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New efficiency opportunities arising from intelligent real time control tools applications: the case of Compressed Air Systems' energy efficiency in production and use

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Abstract

Most of the production facilities in Europe make use of compressed air to drive equipment for manufacturing and Compressed Air Systems (CAS) account for about 10% of the total electrical energy consumption of European industries. Therefore, reducing CAS energy consumption is a crucial task to meet the European goals of improving energy efficiency and reducing environmental impact of the industrial sector. This work is part of a wider research activity aimed at developing a strategy to optimize the energy use in CAS. In particular, this paper shows the importance of monitoring energy consumption and control energy use in compressed air generation, to enable energy saving practices, enhance the outcomes of energy management projects, and to guide industries in energy management. We propose a novel procedure in which measured data are compared to a baseline obtained through mathematical modelling (i.e. regression functions) to enable faults detection and energy accounting, through the use of control charts (i.e. variations' control and the Cumulative Sums). The effectiveness of the proposed methodology is demonstrated in a case study, namely the compressed air system of a pharmaceutical manufacturing plant.

Keywords: Energy Efficiency; Compressed Air Systems; energy data analysis; energy measures

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1. Introduction

The research activities presented herein belong to a larger research project on energy saving in Compressed Air Systems (CAS) in manufacturing plants aimed at assessing the potential of CASs' energy efficiency in energy intensive companies in the Italian context and to provide support tools for the implementation of energy saving opportunities. [1-3]. In the first phase of the project, a massive survey has been performed to evaluate CASs' energy consumption in target companies [3]. Starting from the measurement of the actual operative conditions, a series of analyses has been run in order to quantify energy consumption related to compressed air generation in Italian industry. In particular, the survey revealed that only 14 % of companies measure CAS′ energy consumption through a real-time monitoring system and only 4% measure the compressed air flow rate [3].

Starting from a large dataset made up of more than 15000 energy audits, detailed analyses have been led on enterprises whose CAS electric energy consumption was bigger than 5% of total electric consumption. The selected sample was composed of about 1700 enterprises belonging to 10 different industrial sectors.

In order to get a large amount of detailed information from enterprises, a questionnaire, about technical and management aspects of CAS, has been submitted. The questionnaire contains 12 questions, grouped by the following 3 main contents: general aspects, measurement systems and working conditions of CAS. Each question has from 3 to 5 possible answers sorted by an increasing level of knowledge and awareness of the importance of performance monitoring. Starting from results analysis, the authors have collected a set of guidelines for the enterprises to help them improving CAS energy efficiency in a personalized manner and starting from effective critical issues (i.e. issues highlighted by questionnaire answers). This survey demonstrated that the actual state of the CAS within the Italian industry shows an average-low qualitative level either for dimensional, operational and managerial functions. Therefore, among the expected objectives of our research project, the assessment of the enterprises' state will allow the identification of the variables to be examined both directly and analytically.

Moreover, the answers highlighted, on the one hand, the high weight of compressed air production on the overall energy consumption in the whole Italian industrial sector, and, on the other hand, the low number of monitoring systems installed to measure the energy consumption of such systems [3]. In fact, while most researches and legislations highlight the importance of having a reliable measure of energy efficiency and energy savings in industrial sites, and suggest the adoption of real-time monitoring systems at least for significant energy uses [4-8], this is clearly still quite far from being implemented in practice. One reason for that is the scarce knowledge of the energy efficiency and non-energy efficiency benefits deriving from measuring energy consumption.

The present study aims at showing the importance of energy monitoring, which provides energy managers with feedback on energy saving practices, outputs of energy management projects, and guidance on reducing energy consumption. The technological improvements in the field of ICT have significantly improved the ability and the easiness of smart metering in real time, which, combined with machine learning and artificial intelligence technologies, would enable companies to manage energy use dynamically [9], in an Industry 4.0 perspective.

In fact, through the analysis of process data and the relationships among variables, it's possible to extract valuable information for different applications, such as process monitoring, fault diagnosis, mode clustering, soft sensing of key variables/quality variables, etc. [10]. Therefore, for energy management purposes, this would give the opportunity for more reliable benchmarking based on measured data that can be compared to a baseline obtained through mathematical modelling (i.e. physical models, regression functions, fuzzy neural networks).

Likewise, from a maintenance point of view, for example, the use of advanced techniques can enable real-time smart control of the performances in production with faults detection [11-14] and the prediction of machine health can result in a reduced downtime, supporting the ERP system to optimize manufacturing management, maintenance scheduling, and guarantee machine safety thanks to prognostics information available [15].

Moreover, advanced energy accounting systems [16] as well as real-time optimization [17] would be enabled.

The research presented in this paper originates from existing methods and approaches [18-19] and derives a general methodological approach that can be applied to any energy use in industry. In fact, most of the different approaches available in literature to monitor and control energy performances in industrial plants share the same main phases: measurement plan and data collection, baseline definition, implementation of control over time through comparison between the baseline and the monitored energy consumption. Moreover, a case study is presented focusing on compressed air systems to demonstrate the effectiveness of this approach and the related energy saving opportunities. Therefore, the present work establishes an intermediate step to define best practices to control (i) significant energy uses in general and (ii) compressed air systems in particular in an Industry 4.0 perspective.

2. Methodology

The methodology described herein defines a series of steps that support the users in the identification of changes to energy consumption patterns or degradation of energy performances often linked to sporadic faults or events. Moreover, it also provides a better understanding of the energy consumption behavior of the overall system.

When implementing an energy performance control, the boundaries and the level of detail of the analysis must be defined at first, identifying the main energy vectors and distinguishing between generation and utilization of energy carriers. Then a measurement plan and data collection are needed. As energy consumption is often dependent on several variables, the characterization of the energy consumption behavior requires to collect different types of information: consumption data, production data, environmental data, technical (users) and operational data [19].

According to the technical and physical characteristics of the analyzed system, some of these variables might influence the performance of the system and should therefore be included in the measurement plan.

Data collected must be synchronized and show the appropriate level of detail. Moreover, the duration of data collection should be established considering the selected frequency and process dynamics to guarantee a correct representation of the process. The measurement plan has to be tailored to the scope of the analysis and has to clearly distinguish between energy generation systems and energy uses.

The next step is the definition of a system energy baseline, which is a key factor in enabling an effective control of the energy consumption behavior, as it serves as a reference against which the actual energy consumption is compared. There are several ways to define the algorithm to build the energy baseline. Statistical regression models [18, 20-22] are the most used and proposed in this paper. However, physical models, neural networks or even machine learning techniques [14, 23] are employable.

To develop a statistical regression model that characterizes the energy behavior of a system from a set of historical data, it is important to determine the factors influencing changes in the energy consumption (so called "energy drivers") [16]. Indeed, the energy consumption of a system presents a variability due to both intrinsic and external causes. Preliminary phases in the analysis of collected data include the evaluation of the appropriate frequency for the analysis considering the purpose of the control and the users of the implemented system: for example, it will be lower if the goal is to provide strategic control tools, higher if the recipients are operators that should enact a more recurring control. In this phase, it is also important to acquire operational information related to changes in the system, such as maintenance operations and faults. The first statistical tool to use is the correlation analysis of the previously identified energy drivers and energy consumption. R^2 and "p_values" can be used in order to add quantitative data to correlation plots [20, 24]. After having ascertained the choice of energy drivers, through regression analysis between potential energy drivers and energy consumption, a multiple regression model can be extrapolated and statistically validated, by checking the significance of its coefficients.

Finally, a validation and a first analysis of the historical performance of the analyzed system must be carried out through the observation of two different control charts, widely used in Quality Control [24]: the variations' control chart and the CuSum (Cumulative Sums chart). The first one illustrates the difference between the actual values of energy consumption and the predicted ones over time. Two lines, representing the control limits, estimated as multiples of the standard deviation of the variations' statistical distribution (usually ±2 or ±3), can be added to enable the recognition of anomalous behaviors (e.g. points outside the control limits, non-random patterns like mixtures and shits of the average). The CuSum shows the sum of all the residuals between actual values and predicted values accumulated until then and is therefore very useful to highlight trends in energy performance deviation. A change in the slope of the CuSum represents a variation of the system's behavior: an upward trend represents a decrease in energy performance, while a downward trend signals an increase in energy performance (energy savings). Examining together these two control charts enables the immediate identification of anomalies and trends in consumption behaviors, thus allowing the definition of appropriate corrective and/or preventive actions.

The validation of the baseline model, which allows to verify the suitability of the chosen time period and the effectiveness of the energy drivers i can be performed in the following three ways [16]:

- considering the most recent available set of data (it is the best option when changes to technical, technological or structural configurations of the analyzed center have occurred);
- considering the data set that shows the best energy performance (more challenging in terms of energy objectives and usually considered in terms of continuous improvement);
- considering the data set that shows the most constant and stable energy behavior (generally considered when none of the two options previously mentioned is applicable).

After the model validation, it is possible to use the baseline model to implement a continuous control over time. Real-time data for both energy consumption and energy drivers can be acquired by metering systems the difference between the actual energy consumption and the value predicted from the baseline model can be evaluated at the frequency previously defined and represented on the control charts to highlight the presence of possible anomalies. Moreover, the setting of control limits and other alarm conditions can automatize the generation of alerts, enabling a real-time control by the operators and maintenance personnel.

3. Case study

The methodology described has been applied to the compressed air system of a pharmaceutical production plant located in central Italy. In the present study, the company decided to focus on the compressed air production phase in order to identify additional improvement opportunities and to verify its correct operation and energy behavior. The plant is equipped with five screw compressors divided into two groups: a group of two located in room “A” and a group of three located in room “B”. The compressed air demand is lower than the total production of the five compressors, so that usually only two or three compressors are working contemporaneously. Only compressor 9, located in room “B” has a variable speed drive installed, and it serves as “master” (continuously functioning), while the others serve as “slaves”. The compressors are controlled and turned on and off by a central control system, according to compressed air demand. Some general information on the compressors (nominal and stand-by nominal power) is reported in the figure 1, together with energy and compressed air production data available at 15 minutes frequency. In addition, data related to compressed air pressure and temperature and to external air humidity are available every 15 mins, while the number of hours worked by each compressor are available weekly (cumulated).

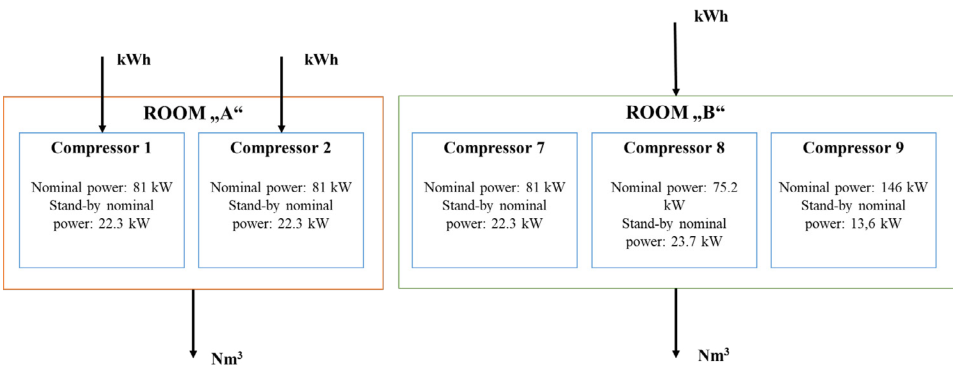

Figure 1 - Scheme of compressors´ groups and main data available.

Basing on the physics of the process, all these parameters are considered potential energy drivers, thus the first regression analysis is conducted taking all of them into account, apart from the amount of hours worked, as it is available at a lower frequency. In fact, for this first analysis, aimed at defining the energy drivers as well as the energy behavior of the system, a daily frequency is considered to be the most appropriate, and an observation period of one year is adopted. This is mainly due to the fact that when weather-related parameters are envisaged as energy drivers, it is advisable to try and observe the energy consumption in different seasons, thus observing the complete range of possible working conditions. This is done through a daily frequency, which does not require to handle a massive amount of data. In addition, the analysis is initially conducted on all compressors (considering the total energy consumption and the total compressed air production) in order to get an overall understanding. As a result, the only parameter showing a satisfying correlation with the energy consumption of the compressors and no multicollinearity with other parameters, is the amount of compressed air produced, as reported in table 1 (multicollinearity analysis´ results are not reported here for sake of brevity).

Table 1. Results of regression analysis.

Regression analysis results considering all parameters		**Regression analysis results considering only compressed air production**	
R^2	0.96	R^2	0.94
P_value	9.45 x 10^{-137}	P_value	1.69 x 10^{-125}
P_value intercept	0.76	P_value intercept	0.34
P_value compressed air production	8.32 x 10^{-119}		
P_value external temperature	2.06 x 10^{-17}		
P_value external humidity	0.01		
P_value pressure	0.84		

The baseline is represented by the following relationship:

$$\textit{Energy consumption [kWh]} = 0.1575 \times \textit{Compressed air produced [Nm}^3\textit{]} - 80.02 \quad (1)$$

The CuSum chart and the variations chart for seven of the twelve months initially considered are given in figure 2, where four energy behaviors for the whole group of compressors are also highlighted using different colors.

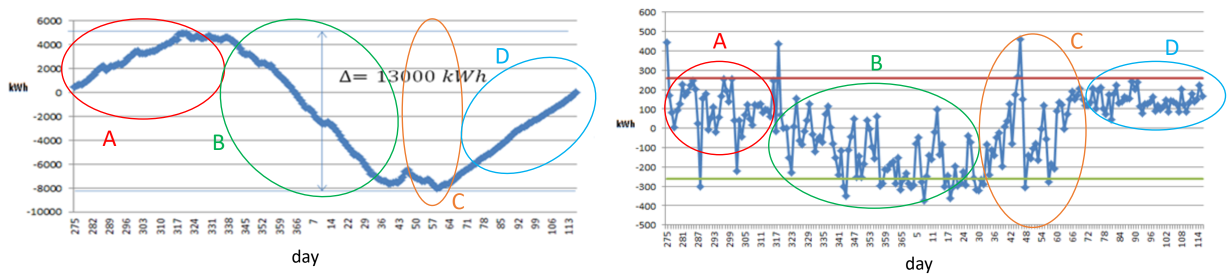

Figure 2 - CuSum and variations charts over a seven months period (daily data).

The causes of these different behaviors are further investigated (mainly through the observation of daily consumption data over time and interviews to operators) and finally identified to be the following:

- Red period ("A"): compressor 2 presented a higher specific consumption, and the problem was solved around day 325 thanks to a maintenance intervention;
- Green period ("B"): following a change to the activation sequence, compressor 7 was mainly working together with compressor 9, while the others were rarely on;
- Orange period ("C"): an evident malfunctioning related to the fact that compressor 1 was stuck in stand-by for three whole consecutive days;
- Blue period ("D"): following a change to the activation sequence, compressor 8 was mainly working together with compressor 9, while the others were rarely on.

From these analyses it is therefore possible to highlight two different maintenance-related events as well as a quite strong dependency of the energy behavior on the set of compressors working and therefore on compressors´ activation sequence (also confirmed by further analyses on the amount of hours worked by each compressor). An optimal activation sequence was therefore identified and uploaded into the central control system. Control charts where used for a continuous monitoring and control and provided to the maintenance team. These actions produced an energy saving that was estimated to be around 10% of the annual energy consumption of air compressors (achieving a lower specific consumption and also preventing higher consumptions due to maintenance issues).

4. Conclusion and future developments

We have developed a methodology to reduce energy consumption of significant energy uses in industrial plants, through monitoring and control. The methodology has been applied to CAS. A baseline of the energy consumption behavior is built through statistical regressions that correlate energy consumption to the main energy drivers. Then control charts are used to identify changes to energy consumption patterns or degradation of energy performances related to sporadic faults or events. The application of the proposed methodology to the CAS of a pharmaceutical production plant allowed to highlight maintenance-related events and to define an optimal activation sequence of the different compressors, thus generating an energy saving of around 10%. This work also demonstrates that the measurement of actual operative conditions are crucial to characterize the energy consumption related to compressed air generation. In our research activity related to energy consumption in CAS, comprising the data analysis, we submitted a questionnaire to Italian industries considering the general aspects, the measurement systems and the operating conditions. Such a survey demonstrated that only few companies perform measurements on CAS, and a high level of awareness on measurements is observed mainly in the pharmaceutical and the chemical sectors.

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