CONCLUSION

This thesis has accounted for the development of an automatic condition monitoring system, which detects and estimates changes in the condition of large diesel engines. The system input is based on AE-RMS signals acquired from AE sensors mounted at large diesel engines. In the work done in this thesis, four digital AE-RMS signals from a single diesel engine were applied as system input signals. The AE-RMS signals were provided by a test, which contains five engine change conditions.

Five re-sampling methods have been implemented to enlarge the original data set. Unfortunately, the methods provide either re-sampled signals, which are too similar to the original signals, or re-sampled signals, which are too different from the original signals. However, method no. 5 was chosen, since it was the best method, and since use of ROC curves was wanted to evaluate the system performance.

Three pre-processing and feature extraction approaches have been implemented and investigated. The method with the best performance was PCA, since it created feature signals where all the condition changes were observable. Mean value of the cycles was the second best approach, because it had more observable changes than the third method, standard deviation of the cycles. From the feature signals it is concluded that sensor no. 1 and no. 3 senses the oil experiments, i.e. when the oil lubrication is turned off and on, better than sensor no. 2 and no. 4. However, the feature signals generated from sensor no. 2 and no. 4 seem to contain more stable conditions, which in the end improves the change detection and change point estimation.

A segmentation approach based on three modules has also been developed and tested. The first module is a fast on-line algorithm, which for each cycle assess when the engine leaves its normal condition and enters a new condition. When the on-line algorithm has detected these two change points, a more powerful and reliable off-line algorithm is activated. It sets up a hypothesis to check whether or not a change has actually occurred. If the hypothesis is true, i.e. a change *has* occurred, then the final module is activated, which is an off-line algorithm that estimates the two change points detected by the on-line algorithm more precisely.

The segmentation approach has been tested on the original data provided by the four AE-RMS sensors and on re-sampled data for the first oil experiment, the oil lubrication turned off, but only for sensor no. 1. The test on the original data revealed that the system is capable of detecting all the changes. However, if only the mean value and the standard deviation of the cycles, and not PCA, is used to generate feature signals, then the change corresponding to the unstable region can not be detected. If PCA is applied, the detection of all changes is possible. It is also possible to create a very reliable off-line hypothesis test, but it depends on how stable conditions the feature signals have. Two maximum likelihood methods have been implemented to estimate the change points more precisely. The first method has difficulties estimating the first change point properly, since it assumes that the drift between the conditions is linear, which is not always the case. The second method has difficulties estimating the second change point, but it is not determined exactly what the cause is. However, the cause seems to be that the new condition is less stable than it is assumed to be.

Conclusion

The first experiment from sensor no. 1 was re-sampled to test the system on more examples. Since the on-line algorithm consists of two decision functions with independent thresholds, first deactivating only one of the decision functions, and then deactivating only the other decision function, provided two ROC curves. The result is that the algorithm has a true detection rate at about 90% if the false alarm rate is less than 20%. This corresponds to the first change point, the one when the engine leaves its normal condition, being detected no later than about 30 cycles after the true change point. For this work, this is adequate, since no further specification has been given.

Two ROC curves describe the off-line hypothesis test performance in a similar way. One of the ROC curves sweep the critical value, when a change in the mean value is assumed, and the other ROC curve sweeps the critical value, when a change in the standard deviation is assumed. For some specific critical values it is possible to state with 100% reliability whether or not a change has occurred. The off-line hypothesis test statements are binomial distributed, and in this test the maximum standard deviation is calculated to be max. 0.016.

Maximum likelihood method no. 1 estimates the first change point to be 152 with a deviation of 3 cycles. The true change point is 153 for the original data, but the re-sampling causes the true change point to be shifted app. 10 cycles to the right. Thus the observation for method no. 1 in the original data set is confirmed. The second change point is estimated to be 261 with a deviation off 12 cycles. The second maximum likelihood method estimates the first change point more precisely to 166 with a deviation of 5 cycles. Unfortunately, the second change point is estimated to be at the very end of the experiment, which is not true.

White additive Gaussian noise has been added to the feature signal of the very same experiment. Three signal to noise ratios were tested: 0, 20 and 40 dB. The performance of the on-line algorithm became worse, but not significantly, since the true detection rate only changes from app. 90 to 85%, which only means that the first detection point will be detected a few cycles later. The off-line hypothesis test is not affected at all, and the maximum likelihood methods estimate the change points to be no more than app. 3 cycles from the estimated change points in the noise free test.

Finally, from the tests and the results, a proposal on how to interface the investigated modules in to an automatic condition monitoring system has been given.