Colour coding:

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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 10 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 performance management method for air compressors?

# Method

To complete this review the following search engines were used:

1. Google Scholar
2. Science Direct
3. Engineering Village

Search terms used were in the form of “compressed air”, “air compressor” and “pneumatic system” together with the particular approach or method being reviewed, e.g. “air compressor fault detection neural networks”.

Papers were summarised under the main categories of:

* What was the higher goal of the method (e.g. FDD, Optimisation)?
* What method did they use?
* What type of compressor were they using?
* Are there any good leads in the references of the paper? If so make a list to follow.
* What parameters were required/used by the method?
* What faults were detected (if it was an FDD paper)?
* Are there any similarities / differences in opinion between this paper and others reviewed?

# 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 have a high level of:

1. Fault detection – monitoring system parameters to determine when the system is in fault condition
2. Fault detection and diagnosis – as for fault detection but with the capability of determining the specific cause of the fault detected
3. 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 (George Vachtsevanos, Frank L. Lewis, Michael Roemer, Andrew Hess n.d.). This can allow for predictive maintenance, ensuring that maintenance is carried out before equipment becomes faulty. Predictive maintenance programs are recognised as more sophisticated than other program types (e.g. corrective, preventive, opportunistic and condition-based). In an analysis of one industrial facility (Bevilacqua & Braglia 2000), compressors were selected from various equipment types as being the type of equipment most warranting the use of a predictive maintenance program. This was decided using an Analytical Hierarchy Process approach, with different equipment types assigned a Criticality Index (CI) based on the potential consequences of failure.
4. Analytics – monitoring system parameters allow the discovery and communication of meaningful patterns which advise on possible improvements to system operation
5. Automated commissioning – automatically achieving, verifying, and documenting satisfaction of the performance of a compressed air system with the current user requirement
6. Optimisation – defining how to achieve the goal of best possible operation of a compressed air system with respect to a defined criterion, typically lowest cost of operation

# Current Methods

This review has categorised different methods for air compressor performance management into three distinct categories, i.e.:

1. Knowledge based (manual methods) - historical
2. Engineering model / rule based (deterministic/quantitative methods) - current
3. Machine learning / data driven (stochastic methods) - current

These three categories of method have different capabilities, benefits and disadvantages, as shown in **Table ####.**

## Knowledge Based Methods

Knowledge based methods are defined for the purposes of this review as those methods which attempt to formalise in code or otherwise the reasoning of a human expert. These systems represent an approach where the engineering or equipment knowledge of an expert is applied in a heuristic fashion.

These systems typically require heavy engagement from system and equipment experts at the time of deployment. This engagement may take the form of interviews and/or site visits with key personnel. The individual opinions of site personnel may vary from facility to facility, and this may prevent lessons learnt being transferred across industries.

From this review it appears that these methods are useful to a certain extent and may be deployed in a facility to ensure that if key personnel retire, valuable knowledge about a compressed air system is not lost. However the amount of time and engagement required for deployment would suggest that for rapid performance improvements in compressed air system performance, other approaches would be more suitable.

### Analytical Hierarchy Process

One such example of a knowledge based system as defined in this review is the Analytical Hierarchy Process (AHP) approach. This is a formal method discussed in detail in (Saaty 2008) to support decision making. Areas including maintenance programming of industrial equipment lend themselves to an AHP approach for decision making, as the approach assists with ensuring all possible factors influencing any decision made are considered.

The AHP method involves initially creating a hierarchy scheme for the decision to be made. An example hierarchy scheme is given in **Figure 1.**

Figure : Example AHP Hierarchy Scheme

The hierarchy scheme has three or more levels. The topmost level is the goal, or the question which must be answered. The intermediate level (which may include sublevels) gives the factors which will influence the decision. The final level are the choices that are available to be made for the decision.

In an AHP process, first the factors (and sub factors) are compared in terms of importance with one another. This is done using a pairwise comparison. A pairwise comparison involves comparing each option with the other options available in each group of two available. The number of comparisons available is determined as follows:

The factors are first compared pairwise with each other, typically on a scale between 1 and 9, where 9 significantly favours the option in question over that it is being compared to in terms of importance. A value of 1 signifies that neither is favoured, and the reciprocal of 9 signifies that the other option is significantly favoured. This generates a comparison matrix similar to that shown in **Table 2.** For example, according to the values in the table, reliability is significantly favoured in terms of importance over efficiency, whereas cost is not as important as reliability.

Table : Example AHP Pairwise Comparison Matrix

|  |  |  |  |
| --- | --- | --- | --- |
|  | Cost | Reliability | Efficiency |
| Cost | 1 | 1/9 | 5 |
| Reliability | 9 | 1 | 9 |
| Efficiency | 1/5 | 1/9 | 1 |

By taking the normalised eigenvector of this table as a matrix, a priority vector may be obtained. Calculating a normalised eigenvector of a matrix is outside the scope of this review, but the priority vector obtained for the matrix of **Table 2** is as follows:

This step is repeated for the lower level for each choices suitability at satisfying each factor. The weights obtained in the first priority vector are combined with those obtained in the second priority vector, to give an overall weight for each choice. The choice with the highest weight may then be taken as the preference with all relevant factors considered.

#### (Bevilacqua & Braglia 2000)

(Bevilacqua & Braglia 2000) presented an application of the AHP method to determine the correct maintenance strategy to use for different types of equipment in an oil refining facility, based on a limited budget. The types of maintenance strategy to choose from were:

1. Corrective maintenance
2. Preventive maintenance
3. Opportunistic maintenance
4. Condition-based maintenance
5. Predictive maintenance

The maintenance strategies given above are arranged in order of increasing cost. It had been determined previously at the test facility in question that equipment types such as air compressors warranted the extra expenditure associated with predictive maintenance. This had been determined through a FMECA process. The authors demonstrated using an AHP approach that air compressors did warrant the extra expenditure of predictive maintenance. This was based on the critical factors determined for the maintenance needs of the facility, namely:

1. Damages that could be caused by a failure in the equipment being analysed
2. Applicability of the maintenance strategy to the equipment in question
3. Added value created by employing the maintenance strategy to the equipment in question
4. Cost of implementation of the maintenance strategy

These four key factors were then split into various sub factors, and the AHP methodology applied to determine which maintenance strategy most suited each type of equipment. Site equipment was split into three distinct groups, with an example, representative machine analysed using the AHP methodology to determine the appropriate maintenance strategy.

It was found that predictive maintenance was most suited for air compressor maintenance at the facility, based on the factors described above. This highlights the criticality of air compressors as industrial utility equipment.

The AHP methodology is demonstrative of the fact that a significant amount of human expert knowledge is required to create and deploy manual knowledge based systems of the type given in this group. The advantage gained by deploying these types of systems is the formal recording of significant amounts of human knowledge, however this comes at a significant time cost, with lessons learned in one facility difficult to apply to another. Ultimately this group of methods is well suited to the role of decision support system.

## Deterministic / Quantitative Methods

Description of broad method category

### Mathematical Modelling

## Stochastic Methods

Description of stochastic methods

### Neural Networks

These high level goals may be achieved using a wide variety of methods. In this review the following methods are considered:

1. Rule based systems
2. Engineering model based systems
3. ~~Machine Learning~~
4. Statistical learning
   1. Generalised linear model
5. ~~Support Vector Machines~~
6. ~~Neural Networks~~
   1. Restricted Boltzmann Machines (leading to)
      1. ~~Deep Belief Networks~~
7. Mixture Model Classification
8. Model Based Methods
   1. (Aitouche et al. 2011)
9. Fuzzy Logic
10. Regression Methods
11. Instance-based methods
12. Regularisation Methods
13. ~~Decision Tree Learning~~
14. ~~Bayesian Methods~~
15. Kernel Methods (SVM)
16. ~~Clustering Methods~~
17. ~~Association Rule Learning~~
18. Deep Learning Methods
    1. ~~Deep Belief Networks~~
19. Dimensionality Reduction
20. Ensemble Methods
21. ~~Principal Component Analysis~~
22. Data Mining
23. ~~Fault tree analysis~~
24. FMEA and AHP (Bevilacqua & Braglia 2000)
25. Failure mode analysis

## Current Methods

|  |  |  |  |
| --- | --- | --- | --- |
| Method | Type | Pros | Cons |
| Machine Learning | Neural Networks |  |  |
| Statistics | Principal Component Analysis (Zanoli et al. 2010) | Can detect multiple faults | Require training period in fault free condition |
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| --- | --- | --- | --- | --- | --- |
| ***Method*** | ***Type*** | ***Description*** | ***Subtype*** | ***Pros*** | ***Cons*** |
| Machine/Statistical Learning | Artificial neural networks | Creation of a network of elements or neurons which may determine variable values based on interconnected element's response to external inputs |  |  |  |
| Association rule learning | Identification of interesting relationships between variables by recognising statistically significant historical relationships |  |  |  |
| Bayesian networks | Creation by learning or using prior knowledge of graphical probabilistic models which give relationships between variables |  |  |  |
| Clustering | Grouping data readings into different groups where intragroup similarity is greater than intergroup similarity |  |  |  |
| Decision tree learning | Definition of the condition a system may be in based on observed variables, represented graphically using a tree structure which may be generated from past data using algorithms such as the ID3 algorithm |  |  | Can suffer from overfitting |
| Genetic algorithms | Determining the optimum point a system can operate at, by selecting random members of a population of samples and using them as parents of successive samples, which tend toward the optimal sample |  |  |  |
| Reinforcement learning | As distinct from supervised and unsupervised learning techniques, this method requires feedback on whether it has correctly predicted the value of a variable and tends toward an optimum based on this feedback |  |  |  |
| PCA | Analysis of a population of variables to determine the population extremes in a given number of directions or components, allowing categorisation of each data point in terms of it's position in each direction |  |  |  |
| Support vector machines | A supervised learning technique which when given a sample data set which is labelled according to which class each point belongs in, can determin the optimal plane which splits classes allowing accurate future classification of variables |  |  |  |
| Statistics |  |  |  |  |  |
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| Data Mining |  |  |  |  |  |
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| Model Based | Linear |  |  |  |  |
|  | Non-linear |  |  |  |  |
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| Rule Based |  |  |  |  |  |
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| Mathematical Optimisation | Simplex Method (Stosic 2003) |  |  |  |  |
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| Maintenance Planning | FMECA |  |  |  |  |
|  | AHP |  |  |  |  |
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### Support Vector Machines

Examples of SVM for valve fault detection on reciprocating compressors are (Cui et al. 2009) and (Qin et al. 2012) and (Verma et al. 2011).

### Neural Networks

#### (Cortés et al. 2009)

(Cortés et al. 2009) 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.

#### (Yu et al. 2007)

(Yu et al. 2007) 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 (Cortés et al. 2009). 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 (Cortés et al. 2009) in that the structure of the neural network (i.e. number of neurons in the input and second layer) was not readily given.

#### (Ghorbanian & Gholamrezaei 2009)

(Ghorbanian & Gholamrezaei 2009) 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 (Yu et al. 2007) 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.

#### (James Li et al. 1995)

This paper used feedforward neural networks to detect valve faults on a four-stage reciprocating compressor.

It is an old paper but come back to this as there is a list of 39 parameters in it that the authors deemed necessary for monitoring to effectively detect valve faults.

### Restricted Boltzmann Machines

Restricted Boltzmann Machines are a type of stochastic neural network with a known layer, a hidden layer, and a bias unit. The bias unit allows a probabilistic characteristic to be assigned to the various units in the two layers. The machine can then describe the relationships between known parameters (sensor readings) and unknown parameters.

### Deep Belief Networks

Deep belief networks are a form of greedy stacked Restricted Boltzmann Machine.

#### (Tran et al. 2014)

(Tran et al. 2014) presented the paper “*An approach to fault diagnosis of reciprocating compressor valves using Teager-Kaiser energy operator and deep belief networks”*.

This paper presented a deep belief network based method for fault diagnosis of reciprocating compressors. The equipment analysed for the paper’s test case was a two-stage reciprocating compressor.

Similar to other work on fault detection and diagnosis for reciprocating compressors (Cui et al. 2009), (Qin et al. 2012), the authors of this paper recognise valve failure in reciprocating compressors to be both a common and costly mode of failure. According to one study (Leonard 1996), valve faults account for 36% of compressor shutdown instances and 50% of compressor repair costs.

The parameters required for implementation of this paper’s method are:

1. Machine Vibration
2. Receiver Pressure
3. Stage 1 Outlet Pressure
4. Discharge Pressure
5. Electrical current drawn

The faults detected by this method were:

1. Suction valve leakage or stuck closed
2. Discharge valve leakage or stuck closed

The paper also trialled Relevant Vector Machine and Backwards Propagation Neural Network (as used in (Yu et al. 2007) for IGV fault detection) methods to detect these faults. The authors found that the deep belief network method had a higher accuracy in fault detection than either of these methods. A conclusion of the paper was that deep learning methods are a developing generation of machine learning techniques that are effective for machine fault diagnosis. This is important to note given the recent nature of this paper.

### Principal Component Analysis

#### (Zanoli et al. 2010)

(Zanoli et al. 2010) presented the paper *“Applications of fault diagnosis techniques for a multishaft centrifugal compressor”*.

In this paper a principal components analysis (PCA) technique was employed for the higher level goal of fault detection and diagnosis of a compressor. The fluid compressed by the compressor analysed was Nitrogen, and the compressor formed part of a larger process of Integrated Gasification and Combined Cycle, where the Nitrogen gas was sent to a turbine after compression. The compressor in question was a multistage centrifugal machine.

PCA is based on a mathematical procedure that transforms a number of possibly correlated variables of the process, into a smaller number of uncorrelated variables called Principal Components.

PCA finds the directions of greatest variance in a data set and represents each data point by its coordinates along each of these directions (Hinton & Salakhutdinov 2006). A key point to consider when employing PCA as a method is the correct selection of the number of principal components (PC). The novelty factor of this paper was that the number of PCs was selected using an ANalysis Of VAriance (ANOVA) technique. An ANOVA test is used to compare population samples by the variance within each sample and the variance between different samples. The paper used the ANOVA test to determine incrementally whether it was worthwhile to add another principal component to the existing number of principal components.

The values recorded from the test compressor were:

1. Mass flow rates of nitrogen
2. Inlet Guide Vane (IGV) positions
3. Throttle valve position

This method required a training period in a no fault state, which is a factor to be considered when applying a PCA method to existing compressed air systems. The method was tested on both single and multiple fault states of operation.

The faults that this paper was able to detect were:

1. Sensor reading errors
2. Actuator error / failure

## Model-Based Methods

(Kopanos et al. 2015)

## Adaptive Clustering

(Petković et al. 2012) presented a method for feature identification

# Discussion

Compare yet again the table

# Conclusion

The best method for compressor performance management is ######.

# Abbreviations

|  |  |
| --- | --- |
| Abbreviation | Meaning |
| AHP | Analytical Hierarchy Process |
| RCM | Reliability Centred Maintenance |
| FMEA | Failure Mode and Effect Analysis |
| FMECA | Failure Mode Effect and Criticality Analysis |
| FDD | Fault Detection and Diagnosis |
| RBM | Restricted Boltzmann Machine |
| WSM | Weighted Sum Model |

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