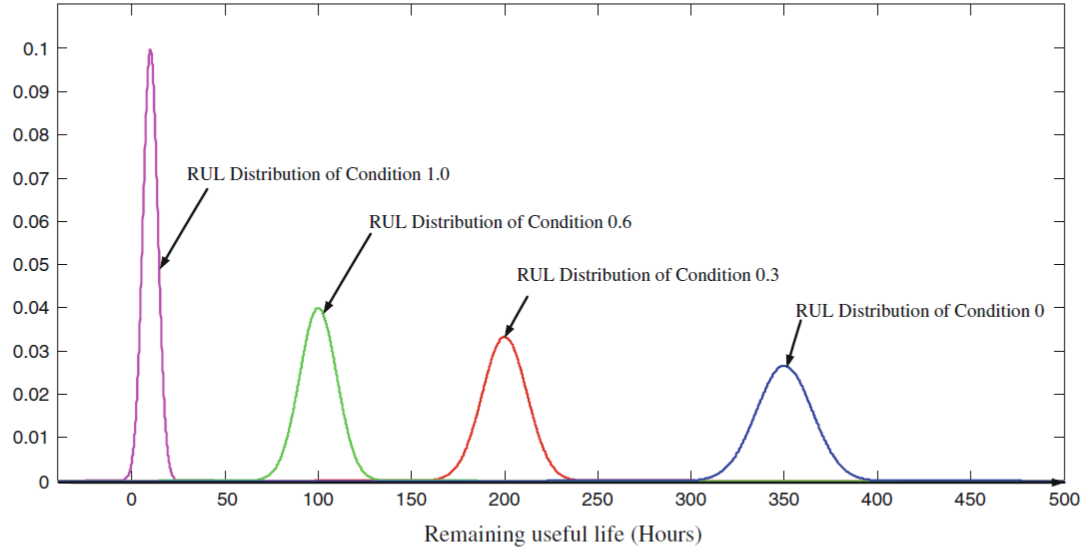
Table 2 Test data and the results

Sensor 1				Sensor 2				Sensor 3				Results		Deviation
PFD1	PFD2	PFD3	PFA3	PFD1	PFD2	PFD3	PFA3	PFD1	PFD2	PFD3	PFA3	NC	TC	
3.71	3.382	2.941	37.608	4.636	4.582	3.018	99.027	4.095	3.719	4.749	107.685	0	0.04	0.038
4.755	3.079	3.049	30.693	6.705	4.092	3.187	81.135	3.951	3.525	3.583	105.698	0	0.05	0.046
4.29	4.083	2.418	20.416	4.258	4.069	3.583	85.343	6.563	3.09	4.254	100.095	0	0.04	0.041
4.803	3.506	3.056	39.464	4.561	3.792	2.952	76.756	4.398	4.545	4.052	111.304	0	0.03	0.033
4.114	3.856	2.557	32.6	4.77	4.005	3.258	112.054	4.752	3.517	3.48	116.38	0	0.04	0.038
4.133	3.684	3.162	275.02	4.114	3.736	3.227	4, 135.45	4.701	3.452	4.835	1, 199.69	0.3	0.28	0.017
4.433	3.475	3.589	280.2	3.944	3.532	3.121	4, 174.94	4.215	3.701	3.25	1, 223.66	0.3	0.28	0.025
5.301	3.352	3.539	280.78	4.89	4.044	4.023	4, 280.03	5.667	4.422	4.008	1, 259.53	0.3	0.29	0.014
5.346	6.322	4.353	257.69	4.934	3.491	3.361	4, 175.62	5.982	5.922	3.044	1, 212.37	0.3	0.28	0.02
3.852	3.516	3.548	303.43	4.874	3.825	3.852	4, 193.24	3.817	3.952	3.428	1, 233.34	0.3	0.29	0.011
4.699	3.421	3.31	311.82	4.327	4.911	5.273	7, 101.38	4.158	3.558	3.183	2, 098.35	0.6	0.61	0.005
4.087	4.644	3.008	278.09	3.865	3.482	5.644	7, 211.46	5.392	4.981	3.51	2, 147.95	0.6	0.54	0.059
3.978	3.719	3.463	286.09	4.321	3.635	5.177	7, 122.77	4.196	3.682	3.883	2, 094.52	0.6	0.6	0.002
4.347	2.976	3.434	279.05	5.284	5.405	4.546	7, 157.75	3.978	4.449	3.333	2, 126.02	0.6	0.57	0.033
4.44	3.505	3.345	262.11	5.521	3.628	4.63	7, 080.4	3.991	3.587	4.037	2, 082.84	0.6	0.57	0.031
3.603	4.235	8.397	910.92	5.633	5.258	9.274	21, 669.1	3.839	3.875	5.985	6, 824.31	1	1	0.002
5.451	3.87	6.187	885.07	4.922	6.128	12.67	21, 416.9	5.687	3.643	8.407	6, 661.59	1	1	0
5.957	3.575	8.829	918.7	5.764	5.873	8.867	21, 244.5	4.995	4.161	4.444	6, 594.82	1	1	0.002
4.818	3.049	8.352	882.03	6.918	5.931	10.12	20, 684.6	5.035	3.511	8.835	6, 461	1	1	0.002
3.745	3.083	8.32	885.89	6.902	5.976	10.9	20, 605	5.183	3.216	8.642	6, 455.84	1	1	0.002

Remaining useful life

- Remaining useful life can be evaluated according to the condition
- The distribution of the Remaining useful life are obtained by the statistical methods

Fig. 17 Remaining useful life distribution for each condition for simulated component



Discussions

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- Number Training Sets are usefull to accurate Condition
- Relationship between accuracy and No. Of Hidden Layer Nodes
- Convergent Time of the training

First Issue – Number Training Sets are useful to accurate Condition

- No. Training Sets increasing from 1 to 200
- No. Hidden Layer Nodes set to 20
- No. Training Epochs set to 5000

First Issue – Number Training Sets are useful to accurate Condition

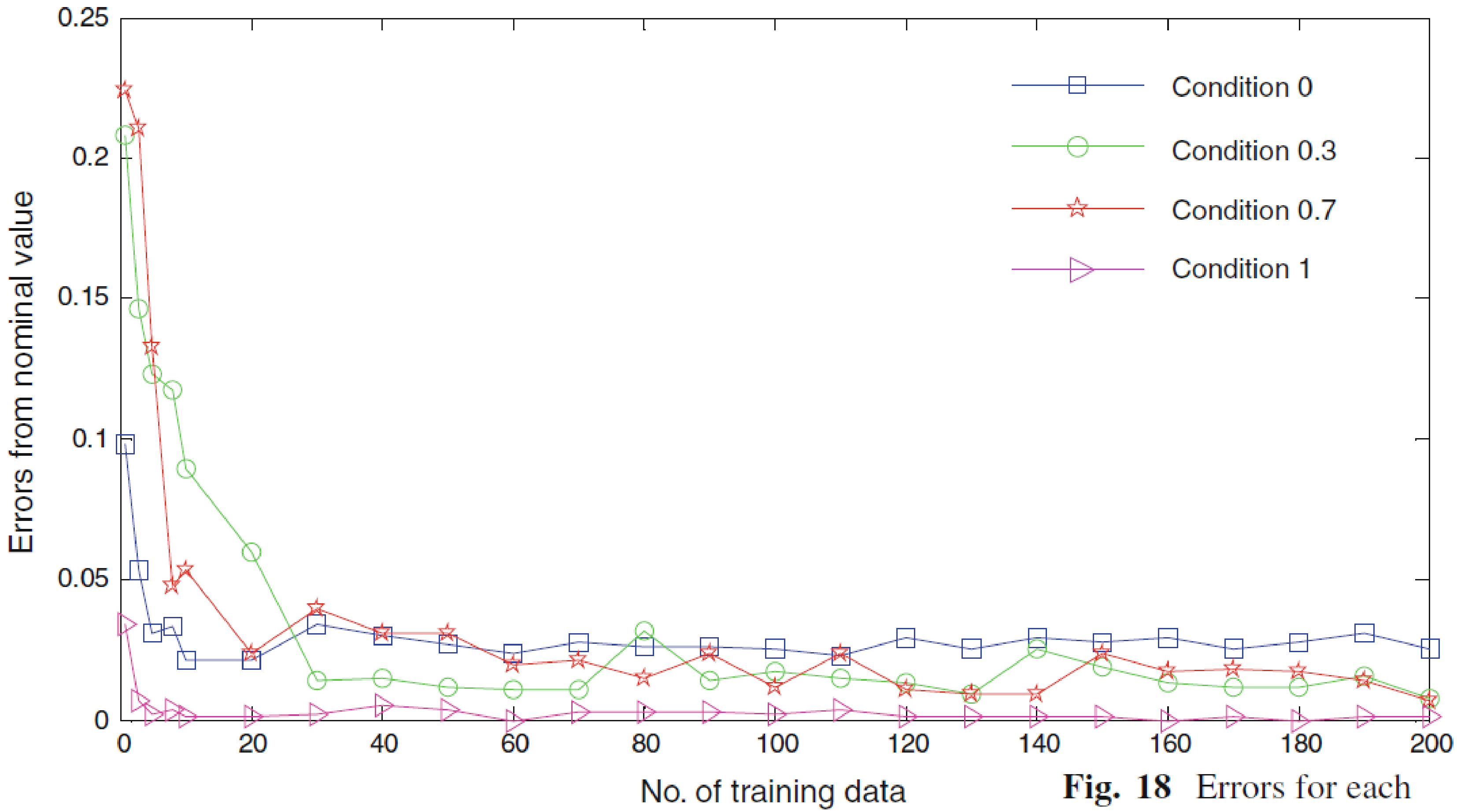

Fig. 18 Errors for each condition

Second Issue – Relationship between accuracy and No. Of Hidden Layer Nodes

- No. Hidden Layer Nodes increasing from 5 to 135
- No. Training Data set to 80
- No. Training epoch set to 5000

Second Issue – Relationship between accuracy and No. Of Hidden Layer Nodes

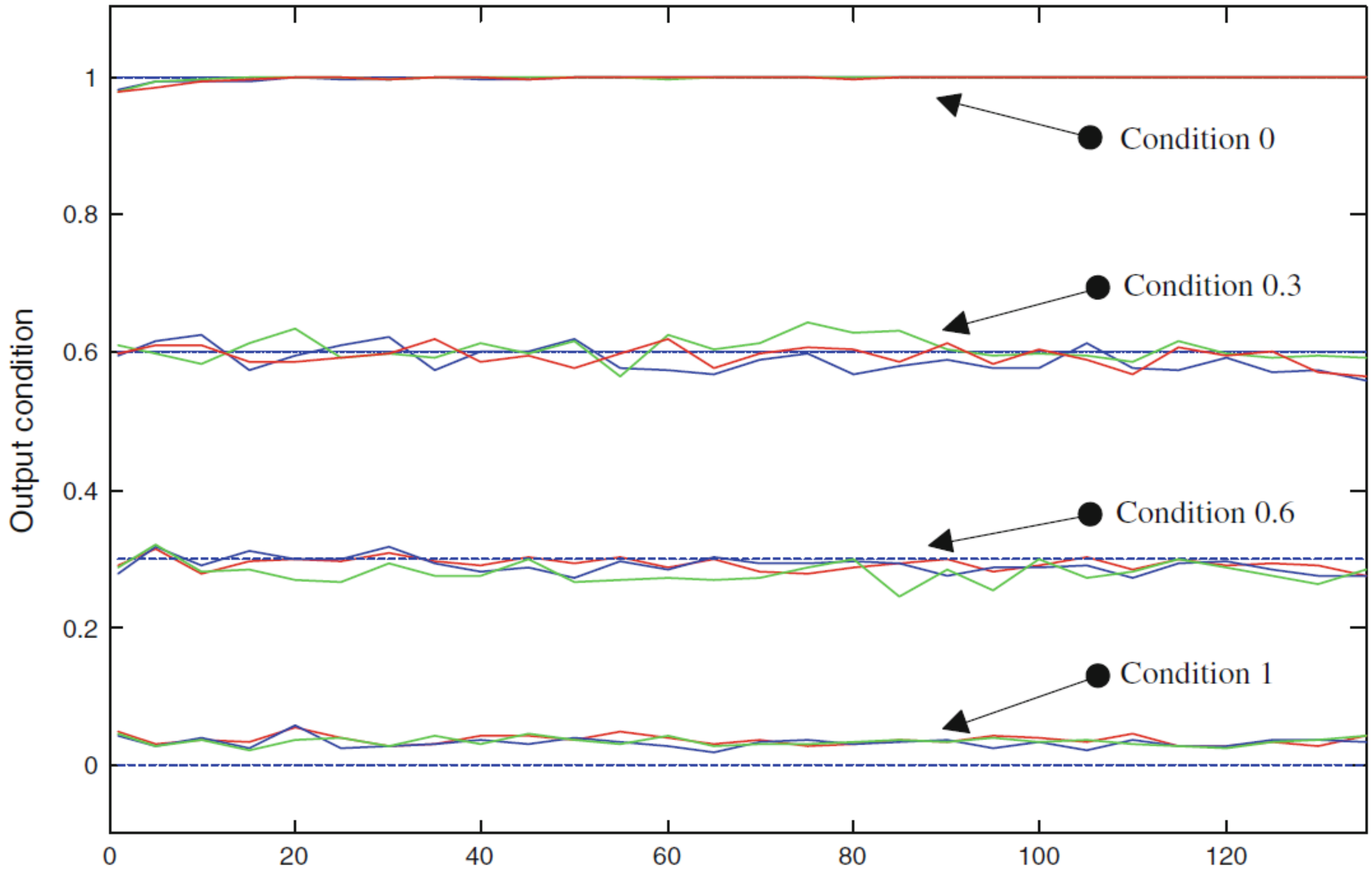

Fig. 19 Output with different number of hidden layer nodes

Third Issue – Convergent Time of the training

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- No. Training Data increasing from 10 to 200
- No. Hidden Layer Nodes set to 20
- Training epoch set to 2000

Third Issue – Convergent Time of the training

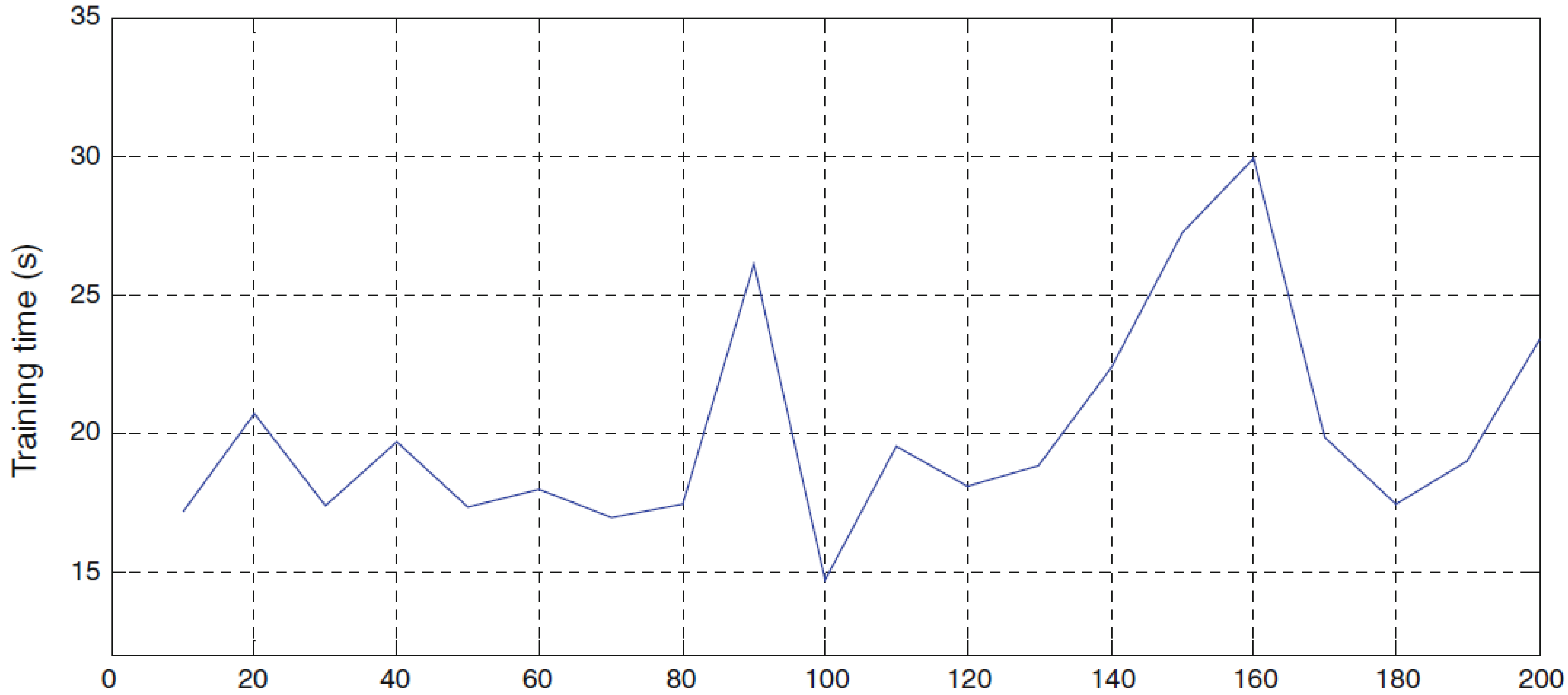

Fig. 20 ANN training time with the increasing of training data

Third Issue – Convergent Time of the training

- No. Hidden Layer Nodes from 1 to 130
- No. Training Data set to 200
- Training epoch is the same

Third Issue – Convergent Time of the training

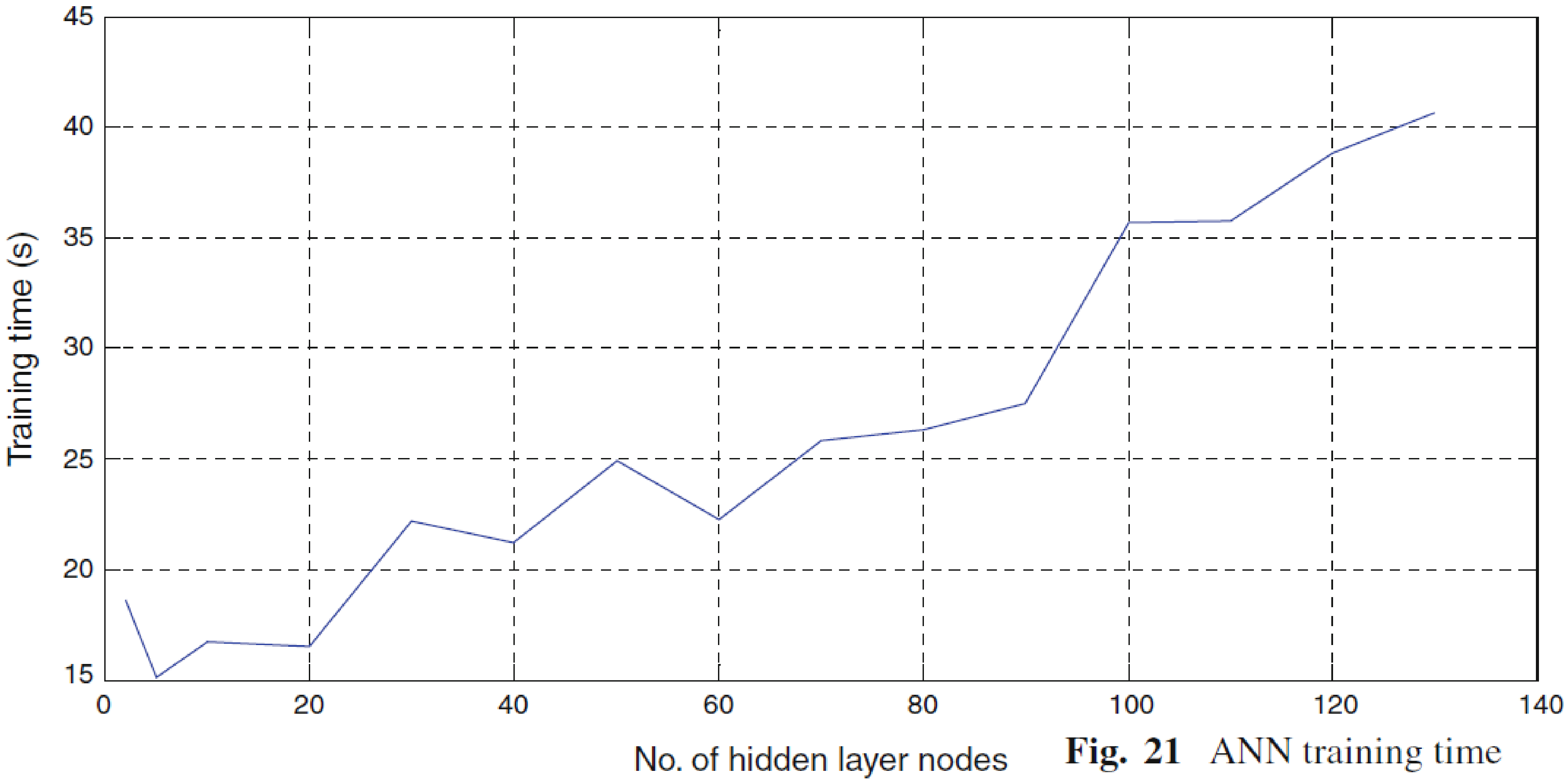

Fig. 21 ANN training time with the increasing of hidden layer nodes

Conclusions

- New Method was applied with WPD,FFT and BP ANN
- Intelligent Blower Fault Diagnosis and Prognosis System was established
- The method can predict degradation and RUL
- ANN can deal with complex problems without sophisticated knowledge

Conclusions

- Minimum bandwidth in this paper was 0-64Hz
- With a fundamental frequency of the vibration signal from 47.5 Hz
- The features are the peak values from FFT transformed from the decomposed signals
- In real systems other features may be chosen

Feature Research

- Multi-fault diagnosis and prognosis
- Degradation information for maintenance decision making
- How to apply this information in maintenance decision making

My Conclusion of the Paper

- Don´t explain interesting methods
- The relationship of RUL and the Condition is not so clear
- Why WPD and FFT are so good methods for Feature extraction
- What tells us the Signals
- BP ANN give us good results
- Real time decision making are very useful

Thank you for your attention

References

Time Domain

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Frequency Domain FFT

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Time-frequency Domain

SFFT

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Prediction of wastewater treatment plant performance based on wavelet packet decomposition and neural networks

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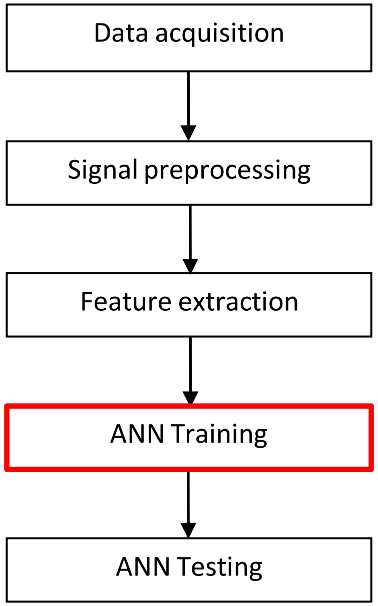
Slides for filling

ANN

- Radial Based Function
  - 3 Layer Model
  - As Hidden Layer we have out Radial Based Functions
  - They calculate our output
- Self organized mapping
  - Ordering or self-organizeing phase
  - Convergence phase
  - Weighted neurons approach to the input data
  - Neurons classifie the data



Their Conclusion

- Very effective and efficient method
- Predict the degradiation and remaining useful life
- ANN deal with complex problems
- The Vibrationssignal was 47.5Hz so the minimum bandwidth is 64Hz
- Peak Values from FFT are the Features
- In real time maybe other features must be chosen according what kind of faults we diagnosed
- Need far less history datasets than event data
- Future Research are multi fault diagnosis and prognosis