APPLICATION OF EXPERT SYSTEMS TO INDUSTRIAL UTILITY EQUIPMENT OPTIMISATION

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ABSTRACT

Expert systems are computer systems which are capable of imitating the reasoning of a human expert within a particular area of knowledge. This reasoning is used to make decisions which solve problems in a particular domain. Applications of expert systems to industrial utility equipment have included fault detection and diagnosis (FDD), automated commissioning and optimisation. Substantial work has been carried out to date in the application of expert systems to the optimisation of HVAC and refrigeration equipment. This paper outlines other industrial technologies which display potential for deployment of remotely based expert systems tools for whole system improvement of operation. An analysis of the suitability of different expert system approaches toward identification of opportunities for improvement in each technology is detailed.

1 INTRODUCTION

Expert systems have been used in the past to solve problems for industrial utilities, with applications including automated fault detection and diagnosis (AFDD) (Bruton *et al* 2014), automated commissioning (Choinière 2008) and optimisation (Choinière 2008).

For an expert system to fault find or optimise an item of equipment a multi stage process is involved comprising; data extraction from existing systems, fault finding or optimisation through rule based or model based approaches, and typically some feedback or fault correction control action.

The range of Building Management Systems (BMS), Supervisory Control and Data Acquisition Systems (SCADA) and Programmable Logic Controllers (PLC) that exist in an industrial facility, coupled with the differing ability of each to archive data drawn from equipment, has led to the development of cloud-based data-extraction processes for analysis with expert systems (Bruton *et al* 2014). Remotely based systems present a number of key considerations including security of both facilities and data (Igure *et al* 2006).

The key industrial utilities examined in this paper as showing potential for deployment of expert system tools are Boilers, HVAC, Air Compressors and Chillers. These technologies have been chosen as many of the opportunities for improvement identified by human experts in the course of review are generic and repeatable. Improvement of these utilities using

expert system tools will lead to continued energy and maintenance savings, along with benefits regarding enhanced operation, control and diagnostics. Furthermore expert system tools lend themselves to measurement and verification of the energy performance of utility equipment.

Section 2 of this paper presents some of the primary objectives which expert system implementations aim to achieve. This is followed by a discussion of previous applications of expert systems to industrial utilities and other relevant areas, categorised by the approach taken. The merits and drawbacks of each approach are discussed.

Section 3 of this paper discusses various utilities in modern industry which are typically managed locally; presenting opportunities for improvement using expert system approaches. Some typical modes of equipment failure and/or increased energy consumption are presented, which show potential for improvement using an expert system implementation.

Section 4 of this paper outlines future work to be carried out regarding the application of expert systems to industrial optimisation, and the benefits achievable by these applications.

2 PREVIOUS APPLICATIONS OF EXPERT SYSTEMS TO INDUSTRIAL UTILITIES

Expert System Applications: Objectives

When an expert system is deployed with the aim of improving the operation of utility equipment, the

higher level focus and objective can take several forms. In this paper, the objectives referred to are AFDD, Commissioning, and Optimisation.

AFDD is taken in the context of this paper to refer to the automatic recognition of when an issue of concern, or fault, is present in a physical system. AFDD furthermore identifies the cause which effected this fault condition. In (Bruton et al 2014), a rule based expert system tool for a HVAC system was developed and deployed in industry, with a key goal or focus being AFDD.

Commissioning in the context of this paper is taken to refer to a process for achieving, verifying, and documenting that the performance of systems meets defined objectives and criteria ("The Commissioning Process" 2005). In (Pacas and Villwock 2008), a model based expert system using a frequency response analysis method was developed for a primary purpose of commissioning electrical drives.

In the context of this paper, optimisation refers to achieving the goal of best possible operation of a system with respect to some defined criteria (e.g. minimal energy consumption), under a given set of circumstances or constraints. In (Zhang et al 2011), a decision support system (DSS), with a model based expert system reasoning mechanism was developed and trialled at an iron and steel enterprise. The objective of this system was to optimise the blend of ore for producing iron in blast furnaces, with the criteria to be optimised being lowest cost.

Expert System Applications: Methods

Industrial utilities have been shown in the past to be suitable for problem solving using expert systems. Methods used by expert system implementations include rule-based systems (Bruton et al 2014); model-based systems (Afgan et al 1998); neural networks (Palau et al 1999), artificial immune systems (Wojdan and Świrski 2007), and signed directional graphs (SDG) (Lee et al 1997). In other relevant areas requiring system improvement, methods used have included Bayes belief networks (Lee 2001) (automotive FMEA).

Rule-Based Systems.

In (Bruton et al 2014), an AFDD tool was developed using a rule-based approach, with the intended goal of detecting faults and their causes in Air Handling Units (AHUs). This detection of faults allows for on-going commissioning of an AHU, removing potential degradation in performance. Degradation in the performance of an AHU can go un-noticed for significant periods of time, during which desired supply air conditions are maintained. Despite achieving these desired conditions, the conditions of operation may give rise to energy wastage.

An example of this form of energy wastage which could occur in an AHU would be the continuous operation of a frost protection setting on a heating coil. Allowing excessively low temperature air to pass through the initial stage of an AHU can cause issues within the unit, including coil tube failure. To prevent this occurrence, the initial stage of an AHU often includes a frost heating coil, which serves to heat the incoming air to a specified minimum temperature.

In practice, an operator may be unwilling to rely on the ability of the frost coil valve controller to react quickly enough to prevent excessively low temperature air entering the AHU. A means to remove this risk is to manually apply a minimum open setting to the frost coil valve. This manual setting is typically applied if the unit is to be unsupervised during a period of expected cold weather. As the operator may be responsible for many other aspects of plant operation, this manual setting may be forgotten about, and remain in place. While desired delivered air conditions are maintained, heating energy wastage takes place due to the continuous, potentially unnecessary (if no heating is required) operation of the frost coil. If the minimum open setting is allowed to remain during periods of hot weather, energy wastage may also occur at the cooling coil of the AHU, to counteract the frost coil. This degradation in AHU performance, caused by human error, can be flagged by an AFDD tool, removing energy wastage.

The rule-based approach of (Bruton et al 2014) began with the usage of the 28 previously defined AHU performance assessment rules (APAR) (House et al 2001). These expert rules require 11 data measurements (e.g. supply air temperature, return air temperature) for the AHU to be assessed. By calculations on the retrieved data, the 28 rules are assessed as either True or False. If any rule is found to be True, a fault in operation is defined. This fault can then be attributed to a limited number of component failures.

(Bruton et al 2014) expanded on the APAR rules, to incorporate additional data measurements where available, allow for alternative configurations of AHUs, and to calculate virtual data measurements in the case of poorly instrumented AHUs. The output from the calculation of rules was altered from True/False to a numerical value, to allow for determination of the degree of a fault, and to predict potential future failures.

The key advantage of rule-based expert systems is their efficiency when assessing a system which operates within a defined set of conditions (Angeli

2010). Software is commonly written using IF-THEN-ELSE statements, which lend themselves to the implementation of defined rule sets. If the original system is required to be altered, e.g. to incorporate new rules, an expert working with a software engineer can relatively easily re-structure the expert system, provided software is structured and specified in accordance with normal procedures (e.g. Unified Modelling Language (UML).

A drawback of rule-based expert systems is the potential for an incomplete rule base (Bernard 1988). A rule-based expert system is incapable of detecting where the rule base may be incomplete, or of noticing where the expert system itself is making errors in calculation, which could be learnt from (Widman and Loparo 1990). Novel situations cannot be dealt with effectively (Angeli 2010), and require modification to the original expert system.

Rule-based systems have also been applied to steam boilers (Cantú-Ortiz and García-Espinosa 1992), chillers (Dexter and Pakanen 2001), and air compressors (Batanov et al 1993).

Model-Based Systems.

In (Afgan et al 1998), an expert system was developed to detect tube leakage in a power plant boiler using a model-based approach. Tube leakage is cited as the most probable cause of power plant boiler failure.

As the tubes of a boiler are located internally, they are inaccessible for inspection during normal operation. A power plant boiler is typically of water tube type. This configuration of boiler is comprised of vertical tubes containing water, adjacent to fuel burners. The heat applied by the fuel burners causes the water to boil, and steam to rise to a steam drum.

Boiler tubes are subjected to extreme temperature gradients through their surfaces. While the materials used in construction are typically designed to allow for certain temperature gradients, inadequate operation and maintenance of the boiler can cause mechanical failure of the tubes. If a tube ruptures, the water/steam within will pass from the water side to the fire side of the boiler. This type of failure typically results in downtime, to allow for tube replacement.

Boiler tube failure is typically detected at a stage when there is an imminent risk of an accident, and urgent action is required (Afgan et al 1998). If boiler tube failure can be detected in advance, the benefits will include minimising the damaging effects of leakage, and improved maintenance planning.

(Afgan et al 1998) developed an expert system, which used heat flux measurements within the fire side of the boiler to detect when internal tube failure was present. When boiler tubes fail, the pattern of heat flux in the boiler will change, due to the lower temperature of the water/steam with respect to the normal fire side temperature. The value of heat flux at each point in the boiler relative to the value with no leak present (standard operation) was defined as the relative heat flux. If this relative heat flux was lower than a predetermined set point, it was indicative of a leak at that location.

By arranging heat flux sensors in a grid on the boiler walls, a heat flux pattern could be obtained. Heat flux patterns were stored in the knowledge base of the expert system, using an object oriented structure. A leakage class was defined, with two major sub-classes: Case and Sensor. The Case class defined the location and intensity of the tube leakage. The Sensor class defined the pattern of readings of the heat flux sensors.

By storing the information regarding heat flux patterns and leakages in the knowledge base, new instances of leakage could be attributed to a specific location and intensity. However, as the actual values defined in previous cases were usually different to those encountered in new instances, a fuzzification of the diagnostic variables drawn from sensor readings was required. This fuzzification was used to draw semantic variables from the diagnostic variables obtained from sensors, to allow inference of likely tube failure.

In order to obtain a confidence level for the diagnostic variables with regard to the sensitivity in detecting a minimum level of leakage, three-dimensional mathematical modelling was used. A previously defined model (Carvalho et al 1987) defined the expected heat flux in the boiler, and was compared to actual measurements taken in an operational boiler for validation of results (Coelho and Carvalho 1995).

While this particular expert system focussed on one single point of failure within a boiler, it demonstrates an advantage of model-based systems in its accuracy. The equations used in the model for sensitivity analysis regarding flow, combustion, and heat transfer allow confirmation that the expert system will detect a minimum level of leakage. The compilation of a detailed object oriented knowledge base of potential leakage locations and intensities will in theory encompass all potential future leakage incidents.

A drawback of this expert system is the detailed level of calibration which is required for each application. The sensitivity analysis which was carried out to ensure the expert system could detect a minimum level of leakage required an extensive mathematical model of the boiler in question to be run. This would be difficult to repeat across varying

ranges of boilers, due to differing geometries and configurations of different boiler types. It would therefore not lend itself to a "plug-and-play" solution.

The expert system, while useful for determining the location and intensity of tube failures, defines both location and intensity in the knowledge base and diagnostic variable as discrete parameters. Intensity is defined as a mass flow rate of steam of Low, Medium, or High (each with corresponding discrete values). Location is determined according to a 3*3 grid on each wall of the boiler. While this is sufficient for leakage detection, it could be argued that the level of mathematical modelling required for the sensitivity analysis was extremely intensive for a relatively low resolution result. It is clear that due to expected deviations between model-predicted values and actual diagnostic variables, fuzzification of variables is required to obtain meaningful semantic results.

(Soyguder and Alli 2009) used fuzzy modelling as one technique, in conjunction with artificial neural networks, in the development of an expert system for HVAC humidity and temperature control. (Grimmelius et al 1995) used a regression analysis model to predict healthy behaviour of a compression refrigeration plant, as part of a failure diagnosis expert system. This expert system again required fuzzification of variables to allow the recognition of failure modes. The more simplistic regression analysis modelling approach taken by (Grimmelius et al 1995) did not allow for complete modelling of the system, e.g. fault recognition during transient operation was not possible. Neural networks were used for system modelling of an air compressor in (Kim and James Li 1995). While not explicitly an expert system, the modelling obtained using neural networks allowed for fault diagnosis of common issues regarding the air compressor.

Neural Networks.

(Tassou and Grace 2005) developed an expert system for fault diagnosis of a refrigeration system, specifically regarding refrigerant leak detection. In this paper artificial neural networks (ANNs) were used to predict the expected values of key parameters pertaining to the chiller in question.

In a refrigeration unit or chiller, maintaining the optimum level of refrigerant is crucial for effective system performance. Due to the refrigerant pressure being higher than atmospheric pressure, there is a potential for refrigerant to leak, reducing the level of refrigerant in the system. In addition, failure of key control instrumentation can cause refrigerant to build up and overcharge in the system.

If refrigerant is lost from a chiller, the consequences include a reduction in coefficient of performance (COP), increased maintenance costs,

and the potential for system failure (Tassou and Grace 2005). It is noted that leak detection systems are available which use refrigerant sensors, however they display a number of inherent drawbacks. A crucial drawback of refrigerant sensor based systems is their inability to detect slow refrigerant leaks, which is cited by (Tassou and Grace 2005) as the most common case of refrigerant loss.

(Grimmelius et al 1995) were mentioned previously as developers of a model-based expert system for failure diagnosis in chillers. (Tassou and Grace 2005) cited model-based efforts such as this as being capable of accurate predictions of system performance. However, it is noted that this method requires a new approach for individual units, and is therefore difficult to propose on a broad scale.

(Tassou and Grace 2005) used a test rig chiller which was instrumented to measure temperatures, pressures, and flows at key points in the refrigeration circuit (e.g. condenser inlet, evaporator outlet, etc.). The key parameters of coolant inlet temperatures to the evaporator and condenser were used as the primary input data to the expert system. A fault-free operation of the chiller was then performed to allow for training of the ANNs. Ten ANNs were used in the prediction module, correlating to ten prediction parameters. The ANNs were trained using the primary input parameters, and the observed conditions of ten parameters within the refrigeration system. Following this training, the ANNs were capable of predicting the expected fault-free values of the ten parameters throughout the chiller.

Following this training period, the predicted values for the ten parameters were available in the knowledge base of the expert system for a range of operational coolant inlet temperatures. Comparing actual observed values during operation for the ten parameters, and those predicted by the ANNs, enabled the calculation of residuals. These residuals were assigned semantic values ranging from Low to High, and formed a residual pattern.

The expert system included a rule set which was able to diagnose the condition of the refrigerant level based on the residual pattern observed. These rules allowed for detection of both under and over charge of refrigerant, which is not readily implemented using sensor based systems.

It was recognised that during implementation of this expert system in the field, a training period for the ANNs during fault-free operation would be required. Since it may be unknown whether the chiller in question is indeed running in fault-free operation, a validation procedure was proposed. This concerned monitoring the degree of sub cooling and superheat of the refrigerant, and comparing these parameters to normal acceptable limits.

In this work, the expert system was concerned with FDD for refrigerant leakage only. Therefore the two critical predicted values were compressor discharge pressure and evaporator coolant temperature. It was acknowledged however that by developing rules which could detect other faults, based on the other key predicted parameters, a more comprehensive chiller FDD system could be developed.

This expert system approach has the key advantage of being readily deployable across a large population of installed equipment in industry. Its ability to train itself to predict the expected parameters for an individual chiller, removes the issue of individuality between equipment types which arises when taking a model based approach.

However, it is noted that this approach is extremely suitable for deployment on refrigeration equipment, but may not be so for other categories of industrial utility. The vapour compression refrigeration cycle is relatively generic between chillers, and it is likely that the required parameters for expert system training and operation would be present on the majority of installed equipment. Where the required instrumentation is not installed, pressure, temperature and flow measurement sensors are in general readily possible to be fitted after market.

For other categories of industrial utility however, generic characteristics are not always the case. Air compressors, for example, have many different configurations (e.g. screw, reciprocating, centrifugal) each of which is significantly different in operation. A generic set of parameters which can be trained on, and then used for residual calculation with an ANN based expert system may therefore not be as readily repeatable across other categories of utility. For this reason, future FDD applications to chillers using ANNs may be restricted from generic rollouts due to different compressor types within the chiller.

A neural network approach for evaluating biomass boiler behaviour, specifically with regard to fouling, was presented by (Romeo and Gareta 2006). This paper is indicative of a general trend for neural network applications to focus on one single aspect of utility operation, rather than a comprehensive system wide approach.

An FDD system for an AHU was proposed using general regression neural networks in (Lee *et al* 2004). This paper again used residuals generated with neural networks, and an expert rule set, to identify subsystem level faults in AHUs. The comprehensive rule set was able to identify faults including stuck coil valves, fouled coils, leaking valves, stuck dampers, and a decrease in fan performance.

(Kim and James Li 1995) presented a fault diagnosis tool for screw compressors which used neural networks to generate indications of common compressor failures. While not explicitly an expert system, the neural network approach was used not only to diagnose faults, but was also able to indicate the severity of issues which arose.

The approaches of expert system applications to industrial utilities discussed in this section are summarised in **Table 1**.

Table 1: Summary of approaches of expert system applications to industrial utilities

Industrial Utility	Expert System Approach		
	Rule Based	Model Based	Neural Networks
Boilers	(Cantú-Ortiz and García-Espinosa 1992)	(Afgan *et al* 1998)	(Romeo and Gareta 2006)
HVAC	(Bruton *et al* 2014)	(Soyguder and Alli 2009)	(Lee *et al* 2004)
Air Compressors	(Batanov *et al* 1993)	(Kim and James Li 1995)	(Kim and James Li 1995)
Chillers	(Dexter and Pakanen 2001)	(Grimmelius *et al* 1995)	(Tassou and Grace 2005)

3 INDUSTRIAL UTILITIES WITH POTENTIAL FOR IMPROVEMENT USING EXPERT SYSTEMS

For the purposes of this paper, four utilities will be discussed, namely: Boilers, HVAC, Air Compressors and Chillers. These utilities are typically managed at site level, with operator supervision of building management systems (BMS), supervisory control and data acquisition systems (SCADA), or local control panels.

While operator expertise is generally capable of reacting to faults and performing corrective measures, guidance using expert systems will improve operation and reduce downtime. The move toward condition based maintenance (CBM) of utilities from planned maintenance systems (PMS) can be assisted by expert systems detecting when utility components' performance is below expected norms.

Boilers

Steam systems are common across a vast range of industries, including food and beverage, oil refining, chemical production, pharmaceuticals, primary metal processing, and pulp and paper. Thirty-seven percent of fossil fuels burnt in industry is attributable to steam production (Einstein *et al* 2001).

Steam boilers can take various forms, with one of the most common types used in industry today being the package boiler. A package boiler is a boiler which is shipped to a facility pre-assembled, and only requires connections for fuel, electricity and feed water.

Package boilers are often run with less than optimal operating characteristics. This may be due to equipment wear and tear, poor operational methodology, or a lack of maintenance. In general, poor operation of a boiler will result in a reduction in efficiency, increasing energy consumption. In drastic cases, poor boiler operation may result in equipment failure, and may pose a risk to site safety.

Many of the issues which arise leading to ineffective boiler operation are common across industry. These issues are not typically picked up until a comprehensive energy review or audit takes place. The implementation of an expert system to highlight these issues before they impact on energy consumption would allow for increased energy efficiency and improved operation.

As previously discussed in **Section 2**, boiler tubes can rupture or fail, causing leakage between the water side and fire side of the boiler. Operational means by which failure can occur include chemical corrosion, erosion, mechanical fatigue, and material failure (Bamrotwar and Deshpande 2014). Boiler tube failure can lead to boiler shut down, and serious safety concerns. The ability to detect and supply prognostics for boiler tube failures would reduce downtime and maintenance.

Boiler blow down is typically used to control the level of dissolved solids within the boiler water. By steam generation in the boiler, the level of dissolved solids increases over time. Surface blow down operates by removing boiler water in order to achieve a desired level of total dissolved solids. However, in practice blow down is often observed to be excessive, representing an unnecessary loss of energy from the boiler. An expert system implementation could recognise excessive levels of blow down, and diagnose the reason, which could be related to feed water conductivity, or component issues.

A boiler should ideally be fed with water that is free of oxygen. Oxygen present in boiler feed water accelerates the rate of corrosion of internal boiler water side surfaces. In practice, oxygen is typically removed using a mechanical de-aerator. This de-aerator operates by sparging steam through the boiler feed water before it enters the feed tank. The steam supply is typically regulated to maintain a feed tank temperature of approx. 105 °C. In practice, boiler feed water may be at a lower temperature than this, but the operation of the steam boiler will remain as expected. Highlighting drops in de-aerator performance using an expert system implementation will reduce energy consumption and decrease corrosion within the boiler.

Boilers are typically tuned at commissioning to have a certain level of excess O_2 in the exhaust gases. This level, which varies according to the fuel burnt, is indicative of overall combustion efficiency. Over time, boiler fouling and deviations from original operating conditions can cause this excess O_2 level to drift from its ideal level, causing a drop in efficiency. While automatic combustion tuning systems can modulate dampers in the boiler to maintain the desired O_2 level, an expert system implementation could establish the root cause of a drift, allowing rectification in a way that does not impact on other operational characteristics of the boiler.

These are a few characteristic issues which commonly arise during steam boiler operation. Due to the measurability of the parameters involved in each case, they lend themselves to being diagnosed using an expert system implementation.

HVAC

HVAC is a utility which is common across industrial, commercial, and office environments. In clean environments such as the pharmaceutical industry, HVAC can be critical to ensuring product quality and safety. In a report on reducing HVAC energy usage in industry (SEAI 2010), of the nine companies involved in the study, on average HVAC accounted for 35% of site electrical usage, and 60% of site thermal usage. This demonstrates that HVAC is a significant energy user in industry, and should be focussed on with regard to improving energy performance. (Pérez-Lombard *et al* 2008) cites HVAC as accounting for 10-20% of total energy consumption in developed countries.

As with other industrial utilities, degradation in performance is often noted in HVAC systems. This degradation in performance invariably leads to increased energy consumption, which is typically rectified following individual health assessments of AHUs, to ensure individual components are operating as expected. Expert system approaches to HVAC have been able to diagnose areas of poor performance, and failed components, through intelligent assessment of key monitored parameters (Bruton *et al* 2014).

HVAC serves to provide air at a condition which is desirable for the space served. In order to achieve this condition, invariably some heating and/or cooling must take place within the AHU. This is typically achieved using heating and cooling coils, which are supplied with steam/hot water and chilled water. The valves which control the flow of the heating/cooling medium can over time deteriorate in condition, and may leak or become stuck open. Modulation of the amount of fresh air which is drawn by an AHU can also be used for temperature control. The quantity of fresh air used is typically regulated by modulating dampers, which over time can leak, allowing fresh air to be used when it is not required. If either of these leakage cases occurs, energy consumption of the AHU will unnecessarily increase, but the desired supply air condition may be maintained. FDD tools using an expert system approach can identify when valves or dampers leak or pass, and highlight this issue in order that increased energy consumption does not go unnoticed for extended periods.

For quality requirements, air is normally filtered during conditioning. Over time, the filters used can become clogged, which increases the electrical load on a variable speed drive (VSD) fan drawing air into the AHU. At many facilities, filter replacement is carried out on a scheduled basis, based on expected service life of a filter. While this practice normally ensures that filters will be replaced before becoming clogged, it does not take into account the condition of the filter at the time of the replacement. Ambient air conditions can have an effect on how rapidly the filter clogs, and this can be detected by a differential pressure sensor across the filter. An expert system implementation could diagnose when a filter is clogged, and issue an alert for replacement. Diagnosis could be based on differential pressure measurement across the filter, or by electrically fingerprinting the AHU VSD fan to allow for detection of an increase in load from the relevant electrical distribution board.

Air Compressors

Compressed air is a common utility in many areas of industry, particularly in the manufacturing sector. It is recognised as an expensive form of energy delivery, as the majority of the energy required for generation is lost as heat of compression. Compressed air has been cited as accounting for 10% of industrial electricity usage in the EU (Saidur et al 2010).

Many different configurations of compressor are common in industry, the most common of which are centrifugal, screw, reciprocating and scroll. A common means for improved energy efficiency in compressed air plants is heat recovery, which can tend to take first priority in energy reviews. There are however, numerous operational improvements which can be undertaken to reduce the energy consumption of a compressed air system.

In a typical compressed air system, accepted normal practice for compressed air leaks is approximately 10%. However in many facilities the level of leakage can account for 25% of compressor output (Kaya et al 2002). While many facilities undertake periodic compressed air leak detection exercises, these are typically schedule based. A comprehensive expert system implementation for a compressed air system would balance compressor output with system flows, and advise when leakage rates were too high and possible locations. This would enable leakage detection exercises to be carried out more efficiently, with efforts concentrated on areas with expected highest loss.

Mechanical and/or electrical failure of compressor components is a key cause for deviations from normal operation, and increased maintenance requirements and energy consumption. It can often be difficult to determine without a complete overhaul of the compressor which is the exact point of failure (Chen and Ishiko 1990). An example given in (Batanov et al 1993) of a compressor failing to start has many possible causes, including damaged transformers, circuit breakers, and incorrectly configured control switches. The expert system described uses a set of 154 rules to effectively manage the maintenance requirements of an air compressor.

Chillers

Refrigeration systems in industry are widespread, with chilled water used for both process needs and HVAC cooling. Refrigeration systems can account for a large proportion of total energy usage in a facility, particularly in industries such as cold storage (90%), retail (70%) and ice cream manufacturing (70%) ("Refrigeration Systems" 2011).

Due to the varying types of compressor normally installed in a chiller, the configuration of a refrigeration system can vary as with compressors. A survey of common faults in chillers was carried out in (Comstock et al 2002), encompassing centrifugal and screw chillers (water and air cooled). The faults in this paper were categorised at system or subsystem level.

As discussed previously, refrigerant leak from a chiller can have consequences impacting on service life of equipment and energy consumption. (Tassou and Grace 2005) proposed an expert system implementation which is able to identify refrigerant leakage in situations where normal, refrigerant sensor based leakage detection systems would not. As refrigerant leakage is a leading cause of chiller issues,

expert systems implementations should include allowance for leak detection.

The fouling of a heat exchanger on the evaporator or condenser of a chiller will cause a reduction in heat transfer, giving a reduction in system COP. The ability to detect degradation in heat exchanger performance would allow for action to be taken to clean the heat exchangers, and highlight when water quality may be a concern.

Slow, degradational faults on chillers such as these, as opposed to immediate mechanical or electrical failure of components, are more suited to detection and diagnosis using an expert system implementation. (Comstock *et al* 2002) cited this degradation category of faults as representative of 42% of service calls made and 26% of service costs in a sample study of chiller services. The ability to provide prognostic information regarding these faults would assist in reducing downtime, and more effectively planning maintenance. In the case of faults such as fouled heat exchangers, the chiller may be able to provide the desired output, but will have a higher electrical power requirement. Detecting fouling and other energy impacting faults would reduce total energy usage.

4 CONCLUSIONS AND FUTURE WORK

This paper discussed three approaches taken when applying expert systems to the improvement of industrial utility equipment operation. It is concluded that each has its merits and drawbacks.

Rule based systems are efficient when operating within a defined domain, but do not allow for novel situations not accounted for in the rule set. Model based systems address this issue by normally providing an all-encompassing physical model of a system. This however is more difficult to deploy across large ranges of industrial equipment, due to the individual nature of modelling required. Work carried out in the area of machine learning models for fault diagnosis (Murphey *et al* 2006) attempts to address this individuality issue by automatically learning about the system in question.

Neural networks based systems attempt to address some of the issues presented by rule based and model based systems, as they are capable of characterising an individual piece of equipment using a training period and a defined list of variables. They do however need to be supported by a rule set to distinguish between residual patterns, which could present the same issue as with rule based systems.

It is the intention of the authors to develop an expert system for industrial utility optimisation using as diverse an approach as possible, drawing from the benefits of all methods. It is acknowledged that many neural network applications focus on one single aspect of equipment operation, and it is envisaged that incorporating neural networks from previous works together into a more complete system would allow for whole system improvements in energy performance. It is also noted that the majority of expert system implementations focus on individual pieces of primary equipment as their highest level. Development of an expert system which takes into consideration parameters from associated auxiliaries of the primary equipment (e.g. considering the pumps associated with a chiller), might allow for whole facility improvements, and may highlight issues which impact on decisions made regarding improvements in the primary plant.

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