1. By end of July complete an up to date literature review of prior work on **machine learning or expert systems (consider various terminology)** on **industrial air compressors**.  Identify **suitable rules**.

* Previous work – restrict to last 15 years – in particular last 5 years
* Expert systems / machine learning – come up with list of different terminologies
* Industrial air compressors – narrow scope to just this

Literature Review

# Research Question

What is the best method for performance management of air compressors through ongoing data analysis?

# Background

Currently industry uses ###% of Irish energy, and ###% globally. Of this energy, compressed air is recognised as consuming ###%. Compressed air is known colloquially in industry as the “fourth fuel”, due to the high electrical cost associated with generation. Compressed air systems are typically running at ###% efficiency, due to energy losses through heat of generation, leakage, and ###.

Compressed air is generated in industry using a wide variety of equipment types and configurations. Different types of equipment are suited to different applications in terms of volumetric and pressure requirements. The three key types of compressor installed in industry today are reciprocating, rotary, and centrifugal machines. Their suitability to different volumetric and pressure requirements is summarised in Figure ####.

Reciprocating and rotary machines are both positive displacement type machines. They work through isolation of a quantity of air in a space which is then reduced in volume. Centrifugal machines are aerodynamic machines, which operate by imparting kinetic energy to air, which is then converted to pressure energy by stopping the moving air.

Given that compressed air represents such a dense form of energy transport, it is beneficial in terms of long and short term overall energy efficiency goals to manage their performance. Performance management of compressors is typically achieved through means such as those in **Table 1.**

|  |  |  |
| --- | --- | --- |
| Performance Management Method | Advantages | Disadvantages |
| Maintenance Contracts |  |  |
| Periodic Audits |  |  |
| Sequence Controllers |  |  |
| BMS Monitoring |  |  |
| Preventive Maintenance |  |  |

Table : Compressed Air System Performance Management Methods

As is outlined in **Table 1**, the key disadvantages of existing methods are either that they are manual and periodic in nature, or require the intervention of a human expert in compressed air systems to be effective. In the case of maintenance contracts and periodic audits, there is also the potential for unnecessary work to be carried out, as both these measures are typically carried out on a timescale basis. The intervention of a human expert also lends itself to an inefficient method of performance measurement. An expert may be particularly well versed with one type of system, but not another. The disparate range of compressed air systems can lead to an expert restricting themselves to one type of system, preventing possible lessons learned to be applied in other suitable cases.

Research is being carried out to define the future of compressed air system performance management. In this review the research considered is that of ongoing analysis of compressed air system data. This ongoing analysis may take the form of:

* Fault detection – monitoring system parameters to determine when the system is in fault condition
* Fault detection and diagnosis – as for fault detection but with the capability of determining the specific cause of the fault detected
* Prognostics – monitoring system parameters to predict the time at which a part or component of the compressed air system will no longer perform its intended function [1]
* Analytics – monitoring system parameters allow the discovery and communication of meaningful patterns which advise on possible improvements to system operation

## Current Methods

|  |  |  |  |
| --- | --- | --- | --- |
| Method | Type | Pros | Cons |
| Machine Learning | Neural Networks |  |  |
| Statistics | Principal Component Analysis |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

# Adaptive Clustering

[2] presented a method for feature identification

# [3]

[3] presented the paper *“Optimization of operating conditions for compressor performance by means of neural network inverse”*.

In this paper an artificial neural network method was applied to a gas turbine’s compressor. It was therefore different to an air compressor as the fluid being compressed was a fuel-air mixture with a different pressure and temperature requirement than normally expected from an air compressor. The compressor type is given as “axial”.

An artificial neural network was first developed with an input layer (10 neurons), a hidden layer (12 neurons) and an output layer (four neurons). The inputs for developing this model were obtained by experimental measurement of 59,049 samples. The outputs were then calculated using a thermodynamic model. Once the neural network was created an inverse neural network was developed. The compressor cooler temperature drop was then optimised with respect to efficiency using the Nelder–Mead simplex method. An advantage of this method was noted to be the low time required to find the ideal cooler temperature drop for a given efficiency (<0.5 s). This would allow the method to be used for on-line operation.

# [4]

[4] presented the paper *“Neural-network based analysis and prediction of a compressor's characteristic performance map”*.

In this paper neural networks are used to develop characteristic performance maps of a gas turbine’s axial compressor when operating in off-design conditions. It was desired to know the relationship between four of the compressor’s key parameters. These four parameters were the same as those defined as outputs in the neural network of [3]. If these four parameters are known, then the compressor’s characteristic performance map may be drawn. This map may be used to determine an accurate state of the compressor’s operation if two of the four parameters are known.

Normally characteristic performance maps are created either experimentally or from manufacturer provided data. In an off-design condition measuring the required parameters experimentally can be difficult. Therefore it was desired to find an easier method of determining the compressor’s characteristic performance map. A tri-layer back-propagation neural network model was developed to give the compressor’s characteristic performance map. While the position of the inlet guide vanes of an air compressor affect its performance map, this variable was ignored in this work. This paper differed from [3] in that the structure of the neural network (i.e. number of neurons in the input and second layer) was not readily given.

# [5]

[5] presented the paper *“An artificial neural network approach to compressor performance prediction”*.

In this paper different neural network model types were reviewed for accuracy in generating a gas generator’s compressor performance characteristic map. The four types reviewed were:

* General regression neural net-work (GRNN)
* Modified GRNN
* Multilayer perceptron network
* Radial basis function network

The two types of neural network found to be most effective in reconstructing a compressor’s performance map were modified or rotated GRNN and multilayer perceptron. Rotated GRNN was found to be most accurate in terms of closest agreement of results with training data, it was limited as a method to predicting the compressor performance map within the limits of training data given to it, and i.e. it is limited to interpolation. Multilayer perceptron networks are more suited to predicting a compressor’s performance characteristic at any operational point of the compressor, i.e. it can extrapolate to outside the given experimental training data. It was determined that multilayer perceptron neural networks are the most powerful of those reviewed in reconstructing compressor performance characteristic maps.

A key accuracy measure was that the performance map of a compressor was able to be reconstructed to 92% accuracy using 50% of available training data. Also by using the output of one neural network together with one measured parameter (corrected mass flow rate of air) as the inputs of another neural network the efficiency of the compressor could be predicted to an extremely high accuracy.

The authors had the same opinion as [4] in that neural networks provide an effective means of reconstructing a compressor’s characteristic performance curve when experimental or manufacturer’s data is not available, e.g. in off-design conditions.

[1] B. W. George Vachtsevanos, Frank L. Lewis, Michael Roemer, Andrew Hess, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. .

[2] M. Petković, M. R. Rapaić, Z. D. Jeličić, and A. Pisano, “On-line adaptive clustering for process monitoring and fault detection,” *Expert Syst. Appl.*, vol. 39, no. 11, pp. 10226–10235, 2012.

[3] O. Cortés, G. Urquiza, and J. a. Hernández, “Optimization of operating conditions for compressor performance by means of neural network inverse,” *Appl. Energy*, vol. 86, no. 11, pp. 2487–2493, 2009.

[4] Y. Yu, L. Chen, F. Sun, and C. Wu, “Neural-network based analysis and prediction of a compressor’s characteristic performance map,” *Appl. Energy*, vol. 84, no. 1, pp. 48–55, 2007.

[5] K. Ghorbanian and M. Gholamrezaei, “An artificial neural network approach to compressor performance prediction,” *Appl. Energy*, vol. 86, no. 7–8, pp. 1210–1221, 2009.