Chapter 8

Appendices

8.1 Appendix A: Summary of articles included from search 1 and 2

Ref.	Input	Feature extraction method	Machine learning model
[13]	Vibration signal.	ARMA model and J48 decision tree	Tests a set of (38) meta-, misc-, rule- and tree-based classifiers for fault detection in blades.
[34]	SCADA data.		Deep autoencoder made of Restricted Boltzman Machines (RBMs) to model normal behaviour of SCADA variables (gearbox and generator temperature). Uses E_e for anomaly detection, with adaptive threshold set using extreme function theory (EFT).
[51]	SCADA data.	Spatiotemporal pattern network	Unsupervised use of RBMs for anomaly detection.
[14]	SCADA data.	Time-frequency domain analysis, DWT and ARMA model	Uses fusion of several classifiers for fault detection in a wind turbine.
[6]	Ultrasonic testing.	Tests linear and non-linear PCA and ARMA models	Neighbourhood component analysis for feature selection. Tests 20 different supervised classifiers for detecting ice on blades.
[28]	Wind-Power curve.		Uses Gaussian Process regression with EFT to determine whether a particular power curve is an outlier.
[22]	Acustic emission.	FFT.	Uses Distinguishability Measure for feature selection, and logistic regression and SVC for binary blade fault classification.
[40]	Power signal, wind speed and ambient temperature.		Hierarchical Extreme Learning Machine (H-ELM) for detection of anomolous behaviour.
[29]	SCADA data.		Gaussian processes regression to estimate wind-power curve

[27]	SCADA data.		Tests KNN, random forest, and SVR to estimate power curve. Detects anomalies by E_e.
[102]	Vibration signals.		Uses unsupervised dictionary learning extracting features which are then used to determine fault in drivetrain bearings.
[38]	Oil temperature, wind speed, rotor speed and active power.		Trains ANN to estimate vibration signal, uses E_e for anomaly detection.
[19]	SCADA data.	PCA.	Sets up baseline model using multiway PCA, then finds outliers by hypothesis testing whether multivariate distribution is equal to baseline.
[16]	FAST wind turbine simulator.	Image texture analysis tools.	KNN, Linear Discriminant Model, decision trees, bag-tree, linear SVC.
[39]	SCADA data.	K-means for outlier elimination.	Uses Auto-Associative Neural Networks as an autoencoder, and the Hotel T2 statistic as a dynamic threshold for the R_e.
[30]	SCADA data.	Grey correlation algorithm for eigenvector extraction.	Use genetic algorithm for feature selection, and SVR for estimating performance curves (active power, rotor speed and blade pitch angle).
[33]	SCADA data.		Uses three NN for normal behaviour modelling of rotor speed, gearbox temperature and generator temperature. E_e sendt to proportional hazard model which sets dynamic threshold.
[44]	SCADA data.		Uses Inductive Transfer Learning and five differen ML classifiers for ice detection on blades.
[46]	Vibration signals.	Variational mode decomposition (VMD).	Uses multi-scale permutation entropy (MPE) used for feature selection, CO-VAL for domain normalization and an SVC for binary fault classification.
[32]	SCADA data.		Uses bins and SVR to estimate blade angle pitch curve.
[35]	SCADA data.		Tests different architectures of ANNs to for estimating temperature of non-drive end bearing. Uses E_e for anomaly detection.
[7]	Images taken by drones		Recurrent Convolutional Neural Network to classify structural damage in blades.
[8]	Uses images taken from ground level		Convolutional Neural Network, and YOLO-based small object detection approach (YSODA) for damage detection in blades and hub.

[17]	Vibration signals, acustic emission and oil particle analysis	DWT.	Uses decision tree for feature selection, and SVC for assessing fault severity in gearbox
[41]	Uses images taken from ground level		Convolutional Neural Network to detect cracks & damage in blades.
[9]	Ultrasonic testing	PCA and ARMA models.	Neighbourhood Component analysis for feature selection and an ensamble of KNN, linear SVC, decision trees, LDA and subspace discriminant to estimate amount of dirt and mud on blades.
[47]	Uses pitch position, rotor speed and generator speed.		Detects faults with an SVC with parameters optimized by Cuckoo-swarm optimization.
[15]	Vibration signals	ARMA model.	Dominating features selected with J48 decision tree, fault classification done with Bayesian- and lazy classifiers.
[18]	Vibration signals, acustic emission and oil particle analysis	DWT and PCA.	Dominating features selected with decision tree, fault detection done with SVC.
[10]	Images taken from imaging array		Uses a deep neural network for binary classification of blade defects.
[11]	Uses images taken by drone	Uses a CNN trained on an unrelated image dataset to extract general features.	Compress features with PCA, and pass them to a unsupervised one-class SVM.
[45]	Uses the FAST wind turbine simulator to get SCADA data.	Random forest.	Uses XGBoost to train an ensamble of classifiers for specific faults.
[36]	SCADA data.		Uses several ANN to build a normal behaviour model of temperature in gearbox and high speed shaft, then uses E_e together with the age of the age of the turbine to predict anomolous behaviour.
[31]	SCADA data.		Uses Pearson product-moment rank correlation to select features, and applies different ANN structures to predict the active power.
[48]	SCADA data from a simulink model of a wind turbine.		Uses DBN for detecting anomolous behaviour. First traines individual RBMs to recreate input, and then uses labeled data to fine tune DBN to detect faults.

[37]	SCADA data.		Uses kolmogorov-smirnov test to compare different turbines at same moment in time combined with the E_e of the gearbox bearing temperature of an ANN to detect anomalies.
[49]	Vibration signals.	Approximates vibration distributions at different rotor speeds with Weibull distribution.	Uses a HMM for statistical fault detection.
[42]	SCADA data.		Compares linear models, ANNs and state-dependent parameter models for fault detection.
[21]	SCADA data.	parallel factor analysis (PARAFAC) as a decomposition method	uses K-means clustering after decomposition for fault detection.
[20]	Uses a wind turbine simulator for SCADA data.		Multiple PCA models are as a statistical reference reflecting the data variability in local zones and used in parallel for online fault detection.
[23]	Vibration signals.	Variational mode decomposition	Uses Fisher score and ReliefF algorithm for feature selection. Feeds selected signals into a multi-class SVC for bearing fault detection.
[43]	SCADA data.		Uses deep neural networks for detection of icing on the blades.
[103]	SCADA data.		Combines NN with alarms generated by SCADA system to reduce false alarm rate.
[4]	SCADA data.		Uses K-means clustering to partition turbines into different operating states, and a specific DBN of RBMs for each cluster to forecast the gearbox main bearing temperature. Uses E_e to detect anomalies, threshold set by Mahalanobis distance.
[104]			This is a literary review of vibration based condition monitoring and fault diagnosis of planetary gearboxes in wind turbines.
[50]			This is a literary review of machine learning methods used for condition monitoring of wind turbines.

Table 8.1: Summary of articles included from search one and two in table 2.1

8.2 Appendix B: Summary of articles included from search 3

Ref.	Representation	Similarity measure	Clustering Algorithms	Evaluation
[90]	Mixture Gaussian hidden Markov model (MGHMM).		Expectation-maximization.	Bayesian information criterion.
[94]	Variance ratio statistics.	Euclidean distance.	Hierarchical clustering mainly, and K-means.	Duda-Hart $Je(2)/Je(1)$ indices.
[91]	HMM. States correspond to concentration regimes.	Which state each HMM is in.	Cluster together time series with corresponding HMMs in the same state.	
[53]	This is a review of time series clustering.			
[57]	Raw time series and some extracted statistics: variance, covariance, spread and differences.		Growing hierarchical self-organizing map.	
[81]	Compares to methods: a model-based approach using a state space model and functional approach where time series are represented as linear combinations of spline functions.	Euclidean distance.	State space modelling, K-means and complete-linkage hierarchical clustering.	L-curve and gap statistic.
[82]	Empirical mode decomposition for filtering out stochastic components, then extract topological features.	Euclidean distance.	K-means.	Precision, recall, F1-score and Matthews correlation coefficient.

[96]	Construct network between time series using dissimilarity matrix. Use KNN, and ϵ-NN to create networks from matrix.	Test a multitude of different distance functions. DTW performs best.	Test many community detection algorithms to sort network into clusters.	Rand index.
[78]	SAX.	Approximate distance, Euclidean distance, and DTW.	Custom three step algorithm, with preclustering, sub-clustering, and merging to form final clusters.	Accuracy, precision, recall and F-measure.
[83]	GARCH model.	Tests different metrics based on squared Euclidean distance between unconditional volitility and time varying volitility.	Tests different variations of fuzzy C-medoids.	Xie-Beni index, and Fuzzy Rand index.
[73]	Bispectral Smoothed Localized Complex Exponential.	Aggragated quasi-distance between smoothed bispectra across blocks.	Agglomorative hierarchical clustering with Ward's linkage.	Silhouette index as stopping criterion, and Rand Index, entropy and purity to evaluate cluster effectiveness.
[92]	HMMs.	Kulback-Leibler distance between the likelihood of a certain observation sequence given HMM.	K-medoids.	Silhouette index, Bavies-Bouldin index and Dunn index.
[95]	Copula-based model for time series.	P-norm of difference between copula of two points, and upper bound copula.	Fuzzy C-medoids.	Fuzzy Silhouette index, adjusted Rand index, fuzzy Rand index.
[66]	DWT, SAX and AR model.	Minimum distance, Euclidean, Minkowski, Pearson correlation coefficient and DTW distance.	Agglomerative Hierarchical clustering with Ward linkage.	Uses the clusters produced to perform regional frequency analysis, and then evaluates model using bias, root mean square error (RMSE), relative RMSE and Nash criterion.
[64]	ICA.	Not specified.	Hierarchical clustering with complete linkage.	

[79]	SAX.	Approximate distance between symbolic representations of time series.	Extended version of K-modes.	SSE for stopping criteria, Rand index, Normalized Mutual Information, Purity, Jaccard, F-measure, Folks and Mallows and entropy.
[74]	Tranforms the covariance matrices of the time series into a tangent space.	Euclidean distance.	Hierarchical clustering with average linkage.	
[71]	Normalized spectral densities.	Total variation distence.	Agglomorative hierarchical clustering with complete and average linkage.	Dunn's index.
[84]	Self-exciting threshold autoregressive model.	Primarily tests Euclidean distance, Haussdorf distance and DTW, but, tests 22 different ones.	Primary method is spectral clustering, but also tests K-medoids, and fuzzy C-means.	Measures accuracy of method on clustering simulated data, and uses Gap statistic as stopping criterion.
[85]	AR model.	A type of exponential Euclidean distance.	Fuzzy C-medoids.	Fuzzy Silhouette index.
[67]	Continous wavelet transform.	Multi-scale PCA similarity matric.	Fuzzy C-means.	Precision and recall of classification according to labels, and silhouette index.
[93]	Preprocessing using Hodrick-Prescott filter, primarily represents time series with state space models.		SOM.	Silhouette index as stopping criterion.
[86]	ARIMA model.	Euclidean distance between AR weights.	Trimmed fuzzy C-medoids.	Decides number of clusters by looking at the rate of decrease, and second derivative of an objective function with regard to a trimming factor α.

[80]	Permutation based coding of time series.	Use four distance metrics based on mutual information, entropy and Cramer's V association measure.	Hierarchical clustering with single, complete and average linkage.	
[54]	Mixture of autoregressions models.		Maximum pseudo-likelihood esitmation using Expectation-maximization algorithm.	
[65]	Use PCA and custom ICA algorithm for feature extraction.	Euclidean distance between extracted features.	Hierarchical clustering with average, single, complete and Ward linkage, and K-means.	CH, Friedman, C-index, Dunn's, SDbw and Silhouette index.
[58]	Extracts various signal statistics, and performs feature extraction using PCA.	Euclidean distance.	Hierarchical clustering with complete linkage.	
[68]	DWT with the Haar wavelet, and a globel sensitivity analysis.	Euclidean distance, to minimize variance.	K-means.	
[97]	Multi-relational network in topological domain, static (time-invariant), and dynamic (time-varying).		Multi-nonnegative matrix factorization. Compares their approach to three other community detection algorithms.	Rand index, adjusted Rand index and purity.
[75]	Uses SVD to represent the cluster centroids.	Pearson correlation coefficient.	Fuzzy C-means with particle swarm optimization.	Precision, and F-measure.
[61]	Multivariate time series are transformed into 3-order hysteresis tensors, then multilinear PCA is used to reduce dimensionality.	Tensor distance metric. Cluster centers initialized based on cycle feature variation.	Tensor K-means.	Rand index,Adjusted Rand index, Jaccard coefficient and Folks and Mallows index.

[105]	Compares ten model-based clustering methods. Gaussian mixture model and Markov-switching model perform best.		Expectation-maximization (EM).	Misclassification rates.
[69]	Vari-segmented DWT.	Euclidean distance.	K-means, hierarchical agglomerative clustering and SOM.	
[70]	DFT.	Euclidean distance.	Delaunay Triangulation method.	Purity and F-measure.
[76]	Piecewise SVD, and piecewise aggregate approximation.	Euclidean Distance.	BIRCH.	
[59]	Extracts signal statistics, and uses PCA for feature selection.	Euclidean distance.	K-means.	Analyses the correlations of specific features with different clusters.
[72]	Fragmented periodogram.	Euclidean distance.	Spectral clustering.	
[60]	Extract statistical features of time series, then use a convolutional auto-encoder for further feature extraction.	Mainly Euclidean distance for the model-based approach.	Tests many clustering algorithms, but will only consider K-means, hierarchical clustering with Ward linkage, expectation-maximization, spectral clustering and BIRCH.	Adjusted Rand index.
[62]	Compares a feature-based approach using PCA, with a model-based approach using state-space models for the individual time series.	Inverse exponential Euclidean distance for feature based approach, and Euclidean distance for model-based approach.		Silhouette index as stopping criterion.
[87]	AR model.	Euclidean distance.	Fuzzy C-means.	
[88]	Flexible space-time AR models.	Use Wald statistic to compare model parameters of univariate space-time AR models, and p-value as a similarity metric.	Hierarchical agglomorative clustering.	Adjusted Rand index.

[63]	Common PCA.	Cluster centroids represented by common projection axis of all time series in a specific cluster, then reconstruction error of time series using cluster centroid used as similarity metric.	Custom algorithm, similar to K-means.	Precision.
[77]	Map the time series to multiple high-dimensional tensors using multiple kernals.	Matrix L^p-norms.	Self-developed multi kernal clustering algorithm.	Normalized Mutual Information and Rand Index.
[89]	Vector AR models.	Euclidean distance.	Test two self-developed algorithms based on performing statistical test of whether time series come from same data generating process.	Purity index.

Table 8.2: Summary of Summary of articles included from search three in table 2.1

8.3 Appendix C: Code

To produce all the relevant plots all the listings can be posted and run in the same file, to produce all the relevant plots used in this report. They are split up into separate listings such that it is easier to link each listing to each plot.

```python
import pandas as pd
from sklearn.decomposition import PCA
from datetime import datetime
import time
import timeit
import numpy as np
import matplotlib.pyplot as plt
import copy

work_directory = 'Not relevant'
data_sets_path = \
'data_sets/big_turbine_data/'
filename = 'big_turbine_data'
path_pictures = work_directory + 'pictures/'

completeDF = pd.read_csv(work_directory+data_sets_path+filename+'.csv',
                         delimiter=',',
                         skiprows=1)

completeDF['Time'] = pd.to_datetime(completeDF['Time'], format='%Y-%m-%dT%H:%M:%S.%fZ')
completeDF.set_index('Time', inplace=True)
```

Listing 1: Module fetching and loading data

```python
# Dropping max/min cols
column_names = completeDF.columns
for name in column_names:
    if ('Max' in name) or ('Min' in name):
        completeDF.drop(name, axis=1, inplace=True)

# Renaming columns
column_names = completeDF.columns
new_col_names = []
for name in column_names:
    split_name = name.split('/')
    turbine_num = split_name[2]
    if split_name[-1] == 's)':
        value_meas = split_name[-3]
    else:
        value_meas = split_name[-1]
    new_name = turbine_num + '/' + value_meas
    split_new = new_name.split('(Avg)')
    new_col_names += [split_new[0] + split_new[1]]
completeDF.columns = new_col_names

# Create a dictionary of windturbine dataframes
column_names = completeDF.columns
dict_of_turbine_dfs = {}
for i in range(1,14):
    turbine_num = 'WTUR' + str(i) + '/'
    tempDF = pd.DataFrame()
    for name in column_names:
        if turbine_num in name:
            tempDF[name] = completeDF[name]
        dict_of_turbine_dfs[turbine_num[:-1]] = tempDF

# Normalize values from each dataframe
dict_norm_dfs = {}
for turb_name in list(dict_of_turbine_dfs.keys()):
        df = dict_of_turbine_dfs[turb_name]
        dict_norm_dfs[turb_name] = (df - np.min(df.values, axis=0)) / (np.max(df.values, axis=0) - np.min(df.va
```

Listing 2: Data formatting and normalization

```python
dict_of_turbine_dfs['WTUR4'].plot(figsize=(12,8),subplots=True, layout=(2,2))
plt.legend(fontsize=10)
name = path_pictures + 'one_turbine_all_vals.png'
plt.savefig(fname=name)
```

Listing 3: Code used to produce plot in figure 5.1

```python
# PCA Finding portions of explained variance
cumulative_explained_variance = {}
for turb in list(dict_norm_dfs.keys()):
    X = dict_norm_dfs[turb].values
    pca = PCA().fit(X)  # project from 64 to 2 dimensions
    cumulative_explained_variance[turb] = np.cumsum(pca.explained_variance_ratio_)

plt.figure(figsize=(10,8))
for turb in list(cumulative_explained_variance.keys()):
    plt.plot(cumulative_explained_variance[turb], label=turb)

plt.xlabel('Number of components', fontsize=14)
plt.ylabel('Cumulative explained variance',fontsize=14);
plt.legend(fontsize=10)

name = path_pictures + 'cumulative_explained_variance.png'
plt.savefig(fname=name)
```

Listing 4: Code used to calculate cumulative explained variance, and produce plot in figure 5.2

```python
mse = {}
for turb in list(dict_norm_dfs.keys()):
    Xstd = dict_norm_dfs[turb].values
    pca = PCA(n_components=2)
    pca.fit(Xstd)
    P=pca.components_
    T = Xstd.dot(P.T)
    Xhat = np.dot(T[:,0].reshape(-1,1),P[0,:].reshape(-1,1).T)
    mse[turb] = (np.square(Xstd - Xhat)).sum(axis=1)

plt.figure(figsize=(12,8))
for turb in list(mse.keys()):
    plt.plot(mse[turb], label=turb)

plt.xlabel('Time', fontsize=14)
plt.ylabel('Mean square reconstruction error',fontsize=14);
plt.legend(fontsize=10)
name = path_pictures + 'reconstruction_error.png'
plt.savefig(fname=name)
```

Listing 5: Code used to calculate reconstruction error, and produce plot in figure 5.3

```
dict_perturbed_norm_dfs = copy.deepcopy(dict_norm_dfs)
dict_perturbed_norm_dfs['WTUR12'].columns
for idx in range(9000,11000):
    dict_perturbed_norm_dfs['WTUR12'].iat[idx,0] = 1
    dict_perturbed_norm_dfs['WTUR12'].iat[idx,2] = 0

df_to_plot = pd.DataFrame()
df_to_plot['Power perturbed'] = dict_perturbed_norm_dfs['WTUR12']['WTUR12/ActivePower (kW)']
df_to_plot['Speed perturbed'] = dict_perturbed_norm_dfs['WTUR12']['WTUR12/WindSpeed1']
df_to_plot['Power'] = dict_norm_dfs['WTUR12']['WTUR12/ActivePower (kW)']
df_to_plot['Speed'] = dict_norm_dfs['WTUR12']['WTUR12/WindSpeed1']
df_to_plot.plot(figsize=(12,8))
plt.xlabel('Time', fontsize=14)
plt.ylabel('Amplitude',fontsize=14);
plt.legend(fontsize=10)
name = path_pictures + 'perturbed_vs_unperturbed.png'
plt.savefig(fname=name)
```

Listing 6: Code used to produce plot in figure 5.4

```
cumulative_explained_variance = {}
for turb in list(dict_perturbed_norm_dfs.keys()):
    X = dict_perturbed_norm_dfs[turb].values
    pca = PCA().fit(X)
    cumulative_explained_variance[turb] = np.cumsum(pca.explained_variance_ratio_)

plt.figure(figsize=(12,8))
for turb in list(cumulative_explained_variance.keys()):
    plt.plot(cumulative_explained_variance[turb], label=turb)

plt.xlabel('Number of components', fontsize=14)
plt.ylabel('Cumulative explained variance',fontsize=14);
plt.legend(fontsize=10)
name = path_pictures + 'explained_variance_perturbed.png'
plt.savefig(fname=name)
```

Listing 7: Code used to calculate cumulative explained variance of perturbed data, and produce plot in figure 5.5

```python
mse_pert = {}
for turb in list(dict_perturbed_norm_dfs.keys()):
    Xstd = dict_perturbed_norm_dfs[turb].values
    pca = PCA(n_components=2)
    pca.fit(Xstd)
    P=pca.components_
    T = Xstd.dot(P.T)
    Xhat = np.dot(T[:,0].reshape(-1,1),P[0,:].reshape(-1,1).T)
    mse_pert[turb] = (np.square(Xstd - Xhat)).sum(axis=1)

plt.figure(figsize=(12,8))
for turb in list(mse_pert.keys()):
    plt.plot(mse_pert[turb], label=turb)

plt.xlabel('Time', fontsize=14)
plt.ylabel('Mean square reconstruction error',fontsize=14);
plt.legend(fontsize=10)
name = path_pictures + 'reconstruction_error_perturbed.png'
plt.savefig(fname=name)
```

Listing 8: Code used to calculate reconstruction error using perturbed data, and produce plot in figure 5.3

```python
plt.figure(figsize=(12,8))
plt.plot(mse['WTUR12'], label='Original reconstruction error')
plt.plot(mse_pert['WTUR12'], label='Perturbed reconstruction error')

plt.xlabel('Time', fontsize=14)
plt.ylabel('Mean square reconstruction error',fontsize=14);
plt.legend(fontsize=10)
name = path_pictures + 'pert_vs_unpert_reconstruction_error.png'
plt.savefig(fname=name)
```

Listing 9: Code used to produce plot in figure 5.6

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