ON CONDITION MONITORING OF EXHAUST VALVES IN MARINE DIESEL ENGINES

T. L. Fog[§] L. K. Hansen[‡], J. Larsen[‡], H. S. Hansen[§], L. B. Madsen[§], P. Sørensen[§], E. R. Hansen[§], and P. S. Pedersen[§]

§ : Research & Development, MAN B&W Diesel A/S
Teglholmsgade 41, DK-2450, Copenhagen SV, Denmark.
E-mail: tof, hsh, lbm, pcs, er, psp@manbw.dk. Website: www.manbw.dk

‡ : THOR Center for Neuroinformatics, Department of Mathematical Modeling,
Bldg. 321, Technical University of Denmark, DK-2800 Lyngby, Denmark
E-mail: lkhansen, jl@imm.dtu.dk. Website: eivind.imm.dtu.dk/thor

Abstract. The feasibility of non-invasive characterisation of exhaust valve conditions in large marine diesel engines, were experimentally investigated on a four cylinder 500 mm bore 2-stroke marine diesel engine at MAN B&W Diesel's Research Center in Copenhagen, Denmark. The experiments comprised three different valve conditions, where two were concerned with artificially induced valve burn-through situations. The primary potential monitoring measurements were vibration and structure-borne stress waves, also known as Acoustic Emission (AE). Results have shown that the AE signals have a major advantage over other involved sensors, indicating sensitivity to both mechanical and fluid-mechanical combustion related activity. Recorded data has been preprocessed and features extracted using Principal Component Analysis (PCA). From a number of applied heuristics and statistics, a search for the optimal sub-space of principal components to use, have been carried out. The chosen feature-space have been used for classification of involved exhaust valve conditions by applying both regularized feed-forward neural classifiers and linear discriminators. The complexity of the neural networks have further been optimized by Optimal Brain Damage (OBD) pruning, leading to increased generalization.

INTRODUCTION

The exhaust valve is an important part of a combustion engine. Its main purpose is to seal during the compression stroke, thereby providing maximum combustion pressure for maximum engine performance. Further, during the expansion stroke at engine-builder specific timing, to lift its seat and thereby provide scavenge (from scavenge air system) of the polluted air in the cylinder and fresh air intake for the following compression and combustion.

Valve burn-through, or leakage, can be caused by dent marks from deposits (combustion particles) on the sealing face or material damage from for instance knocking [14]. Leakage's causes reductions of both pressure and power (i.e. performance) in the cylinder(s). Moreover, the high temperatures and gas pressure impulses during the combustion phase, can further aggravate the exhaust valve condition. In case of valve leakage, the valve can in some cases be reconditioned and re-installed for further use. But in severe cases it has to be replaced. In both situations, it is a time consuming operation and it might cause serious transport delay. Different attempts have been made to investigate possibilities to monitor the exhaust valve condition by means of exciting vibrations from the exhaust valve housing [1, 16].

Having a condition monitoring system which could offer industrial users the ability to carry out planned maintenance by indicating the level of degradation before a fault occurs or efficiency is reduced to unacceptable levels, is of great interest. Further, integration of an adaptive condition monitoring system with other electronic engine control and maintenance systems, is an important progress towards fully automated maintenance scheduling and the concept of the *Intelligent Engine* [13].

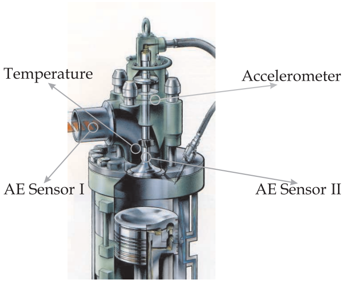
To investigate possibilities for detection of exhaust valve burn-through, experiments were carried out on MAN B&W Diesel's Research Engine in Copenhagen. The aim of the experiments was to establish whether it was possible to derive any information's of exhaust valve leakage under different engine and valve conditions. Three different valve conditions were considered; normal valve, a small valve leakage, and a large valve leakage. These were evaluated over a broad range of engine operating conditions.

Since engine signals are quasi-periodic the recorded time-series have been preprocessed for improved stationarity. Extraction of features of importance have been investigated using principal component analysis (PCA) and transformations carried out for investigation of the optimal feature sub-space. From a number of applied heuristics and statistic methods as suggested in literature [7], a search for the optimal set of principal components have been carried out. Two types of models are investigated for automatic classification of involved exhaust valve conditions, based on features derived via PCA. These comprises a linear discriminant, similar to Fisher's discriminant for two classes, and a Bayes optimal classifier using a neural network which outputs estimates of the posterior probabilities of class membership. The regularized neural classifier has been trained via second order learning and model complexity optimized using Optimal Brain Damage Pruning (OBD).

EXPERIMENTAL INVESTIGATIONS

The Research Engine is a 2-stroke 4-cylinder marine diesel engine with an approximate max. output on 10,000 BHP[1]. The aim of the experiment was to establish whether it was possible to derive informations of exhaust valve leakage under different engine and valve conditions. Three different valve conditions were considered: 1) normal valve, 2) relatively small grinded valve leak, with a cross-sectional area of approximately 4mm^2, 3) large grinded valve leak, with a cross-sectional area of approximately 20mm^2.

For each valve condition, measurements were obtained from 8 different engine operating conditions, varying both speed and load. As a side experiment, misfire was simulated by taking off combustion on the cylinder unit, which thereby simply pumped air. During the experiments, "snapshots" of time-series over a number of piston revolutions were captured by data acquisition systems for all involved engine and valve conditions. The signals obtained comprised the primary potential monitoring measurements, which were vibration and structure-borne stress waves, also known as Acoustic Emission (AE) (see e.g. [12, 10]). Further, shaft timing signals revealing 2048 angle



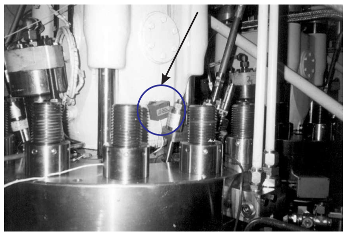


Figure 1: Left panel : Approximate positions of the two AE sensors on the outside surface of the valve housing, the placement of an accelerometer, and the approximate position of a thermocouple. Right panel : AE sensor mounted in a magnetic hold-down on the valve housing.

specific pulses per piston cycle and a TDC[2] signal, together with cylinder pressure, exhaust gas temperature and other pressure measurements. All recordings were obtained from cylinder 1 only which was the unit used for the experiments. The sensors were positioned on the exhaust valve housing as indicated in Fig.1.

The 8 involved engine operating conditions where measurements were recorded for each valve condition comprised:

1.	25% load, propeller curve	2.	25% load, propeller curve, misfire
3.	50% load, propeller curve	4.	50% load, propeller curve, misfire
5.	75% load, propeller curve	6.	100% load, propeller curve
7.	25% load, generator curve	8.	25% load, generator curve, misfire

[1] Brake Horse Power
[2] Top Dead Center

Here, the term, propeller curve, refers to engine propulsion usage with a fixed pitch propeller while generator curve refers to constant speed as using the engine for stationary power plant purposes. Since the Research Engine is a stationary plant the propeller was simulated by a water brake.

The measurements recorded, initiated the ability to investigate data from different engine conditions and with the same load and speed values. Hence, in this experiment, engine condition 1, 2 and 7, 8 have the same engine load (i.e., 25% load), while engine condition 6, 7, and 8 have the same engine speed values. Conditions 3, 4, and 5, further yielded possibilities to broaden the investigations over a larger range of different engine operating conditions.

While vibrations and pressure measurements are traditional widely used techniques for monitoring reciprocating machinery such as engines and compressors, AE has only recently been applied for engine monitoring. Some recent results can be found in [3, 4, 15]. AE has further proven advantageous to the other measurements obtained, indicating sensitivity to mechanical and fluid-mechanical events, where acceleration is sensitive only to the mechanical activity of involved machine parts. AE has proven capability to monitor valve activity and condition and fuel injection. Interference of AE events from adjacent cylinders have been found to be minimal, hence allowing easy isolation of mechanical events related to the monitored cylinder. Another important result is that detection of AE events seems possible anywhere on the valve housing from which the signals were acquired. This makes AE measurements relatively easy to carry out, since the non-intrusive measurements are not too sensitive to the positioning of the sensors. The results obtained by recording RMS AE signals, shows good discrimination between both normal valve condition and the small valve leak, and further the visual "difference" is also clearly observed in the time-series between the small and the large valve leak (cf. Fig. 2).

FEATURE EXTRACTION

Since engine signals in general are quasi-periodic the RMS AE time-series were trigger sampled by use of a shaft timing signal obtained from an angle encoder pulse signal yielding 2048 angle positions per piston cycle. Hence, stationarity has been obtained revealing time-series consisting of 2048 samples per piston cycle. While the trigger sampling process corresponds to a huge dimensionality reduction, we want to explore whether it is possible to represent, for the problem, relevant features in yet a lower dimension of *feature-space*. In situations where the input dimension of data is large and the data vectors are highly correlated, PCA might prove useful as a dimensionality reduction method. The main objective of PCA is to provide a lower dimensional data description by projection of the data vectors onto the eigendirections corresponding to the *largest* eigenvalues of the sample

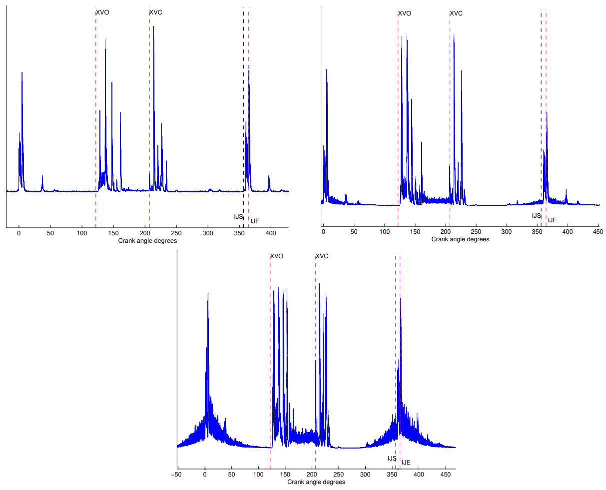


Figure 2: RMS AE time-series from 25% engine load (propeller curve). Time-series obtained from AE sensor II (see Fig.1) for the large valve leakage. Dotted vertical lines indicate timing of mechanical combustion related events, such as exhaust valve open (XVO), exhaust valve close (XVC), injection start (IJS) and injection end (IJE). Left panel demonstrates RMS AE for normal valve condition while the middle and right panel illustrates RMS AE results for the small and large valve leak, respectively.

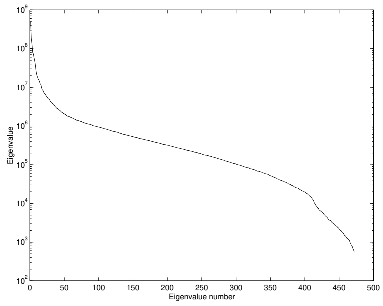
covariance matrix $\widehat{\mathbf{\Sigma}}$. Consider the *centered* data matrix, $\widetilde{\mathbf{X}}$, holding data observations of preprocessed RMS AE time-series, as column vectors. To carry out PCA, we use single value decomposition (SVD)

$$\widetilde{\mathbf{X}} = \mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{V}^T \tag{1}$$

decomposing the centered data matrix, $\widetilde{\mathbf{X}}$, into a product of the eigenvectors of the constellation, $\widetilde{\mathbf{X}}\widetilde{\mathbf{X}}^T$, which is represented as column vectors by $\mathbf{U}$, $\widetilde{\mathbf{X}}^T\widetilde{\mathbf{X}}$, represented as column vectors by $\mathbf{V}$ and a diagonal matrix, $\mathbf{\Lambda}^{1/2}$ holding the standard deviations, i.e. the square root of the eigenvalues. The principal components (the PC's) can now be computed from

$$\mathbf{PC} = \mathbf{U}^T\widetilde{\mathbf{X}} = \mathbf{\Lambda}^{1/2}\mathbf{V}^T \tag{2}$$

The PC transformation from SVD produces transformed data vectors which holds uncorrelated components, ordered according to their variance level. To find a representative sub-space with dimension $k < p$, the k largest eigenvalues from the eigendecomposition of the covariance matrix is sought, as a choice for mapping a p-dimensional data space into a k-dimensional space spanning the new feature-space. From SVD, the eigenvalues ordered according to their magnitude is found in the diagonal of $\mathbf{\Lambda}$. These are illustrated in Fig.3. The main objective of applying feature extraction in the form of a dimensionality reduction technique (here PCA), is to preserve as much *relevant* information as possible in the new transformed data. Selection of



Method	No. of PC's retained
Broken stick	17
Average root	36, 46
SCREE-plot	70
Bartlett's test	66
Velicer's method	76
Neural network	61
Linear model	65

Figure 3: Left panel : $n-1=472$ ordered eigenvalues of the $\widetilde{\mathbf{X}}^T\widetilde{\mathbf{X}}$ covariance matrix with $\text{rank}(\widehat{\mathbf{\Sigma}}_{min}) \le (n-1)$ from the synchronized RMS AE data. Right panel : The table indicates various methods used as selection criterion for retaining PC's. Note that the neural net and linear models are supervised schemes (by valve conditions) whereas the remaining are unsupervised.

the optimal sub-space of features, constitutes though a non-trivial problem. To evaluate selection criteria's for retaining a number of PC's, we have employed various heuristics and statistics as suggested in literature (see e.g. [7, 8]). The suggested number of PC's to retain for the applied selection methods, is given in the table in Fig.3. For comparison, the number of PC's to select have been investigated in the context of minimizing a generalization term for involved neural network classifiers and linear discriminators, similar to Fisher's discriminant for 2 classes. This is similar to the work reported in [5]. Some ambiguity among the retained number of PC's is present. We recommend that the number of PC's to retain is 60–65, as suggested by the *supervised* selection methods (linear model, neural network), see Fig. 4. The PC subspace selected by these methods is optimal with respect to the overall objective; minimizing the classification error. But in the following we will base the classifiers on a 76 dimensional subspace corresponding to the largest subspace suggested by any of the methods.

PATTERN RECOGNITION

Our classification tasks aim at classifying levels of degradation of the three involved exhaust valve conditions. The data set, consists of 473 observations each holding 76 chosen features, corresponding to the largest suggested PC subspace to choose.

For performance comparison, in sense of misclassification rate, we employ two different classifiers; a linear discriminant, which for 2 classes is similar to Fisher's discriminant, and a regularized softmax [2] neural classifier. The linear model which has been chosen is the so-called *best linear rule* [11]. A discriminant function can be expressed as [11]

$$F_i(\mathbf{x}) = \left[-2\widehat{\mu}_i^T\widehat{\mathbf{\Sigma}}^{-1}\mathbf{x} + \widehat{\mu}_i^T\widehat{\mathbf{\Sigma}}^{-1}\widehat{\mu}_i - 2\log\pi_i\right], \tag{3}$$

and the class membership is given by $C_i = \arg\min_i F_i(\mathbf{x}^n)$. In Eq.(3) the class mean is found as $\widehat{\mu}_i = N_{\text{train},i}^{-1} \sum_{n_i=1}^{N_{\text{train},i}} \mathbf{x}^{n_i}$ with $N_{\text{train},i}$ denoting the number of training data examples in each class and $\mathbf{x}^{n_i}$ denoting data example n belonging to class i, drawn from the pool of data. The covariance matrix, $\widehat{\mathbf{\Sigma}}$ is estimated as

$$\widehat{\mathbf{\Sigma}} = \sum_{i=1}^{c} \frac{n_i}{N_{\text{train,tot}}} \widehat{\mathbf{\Sigma}}_i = \frac{1}{N_{\text{train,tot}}} \sum_{i=1}^{c} \sum_{n_i=1}^{N_{\text{train},i}} (\mathbf{x}^{n_i} - \widehat{\mu}_i)(\mathbf{x}^{n_i} - \widehat{\mu}_i)^T \tag{4}$$

under the assumption of equal covariances. $N_{\text{train,tot}}$ is here the sum of data examples for each class involved, i.e. $\sum_{i=1}^{c} N_{\text{train},i}$. Further the prior, $\widehat{\pi}_i$, is estimated from data as [11] $\widehat{\pi}_i = N_{\text{train},i}/N_{\text{train,tot}}$.

Following [6] for the construction of the neural classifier, we aim at modeling the posterior probabilities, $p(C_i|\mathbf{x}), i = 1 \cdots c$, of class membership by assigning class label C_i to $\mathbf{x}$ if $i = \arg\max_j p(C_j|\mathbf{x})$. Above, C_i refers to the i'th class, c to the number of classes, and $\mathbf{x}$ is a PC feature vector. Since the neural network outputs, $\widehat{y}_i$, are estimates of the posterior probabilities which sum to 1, we need only to estimate $c-1$ posterior probabilities. Our initial 2-layer feed-forward network consists of $n_I = 76$ inputs, corresponding to our principal components, $n_H = 4$ hidden neurons, and $n_O = c - 1 = 2$ outputs reflecting the 3 classes of exhaust valve conditions involved. We next define our network as : $V_j(\mathbf{x}^n) = \tanh\left(\sum_{k=1}^{n_I} w_{jk} x_k^n + w_{j0}\right)$ and $\phi_i(\mathbf{x}^n) = \sum_{j=1}^{n_H} W_{ij} V_j(\mathbf{x}^n) + W_{i0}$ where V_j denotes the activity of the hidden neurons and ϕ_i the output activity. The network parameters are represented by the input-hidden weight-space, w_{jk}, and the hidden-output weight-space, W_{ij}. W_{i0} and w_{j0} are thresholds in the respective network layers. To be able to interpret the outputs as posterior probabilities, we use a modified normalized exponential activation function, $\widehat{y}_i^n = \exp(\phi_i(\mathbf{x}^n)) / \sum_{j=1}^{c-1} \exp(\phi_j(\mathbf{x}^n)) + 1$ and $\widehat{y}_c^n = 1 - \sum_{i=1}^{c-1} \widehat{y}_i^n$, similar to softmax [2]. All the input vectors, $\mathbf{x}^n$, in the entire data set has been assigned to targets, y_i^n, labeled for class membership as

$$y_i^n = \begin{cases} 1 & \text{if} \quad \mathbf{x}^n \in C_i \\ 0 & \text{if} \quad \mathbf{x}^n \notin C_i \end{cases} \tag{5}$$

with i denoting the ith class. When training the network, we divide the data into a training set consisting $N_{\text{train}} = 70\%$ of available observations, and the remaining 30% kept in an independent evaluation set. Training is carried out by minimizing the negative log-likelihood, where the likelihood parameters is given by $P(\mathcal{D}_{\text{train}}|\mathbf{w}) = \prod_{n=1}^{N_{\text{train}}} \prod_{i=1}^{c} (\widehat{y}_i^n)^{y_i^n}$. The training error is thus found by $E_{\mathcal{D}_{\text{train}}}(\mathbf{w}) = -N_{\text{train}}^{-1} \log P(\mathcal{D}_{\text{train}}|\mathbf{w}) = -N_{\text{train}}^{-1} \sum_{n=1}^{N_{\text{train}}} \epsilon(\mathbf{y}^n, \widehat{\mathbf{y}}^n, \mathbf{w})$ with $\epsilon(\mathbf{y}^n, \widehat{\mathbf{y}}^n, \mathbf{w}) = \log\left(1 + \sum_{j=1}^{c-1} \exp(\phi_j(\mathbf{x}))\right) - \sum_{i=1}^{c-1} y_i \phi_i(\mathbf{x})$. In order to reduce overfitting, the networks are trained with a regularized cost function consisting of the training error augmented by a weight decay regularization term. Weight decay parameters have been chosen separately for each layer, and both have been optimized during initial investigations. The weight decay parameters were found to be $\alpha_H = 0.21$ for the input-hidden layer and

$\alpha_O = 1.6 \cdot 10^{-5}$ for the hidden-output layer. Next, using the optimal weight decay parameters, 10 fully connected networks were pruned by Optimal Brain Damage (OBD) [9], by removing two weights in turn. The training scheme consisted of a hybrid first-order/second-order approach, initialized by a few gradient descent steps and followed by pseudo Gauss-Newton diagonal approximation to the Hessian in the remaining iterations.

The two types of classifiers, i.e. the non-linear neural network classifier and the linear discriminant, are not directly comparable since they are derived under different assumptions and with different cost functions. One way to compare performance is to investigate each of the classifiers generalization performance on the independent test set in the form of the number of misclassifications. We find the "best" network around 104 parameters, where the initial network consisted of 323 parameters. Further, among the ensemble of the 10 pruned networks, 4 nets had pruned away 29 inputs, while the remaining had removed 21-28 inputs. More than 50% of the networks further agree to delete the *same* 28 inputs.

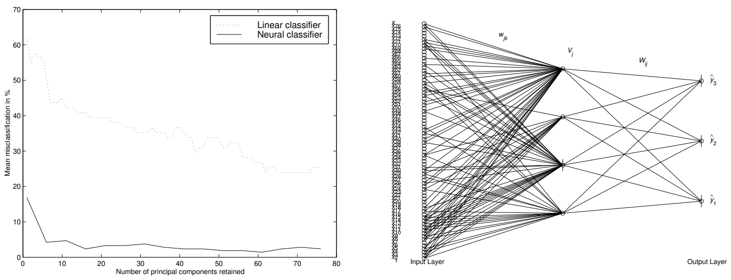


Figure 4: Left: Comparison of generalization performance for the linear model and neural networks, evaluated as the mean misclassification rate on the independent test set vs. the number of principal components utilized for the models. Right: Typical net among the 10 best nets found via OBD pruning. The number of parameters has been reduced from 323 to only 104 parameters. Further, 29 inputs are unused.

CONCLUSIONS

We have in this work carried out experimental investigations of exhaust valve burn-through on a large marine diesel engine situated in Copenhagen, Denmark. The engine involved in the experiments is MAN B&W Diesel's Research Engine, which is a 2-stroke 500 mm bore 4-cylinder marine diesel engine with an approximate output on 10.000 BHP. Measurements have been recorded for 3 different exhaust valve conditions (normal valve, small valve leak, large valve leak) over a broad range of engine operating conditions, varying speed and load and simulating misfire. Results from the measurements show that Acoustic Emissions (AE) have a major advantage over other involved more traditional used sensors (pressures, temperatures, vibrations) for monitoring reciprocating machinery.

Attention in this work, has been given to classification of different degradation levels of exhaust valve leakages as normal condition, acceptable fault, and unacceptable fault. Two different classifiers have been involved, namely a linear classifier, similar to Fisher's discriminant for two classes, and a neural classifier. Results from using time-series obtained by non-intrusive AE sensors, show that the neural classifier had a largely better performance than the linear discriminant (cf. Fig. 4). The neural classifier had a misclassification rate as low as 2%, while the linear discriminant yielded a lowest misclassification rate on 25%. By OBD pruning of the neural classifier, the number of parameters were reduced from initially 323 to 104. This reduction have reduced the computational burden, but the performance of the classifier, measured in terms of misclassification rate, seems not to deviate significantly even with smaller networks. This suggestion is further supported by generalization based investigations of the PC feature sub-space to choose. Despite the various heuristics and statistics involved to indicate a suitable PC subspace (cf. table in right panel of Fig. 3), the generalization performance based PCA investigations (cf. left panel in Fig. 4), shows no significant difference by choosing a lower number of PC's.

Acknowledgements. T. Fog wishes to acknowledge the European Commission and the Danish Academy of Technical Sciences (ATV) for supporting this work. Additionally, partial funding has been provided by the Danish Research Councils through the THOR Center for Neuroinformatics. We also want to address special thanks to Ewan Brown, Dept. of Mechanical & Chemical Engineering, Heriot-Watt University, Edinburgh, Scotland, UK, for his participation in the involved exhaust valve experiments.

REFERENCES

[1] O. Bardou, M. Watremetz and M. Sidahmed, "Early Detection of Leakage in Outlet Valves of High-power Diesel Engine using Vibration Analysis," in **Proceedings of the Third Internalional Machinery Monitoring and Diagnostics Conference 1991**, Las Vegas, NV., 1991, pp. 249–253.

[2] J. Bridle, "Probabilistic Interpretation of Feedforward Classification Network Outputs with Relation-ships to Statistical Pattern Recognition," **Neurocomputing Algorithms, Architectures and Applications**, vol. 6, pp. 227–236, 1990.

[3] T. L. Fog, E. R. Brown, H. S. Hansen, L. B. Madsen, P. Sørensen, E. R. Hansen, J. A. Steel, R. L. Reuben and P. S. Pedersen, "Exhaust Valve Leakage Detection in Large Marine Diesel Engines," in **In Proceedings of the 11th International Conference and Exhibition on Condition Monitoring and Diagnostic Engineering Management (COMADEM '98)**, Launceston, Tasmania, Australia, 1998, vol. 1, pp. 269–278.

[4] J. D. Gill, R. L. Reuben, M. Scaife, E. R. Brown and J. A. Steel, "Detection of Diesel Engine Faults using Acoustic Emission," in **Proceedings of**

the Planned Maintenance, Reliability and Quality, 2nd International Conference, 1998, Oxford, England, 2nd–3rd April 1998.

[5] L. K. Hansen and J. Larsen, "Unsupervised Learning and Generalization," in **Proceedings of the 1996 IEEE International Conference on Neural Networks**, Washington DC, USA, 1996, pp. 25–30, Vol. 1.

[6] M. Hintz-Madsen, L. Hansen, J. Larsen, M. Pedersen and M. Larsen, "Neural Classifier Construction using Regularization, Pruning and Test Error Estimation," **Neural Networks**, vol. 11, no. 9, pp. 1659–1670, Dec. 1998.

[7] J. E. Jackson, **A User's Guide To Principal Components**, Wiley Series in probability and Mathematical Statistics, USA: John Wiley & Sons, INC., 1991.

[8] I. T. Jolliffe, "Discarding Variables in Principal Component Analysis. I: Artificial Data," **Applied Statistics**, vol. 21, pp. 160–172, 1972.

[9] Y. Le Cun, J. Denker and S. Solla, "Optimal Brain Damage," in **Advances in Neural Information Processing Systems**, 1990, vol. 1, pp. 598–605.

[10] Paul McIntyre and R. K. Miller, **Acoustic Emission Testing**, vol. 5 of **Nondestructive Testing Handbook**, American Society for Nondestructive Testing, 2nd edn., 1987.

[11] B. D. Ripley, **Pattern Recognition and Neural Networks**, New York, USA: Cambridge University Press, 1996.

[12] L. M. Rogers, "Use of acoustic emission methods for crack growth detection in offshore and other structures," **The Institute of Marine Engineers : Transactions**, vol. 110, no. 3, pp. 171 – 180, 1998.

[13] P. Sørensen and P. S. Pedersen, "The Intelligent Engine and Electronic Products - A Development Status," in **Proceedings of the 22nd CIMAC International Congress on Combustion Engines**, Copenhagen, May 1998, pp. 551 – 564.

[14] P. Storegård Jensen, **Skibsdieselmotorer: Konstruktion Drift Vedligehold**, Copenhagen, Denmark: G-E-C Gads Forlag, 1994, In Danish.

[15] G. T. Venkatesan, D. West, K. M. Buckley, A. H. Tewfik and M. Kaveh, "Automatic Fault Monitoring Using Acoustic Emissions," in **Proceedings of the IEEE 1997 International Conference on Acouistics, Speech, and Signal Processing (ICASSP '97)**, Munich, Germany, 1997, pp. 1893–1896.

[16] J. Yang and Y. Zhou, "Diagnosis of Moving Components of Internal Combustion Engines by Analysing Vibration Signals," **Machine Vibration**, vol. 5, no. 3, pp. 163–169, 1996.