Intelligent Energy Management of Compressed Air Systems

***Abstract*—This work considers the use of real time sensing and AI (machine learning) to increase Compressed Air Systems (CAS) efficiency. Algorithms that automate the detection of energy inefficiencies and make decisions regarding suitable troubleshooting procedure will be created. Systems using compressed air are often inefficient and expensive to operate. Less than one unit of energy is turned into useful compressed air for every ten provided. Intelligent systems will be used to reduce energy consumption in compressors by considering real-time circumstances and the predicted needs. Sensor data will deliver information about the real time performance. AI will interpret the data and then act automatically. New intelligent techniques will be applied to save energy. This paper presents a review of the recent literature covering the topic of CAS energy efficiency. Some gaps in research were identified in the area of developing technologies and methods to detect and treat energy inefficiencies in CAS.**

Keywords-Component; Compressed Air; Energy; Efficiency; Intelligent; Systems; Machine; Learning

I. Introduction

In the past two decades, the topic of saving energy in CAS received considerable attention, and has been investigated by numerous researchers. Compressed air is versatile and frequently in use within processing and manufacture [1]. Studies indicate that compressed air can consume more than ten percent of UK energy used within industry [2].

CAS are common in industrial plants, because of some favourable characteristics such as: transportability, storability, safety and ease of use [3, 4]. Most industrial plants, regardless of their size, have some sort of compressed air system.

CAS have a demand and a supply side. A supply side converts inlet air into compressed air, and typically includes compressors, dryers, filters and coolers, as shown in Fig. 1[4].

The demand side delivers required compressed air to end users and it normally includes piping networks, controllers and end use equipment. Many of these systems could operate more efficiently [6]. Research on improving energy performance of CAS is reviewed in this paper, and gaps in research are identified.

In this work a literature review is performed and research is categorized into four main areas: measures to reduce energy consumption; simulation and modelling; methods to determine air leakage; and innovations in energy management. Based on that review, gaps in research and future work are identified. A new concept of combining sensing, knowledge management (KM) and AI to improve energy efficiency is proposed that could address some gaps. Machine learning methods are considered for use with sensor data so that AI can ask questions and then automatically take action.

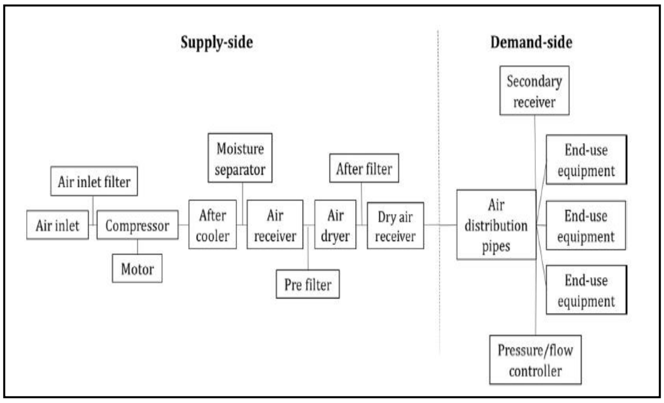

Figure 1. Main equipment in a typical compressed air system [4]

II. Reducing Energy Consumption

Measures that could lead to energy savings of 20-50% [7, 8] are: repairing air leaks [1, 8, 9-12], reducing average air inlet temperature [1, 8, 9, 13], reducing operating pressure of compressors [1, 9, 10] and using efficient equipment [1, 8-10]. Other measures include: deployment of compressor variable speed drives [8, 10], recovering waste heat [8, 10] and harmonizing production and consumption of compressed air [11].

Nehler [4] presented a comprehensive review of energy efficiency within industrial CAS. Around half of the supply side measures concerned a compressor, while the demand side focused on reducing demands [4]. Although measures for energy efficiency were addressed, they were not always applied [4]. Several papers investigated barriers to implementation [14-16]. Trianni and Cogno [15] studied barriers in Italian small and mid-size enterprises. It was concluded that a lack of trust in sources of information was the main barrier.

Nehler [4] indicated that no previous publication defines the order in which measures should be implemented. Aside from investigating additional measures that could be applied, future research might consider the decision making process or the mechanism for selecting measures.

III. Simulation and Modelling

Measures and best practice for minimizing energy consumption in CAS require investment and changes to system operation. Without a clear view of the benefits, production facilities hesitate to apply the best practice [17]. Therefore, it is necessary to perform an analysis that quantifies projected savings in energy and economic terms and expected cost of these measures [18].

Friedenstein [19] presented a methodology to evaluate CAS energy efficiency measures through simulation. The methodology divided the simulation process into three main steps: system investigation, model development and execution of simulation scenarios. Measures were determined and prioritized. The methodology was applied to a case study in a mine, where it helped identify energy and operational improvements.

Other researchers highlighted the importance of determining current performance before applying energy saving measures [17, 20]. Dindorf [20] used simple mathematical expressions to define the major performance indicators of a CAS: power, energy cost, compressed air cost, leaks and pressure drop. Meskell [17] presented a practical approach to quantify compressed air at an industrial site by describing the behaviour of system components with simple mathematical formulas. To quantify consumption, the types and characteristics of the end use applications were surveyed for their pressure, geometric parameters and operational data.

In [18] and [21], methods to simulate the dynamic performance of a CAS were presented. System components were based on mathematical expressions that took into account key variables. Both models were developed with Simulink, following a modular approach dedicating a block for each system component. In [18], the simulation evaluated the impact of compressor control strategy on energy efficiency, whereas in [21], modelling of the storage tank was expanded and the role of air storage in energy management was studied.

Systems with multiple compressors were also investigated and modelled. In [7, 22, 23], modelling of CAS with multiple compressors was studied. In [7], the simulation of multiple compressors was studied using three different control stratagems: network sequence control, pressure band control and automatic sequencer control. In [22], different controller approaches with fixed and variable compressor speed drive modes were investigated. In [23], an analytical approach to modelling cascade and frequency control modes for CAS with multiple compressors was presented.

The mentioned works show how effective simulation tools are used for the evaluation of CAS in design or during the retrofitting phase. To provide accurate and reliable results, these simulations normally require detailed input and definition of physical properties and relations. Moreover, in the common case where changes are applied to the systems configuration, models should be altered to take changes into account, otherwise the results would be inaccurate. Most of the studies did not develop comprehensive models that coupled both supply and demand side sub-system components. Future research might investigate developing supply and demand component blocs and coupling them in a single dynamic model. Moreover, a model that simulates the overall energy performance of a plant (that includes CAS, other processes, building energy consumption, etc.) had not been investigated.

IV. Innovations in Energy Management

Systems to perform energy management are slowly being created in companies [24]. The main role of such systems is to control energy consumption by assisting in the evaluation of performance, to identify faults or opportunities to improve efficiency and to recommend the corrective action [24]. Controlling energy performance of complex systems for long periods of time is challenging. Because they have a high variability in energy consumption, they are influenced by a large number of factors/variables and require frequent attention and updates. Self-learning technologies and automation could play an important role in optimizing the control of complex energy systems.

Energy and performance optimization of CAS with machine learning was investigated by Santolamazza [25-27]. In [25], a methodological approach that could be applied to monitor and control energy performance in industrial plants was presented. The methodology was based on a series of steps that supports the identification of variations in energy usage patterns or the deterioration of energy performance associated with irregular faults or events. In [26], the implementation of ANNs in monitoring energy performance of CAS and detection of failure, which was usually preceded with anomalies in energy consumption, was studied.

Santolamazza [27] evaluated three different methods to monitor and control energy consumption in CAS, the classical statistical approach and two machine learning approaches: support vector machine(s) and ANN(s). The results showed that statistical methods were simple and effective in determining main anomalies in common systems, whereas machine learning techniques enabled the implementation of additional functions such as failure analysis and prescriptive maintenance. It was concluded that real data obtained from CAS and operating environments, could assist in the detection of abnormalities (faults or energy inefficiencies) and in the recommendation of suitable counter measures. However, the association of these abnormalities with their possible causes, and the generation of a troubleshooting procedure, was not investigated thoroughly. Moreover, the methodology and the algorithm were not validated experimentally.

Energy management systems could be combined with sensors and information systems that help with data collection and analysis. Boehm and Franke [28] introduced the concept of cyber physical CAS (CPCAS), which are industrial CAS equipped with automation technology and AI. These systems capture basic operating parameters (such as pressure, volume, temperature, etc.) and they might enable a more efficient and flexible operation.

Other studies investigated machine learning for the design and monitoring of compressors. Ghorbanian investigated using ANN models, instead of the traditional expensive and time consuming experimental models, to construct compressor design performance maps [29]. Results obtained with ANNs reduced the development time and the cost at the initial design stages. Belman-Flores compared two techniques for modelling a reciprocating compressor: ANN and physical modelling [30]. ANN had higher accuracy than physical models.

The control of complex energy systems utilizing smart devices and technologies is still a developing field [24], especially for CAS. A main gap in research in this field included the development of algorithms capable of detecting abnormalities in performance and associating them with proper causes and developing suitable troubleshooting action plans. Another gap was the development of characteristics and specifications of CPCAS.

V. Methods and Equipment to Detect Air Leakage

Leaking air from a CAS could cause energy loss, estimated at 20-30% [5]. A leak would create a drop in pressure and that would affect normal operation and interrupt production [31]. It should be routine to try to eliminate leaks, and that can be achieved through maintenance and inspection [32]. There are several methods and technologies for the detection of air leaks.

Methods presented in [33] and [34] required measurements during non-production periods. Doyle and Cosgrove [33] quantified leaks by comparing energy use during production and non-production periods. This method was easy and cheap, however proper experimental verification was not reported. Poyhonen [34] presented a method to estimate the air leakage rate that was based on an identification run sequence applied in the control scheme of the variable-speed drive during times of no compressed air consumption. The feasibility of the approach was verified with laboratory measurements and it offered a practical solution for monitoring and quantifying leakage.

Dindorf [35] proposed a new compressed air leakage measure method that could be used in and outside production hours. The method was independent of receiver and compressor parameters, which was not the case with traditional methods. The method used an automatic measuring device connected to a branch of a pipeline. The device could measure compressed air leakage in any part of a pipeline network.

Fileti [36] investigated detection of leak using an acoustic method. Noise generated by leakage was recorded with a microphone. Noises were then decomposed into sounds of different frequencies using an ANN. The occurrence and magnitude of leakage were predicted. The method was accurate except for small orifice leaks (<1mm).

Several studies discussed techniques used in detection, location and quantification of leaks. The literature indicated several research gaps. One was the lack of accuracy in ultrasonic and acoustic methods when dealing with small leaks (orifice smaller than 1mm). Future research would investigate ways to increase the range of leak sizes that are detectable.

VI. Gaps in Research

The following six gaps were identified:

- High cost of gathering information and deciding on the most cost effective and applicable measures. A typical way of saving energy has been through costly energy audits. Developing a method to support making decisions about saving energy in CAS might result in a useful and innovative tool to improve energy efficiency.
- Modelling and simulating CAS plays an important role in evaluating performance. Most models focus on modelling either the supply or the demand side. Future research might develop models that couple both. Another aspect to consider was integrating other plant energy usage (heating, cooling, lighting, etc.) with CAS, to create a model that describes the total consumption.
- Development of smart energy management technologies in CAS is rapidly gaining momentum. Machine learning techniques were confirmed as a suitable tool for optimizing performance by detecting abnormalities. Studies concluded that the association of abnormalities with their causes and suitable troubleshooting procedures was possible, however, that was not investigated thoroughly. The development of an energy management system that detects abnormalities, associates abnormalities with suitable causes and sets up a troubleshooting procedure has not been achieved.
- The work on the development of smart energy management technologies for CAS, using machine learning and real-time manufacturing data was not validated experimentally. The future work needs to experimentally validate the theoretical work.
- CPCAS were introduced in [28]. Such systems are equipped for self-sufficient control with sensors, actuators and equipment for data processing. In addition, they exchange information with energy management systems, and they might play a role in smart energy management of CAS. However, CPCAS was not well developed. There was a gap in the research regarding technical characteristics and functionalities of CPCAS components.
- Leak detection and treatment are an essential step to reduce waste. Several technologies were discussed. These face several challenges such as: inability to operate during production, inaccuracy and noise. Moreover some techniques, such as ultrasound and acoustic leakage detection, failed to be effective in identifying leaks from small orifices. Future research needs to develop these techniques to increase accuracy, range of applicability and ease of use.

VII. ADDRESSING THE GAPS

A. *The Proposed Concept*

The proposed concept is to address the gaps by combining sensing and AI to improve real time energy efficiency. Deep reinforced learning and recurrent neural networks will be examined for use with sensor data to make information regarding systems performance available for machine learning. The AI will question and then automatically take action and knowledge management (KM) will facilitate processing the information.

Intelligent data processing will be conducted and AI will then act on it. That data may be deposited in a recurrent neural network with information and expert knowledge within a Common Store (Fig. 2 Red). KM will be used to process information to provide outputs (Fig. 2 top left / green).

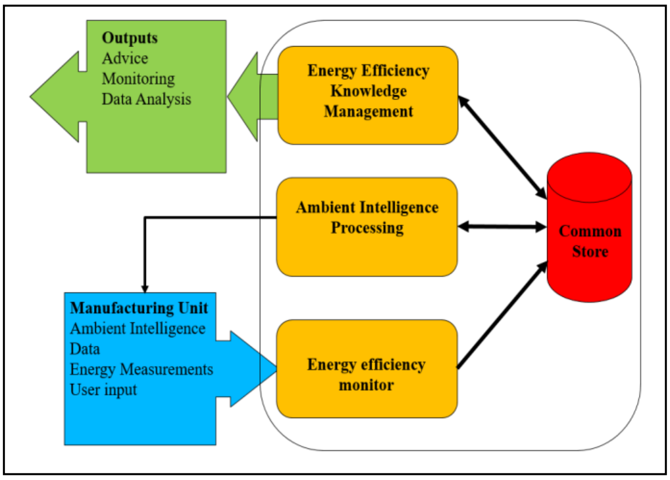

Figure 2. Concept for combining sensing, AI and KM [2]

The analysis of energy consumption will utilise data coming from sensors. Such data can be obtained from interactions between machines and operators as well as from smart tags. In addition, measurements such as production rates and line temperatures can be accessed. Systems can use deep reinforced learning to give advice and to monitor and analyse data. New intelligent techniques will be created to save energy. Specifically, the objectives are to:

- Realise an improvement in energy management.
- Monitor the environment and performance.
- Utilise AI to assess the environment and the performance.
- Apply KM to help reduce energy consumption and waste.
- Build a new human computer interface (HCI).

The three data streams from the manufacturing unit are shown in Fig. 2 in blue (bottom left). Intelligent processing of this lower level data will be carried out using machine-learning to make data usable by a KM stage.

Research will investigate existing systems hardware and circuit diagrams to comprehend and evaluate them. Input devices will be interpreted using a Fuzzy Rule Based System. Smoothed data from inputs will be interpreted by conditional statements, expressions and constructs as they are appropriate for precise knowledge. Fuzzy Systems will identify information from human beings (supervisors or operators) and decode what they are actually doing. Uncertainties generated by incomplete or partially corrupt data will be handled by fuzzy logic. Information/data will be added to a store. AI will take action automatically through a recurrent neural network and KM will process the information. The output will be a range of energy efficiency suggestions through the HCI.

B. *Data Processing*

Data will be gathered by energy-consumption-sensing and measuring-systems, and stored within a common-store.

One significant challenge is to relate the energy consumption to the data. That will be a starting-point for optimizing the systems. Data from present energy consumption sensing equipment will be merged with new systems to determine the interaction between machines, operators, processes, and measures such as production rates and line temperatures. Systems will portray energy use and environmental/process data to be used in intelligent event computation and processing. Data from sensors will be transformed into object model(s), and then employed to establish any adjustments that may be required. Rule Based Systems will contemplate sensor information and appropriate fuzzy systems will be selected to deliver input(s) to a Decision-Making-System (DMS). That DMS will evaluate output(s) from AI subsystem(s) and propose options. That new hybrid system will combine the desirable elements of diverse AI methods. Suggestions from the various systems and methods will be assessed by the DMS. Sensor data will come from: Smart tags; Man-machine interfaces; Miniature information systems; Miniaturised optics and cameras; and Micro-sensors.

Data will be filtered and processed to deliver organized representations. The DMS will filter suggestions in the same way that a group of experts around a table would consider options. Case Based Reasoning (CBR) will deliver confidence-weights for AI outputs so the DMS can choose outputs. AI sub-systems will provide proposals for the DMS to consider. Sets of problems will be generated. CBR will then adapt answers from earlier problems to existing problems. Solutions will be saved in a simple data base that represents experience. When problems occur that have not been experienced, then it will be compared to previous cases and one will be selected that is close to the existing problem. It will then take automatic action and update databases, depending upon the failure or success of actions. CBR will represent knowledge to humans, but will also learn from past examples. DMS will mediate between different AI systems if they do not agree and algorithms will be assessed to provide balanced arbitration, including: Bonus Loading, Static and Dynamic Weighted, Highest Confidence, Summation of Confidences, and Best/Worst. Confidence values from AI with dynamic weights from DMS, will improve decision making. The common store will store data to make it readily available. It will be a main knowledge and information source. Research will contemplate: IEM, CIMOSA, PERA, ARIS, GRAI/GIM and

EN ISO 19440. They will be used to accomplish a suitable solution and to combine sensing, KMK and AI. The store is shown in red in Fig. 2 on the right.

C. Intelligence Information

To achieve mapping, existing knowledge and new knowledge will need to be correlated and applied. The new methods will reduce energy use and deliver a state-of-the-art method for combining AI, KM and sensing technologies. Technological and organisational aspects will be addressed. Research will contemplate the way that information from sensing and AI can be used to improve efficiency.

Information will be transformed into knowledge by adding some context. Existing knowledge will be combined with information and context models. Processing will utilise information from classical (legacy) data sources and sensors. AI will question the system and be able to automatically take some action. The Energy Efficiency KM systems will give advice, monitor the system and analyse data. It will adapt derivation models using measured and processed data; for example, on-line diagnostics. The system will interactively give suggestions to improve the efficiency. Systems will use middleware to give measured data on-line. Middleware will share knowledge and information held within the store and it will underpin the classification of pertinent knowledge about energy and efficiency within the store.

D. Outputs

The output from Data Analysis will give an analysis of past historic data. Existing sensors will be upgraded and they will be bespoke. Solutions will be created (written in code) for common equipment such as pumps, motors and valves. Measured data will identify the state of energy use and it will allow the energy management. Processes and consumption will be examined to provide advices about knowledge being gathered and real time measurements. That will involve a new prediction sub-module to identify weak points (preferably before they actually occur).

E. Experimentation

A test rig will be constructed to evaluate the new methods and ideas. That will examine the legitimacy of the methods to ensure an increase in efficiency is achieved. The elements will comprise: sensors (line pressure, temperature, etc.), software for measuring energy consumption, interfaces and the store. Systems will be tested within the University of Portsmouth and at industrial collaborators. Collaborators will supply testing sites and equipment and valuable sources of data.

VIII. Discussion

Research gaps relevant to increasing energy efficiency in CAS were investigated. Measures to reduce energy consumption were well developed, with numerous papers covering the subject. Measures were divided into supply side and demand side, some targeting specific components while others the system as a whole. Even though these measures were well established, several barriers stood in the way of their implementation. Obtaining information about energy efficiency required costly and periodic energy audits. Developing a mechanism or system that facilitates the detection of energy efficiency measures might encourage implementation of these measures, and therefore reduce CAS energy consumption.

Simulation and modelling of CAS was also reviewed. These could help evaluate and justify the technical and economic feasibility of energy efficiency measures. Some models were more detailed and they considered more system components and variables. The main gaps included the development of more detailed models that they considered all possible system components in addition to other aspects of energy consumption. The main challenge in modelling CAS was that accurate simulations required detailed knowledge about engineering properties and the relations between system components. Developing these models is costly. Moreover, CAS are subject to frequent modifications and upgrades, which would require updating of previously created models.

Innovations in smart energy management were investigated since controlling consumption is important. Operational data obtained from CAS environments can be fed into machine learning algorithms to flag abnormalities in performance. Detecting that something might be wrong is helpful, however, a further improvement would be associating fault with its cause and setting up a troubleshooting procedure. Such systems might automate detection of faults and energy efficiency measures, which may be an innovation in CAS performance management.

Methods and techniques used in determining air leaks in CAS were considered. Several methods exist to locate and evaluate the magnitude of air leaks. Methods that used ultrasonic, acoustic and thermal monitoring did not intervene with normal operation, and they were effective in locating leaks when they were greater than 1 mm. Although methods that measured time to fill CAS storage were cheap, but they interrupted normal operation and did not locate leaks. New systems and methods were suggested to address these gaps.

IX. Conclusions

The performed literature review divided past papers into four categories: energy efficiency measures, simulation and modelling, energy management and methods to detect leaks.

Our current research is now investigating algorithms that automate detection of abnormalities in energy performance and associate them with their causes. To understand possible events that influenced CAS energy efficiency, the main variables describing the performance of CAS will be investigated. This will provide an understanding of data required to describe the current state of CAS. The intent is to use this data with algorithms capable of detecting energy performance abnormalities and associate them with a suitable cause.

Deep Reinforced Learning and Recurrent Neural Networks have been proposed here as possible approaches for improving the state-of-the-art in CAS. Deep learning is usually a recommended approach when dealing with unstructured data, such as: images, speech, and video. It is often used to extract hidden representations (features). CAS data may be more structured because the data will mainly be generated from sensors, for example: production rates, pressures, and temperatures. Data may turn out to be less suitable for Deep

Learning and more suitable for Neural Networks. That will be explored in the next stage of the research.

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