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Multivariate KPI for energy management of cooling systems in food industry

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Abstract

Within EU, the food industry is currently ranked among the energy-intensive sectors, mainly as a consequence of the cooling system shareover the total energy demand.
As such, the definition of appropriate key performance indicators (KPI) for ammonia chillers can play a strategic role for the efficient monitoring of the energy performance of the cooling systems.
The goal of this paper is to develop an appropriate management approach, to account for energy inefficiency of the single compressors, and to identify the specific variables driving the performance outliers.
To this end, a new KPI is proposed which correlates the energy consumption and the different process variables. The construction of the new indicator was carried out by means of multivariate statistical analysis, in particular using Kernel Partial Least Square (KPLS).This method is able to evaluate the maximum correlation between dataset and energy consumption employing nonlinear regression techniques.
The validity of the new KPI is discussed on a case study relevant to the cooling system of a frozen ready meals industry. The assessment of the proposed metric is one against Specific Energy Consumption (SEC) like indicator, typically used in the context of the Energy Management Systems.

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1. Introduction

In the present transition toward zero-fossil fuel era, energy efficiency technologies and goals are considered the ingredients of every development recipe. In the industry arena then, some of the most promising strategies for energy efficiency are linked to the implementation of Energy Management System (EnMS), according to ISO 50001 [1], [2]. Within an EnMS, monitoring the energy performance of systems, processes and equipments plays a central role, advocating the definition and use of specific indicators, so called Key Performance Indicators (KPI) or Energy Performance Indicators (EnPIs). However, depending on the specific situation and given the criticality in the identification of correlations between energy consumption and independent variables (e.g. process, maintenance and environmental parameters), the definition of correct energy performance indicators remains the most critical element [3].

An area of particular relevance to the implementation of energy efficiency policies is the food industry, which has been recently rated by the European Union among the most energy-intensive sector. This was partly due to the growing energy consumption of cooling systems driven by production volumes and the requirements enforced by quality, hygiene and food safety standards. Among the state-of-the-art and the emerging refrigeration technologies (i.e. mechanical vapor compression, absorption and/or adsorption, ejector refrigeration, air cycle refrigeration, trigeneration, Stirling cycle, thermoelectric, thermoacoustic and magnetic refrigeration technology [4]), still ammonia chiller using, reciprocating or screw compressors, dominates the food processing and cold preservation sector. Customary monitoring of ammonia chiller relays on the measurement of electricity demand, duty cycle pressures and temperatures, heat extracted, and environment data (e.g. temperature and humidity).

The most common way of measuring the refrigeration efficiency of a cooling system is to compute the Coefficient of Performance (COP) for the core refrigeration system only, or the Coefficient of System Performance (COSP) for the complete refrigeration system. The latter being defined as the ratio of cooling loads to total power input into compressor and ancillary equipment, condenser fan and other devices [5]. Following the eco-design European directive on cold appliances [6], novel mathematical models have been proposed in order to analyze the appliances performance on the basis of the real operations(i.e. door opening events, defrost cycle, or thermal load associated to different foods [7]). In this vein, Acha et al. [8] proposed the definition of non-standard KPI to evaluate the combined performance of cooling system and chilled or frozen foods in food retail buildings. Whereas in industrial applications, Nunes and coworkers [9] have carried out studies on the energy signature of food industry by proposing energy indicators to combine energy and process data. The above mentioned performance metric are usually casted to absolute or aggregate measures of energy fluxes generally based on historical data series and as such unable to fully account for the multivariate dynamics of complex industrial process [10].

Recent literature contributions have underlined the need to develop new methodologies to define energy related key performance indicators, based on a proper multivariate statistical data analysis, as a mean to evaluate the energy efficiency of production process/equipment, machine tools, and factories [10], [11]. Among multivariate statistical process monitoring (MSPM) methods, the data-driven ones (i.e. process history-based methods), such as Principal Component Analysis (PCA), Partial Least Squares (PLS), Canonical Variate Analysis (CVA), Independent Component Analysis (ICA) and Fisher Discriminant Analysis (FDA), have received much attention in the last decades. Those methods are yet an area of active research aiming at online KPI-based process monitoring and fault diagnosis (PM-FD) implementation [12], [13].

To this end, this paper focuses the definition and assessment of a multivariate KPI for ammonia chillers in food industry. The new KPI is based on kernel-PLS (KPLS) approach that outperforms the standard KPI (e.g. Specific Energy Consumption) in evaluating the energy performance of the single compressor, and that of cluster of compressors. The novelty of proposed methodology consist in the capability to obtain an indicator able to correlate the energy consumption with different process variables monitored on-board compressors.

This paper is structured as follows. First, will be described the method to define standard KPI (sKPI) and multivariate KPI (mKPI) for ammonia compressors. Then, the energy analysis will be applied and tested in the case study of an industrial ammonia chiller. Finally, the trend of monitored variables have been compared to compressor mKPI to understand the inner working of indicators, and identify the operation causing specific outliers.

2. Methodoloy

The methodological approach advocates the definition of single variate or standard KPI (sKPI) and multivariate KPI (mKPI). Both indicators are used to study the dynamic behavior of a compressor cluster at system level (sKPI) and at component level (mKPI).

2.1. Standard KPI (sKPI)

The single variate KPI is defined by using a specific energy ratio (SER). The sKPI is set as the ratio between the energy consumption (kWh) and the production output (ton), as customary of energy performance indicators (EnPI) widely used in the field of energy management [14]. Namely, the sKPI reads:

$$\boldsymbol{sKPI} = \frac{\boldsymbol{Energy\ Consumption}\ [\boldsymbol{kWh}]}{\boldsymbol{Production\ Output}\ [\boldsymbol{ton}]}$$

Here the energy consumption is the sum of the kilowatt-hour absorbed by all the compressors (system level) in a given time interval, while the production output is the total tons of frozen product in the same time lapse.

2.2. Multivariate KPI (mKPI)

Multivariate KPI was computed using Kernel Partial Least Square (KPLS) methodology. KPLS belongs to the group of Non Linear Partial Least Square (NPLS) methodologies, which aim to extend the Partial Least Square regression (PLS) to non linear dataset. NPLS regression is used in many applied sciences [15], from social and economic science to chemistry. Developed by Wold [16] as Non linear Iterative Partial Least Square (NIPALS), after it was extended by Lohmöller [17] for modeling complex multivariate correlation among observed variables [18].

In the number of the different avenues to perform PLS, the most popular is the algorithm presented in [19], [20]. This algorithm is based on two assumption: the latent variables of X are good predictors of Y and there is a linear relation between the latent variables of X and of Y [21]. The basic PLS algorithm considers two datasets X and Y and maximizes the covariance X^TY by finding a linear subspace of the explanatory variables. This could be carried out either as an iterative procedure or as an eigenvalues problem.

This new subspace allows the prediction of the Y variable based on a reduced number of features (PLS components or latent variables). These features describe the behaviour of dependent variables Y and they constitute the subspace onto which the independent variables X are projected [18], [20], [22], [23].

The stability of predictors derived from PLS methods make this methodology better than multiple linear regression, ridge regression and other well known regression technique [20].

Furthermore often in many real process variable are not linearly related, for this reason different non linear versions of PLS have been developed. These methodologies could be categorized in two different approach: the PLS variant in which the linear relation among the variables is substituted by a non linear relation, and the kernel variants in which the PLS is modified to fit a kernel approach.

In this work the kernel variant is used. The input data is mapped by a non linear function into a high dimensional feature space, corresponding kernel Hilbert space [24], [25], in which ordinary linear PLS is performed on the transformed variables. The central property of the approach is that only the inner products in the transformed space are necessary and not the non linear mapping. The first non linear KPLS was proposed by Rosipal and Trejo [26] for the modeling of relations between sets of observed variables, regression and classification problems [27], [28]. The interesting feature of kernel algorithms is the capability to have the flexibility of nonlinear expressions, solving only linear equations. On the other hand, the disadvantage of kernel methods is that for a dataset of n samples, the kernel matrix has n x n dimension so require both more memory and computing time.

3. Case study

3.1. Description

The case study focused on a refrigeration system for the production of frozen ready meals, including a selection of pasta and sauces. After the cooking process, the food is sent to the freezing tunnels, in which the product is instantly chilled to temperatures between -30 °C and -37 °C.

The refrigeration system employs R717 ammonia as a refrigerant fluid, and it is based on a two-stage compression process. In the low pressure (LP) stage, 5 screw compressors are used to compress the ammonia up to 2 bar, while in the high pressure (HP) stage 3 screw compressors are used to increase ammonia pressure to 11 bar. Figure 1 shows the schematic representation and the pressure-enthalpy diagram of the process and Table 1 specifies the rated power of the compressor clusters.

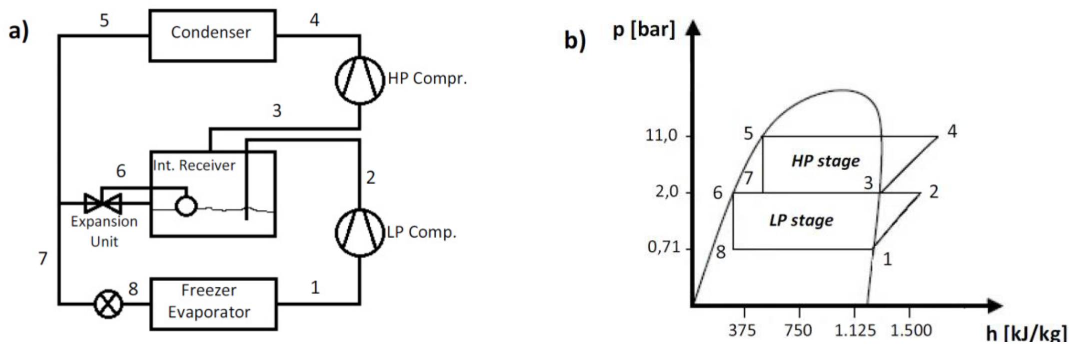

Figure 1: (*a) Schematic representation of the refrigeration system;(b) P-H diagram of the compression process.*

All the compressors were monitored simultaneously for two weeks of February, with a data acquisition frequency of 5 min. The monitored parameters on each compressor are: the energy consumption, the output pressure and temperature of the ammonia, the oil pressure and temperature and the on-off. Simultaneously, the tons of products within the freezing tunnels were accounted.

Table 1. Compressors involved in LP and HP stages.

LP stage		***HP stage***	
Compressor ID	***Rated Power (kW)***	***Compressor ID***	***Rated Power (kW)***
CL1	37	CH1	315
CL2	37	CH2	250
CL3	88	CH3	250
CL4	200	-	-
CL5	200	-	-

4. Results

First, to verify the reliability of the system indicator sKPI, the energy/product measured data sets were analyzed using a linear regression (Fig. 3).

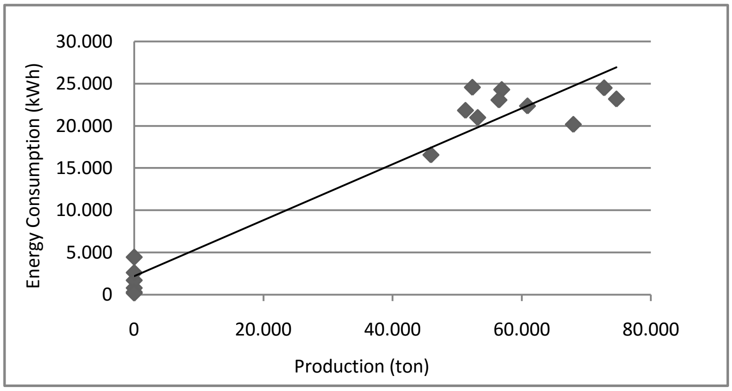

Fig. 2: Correlation between energy consumption (kWh) and production (ton).

This analysis resulted in a R^2 value equal to 0.937, confirming the high correlation between the process variables and support the validity of SEC like indicator.

The standard sKPI (kWh/ton), defined as the total daily energy consumption over the energy production, is illustrated in Fig. 2 for the interval of the present investigation.

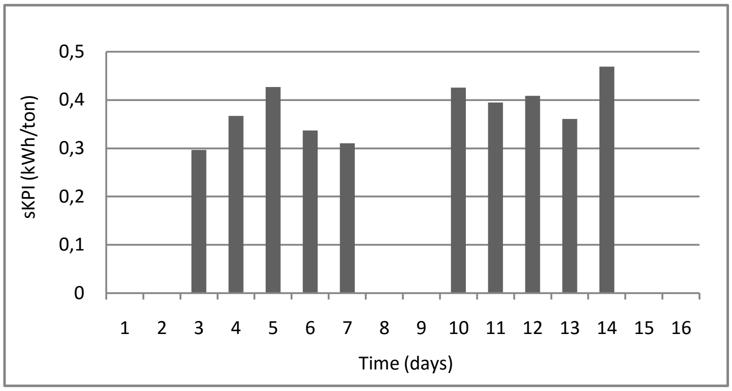

Fig. 3:Trend of sKPI (kWh/ton) in the reporting period.

As evident, the best energy performance were found by the sKPI minima on days 3 and 7. Whereas, days 14 and 5 indicated system operations of derated efficiency (i.e. as per the higher energy per tons of product). Notably, the definition of the sKPI features a singularity during the weekends and the periods of stops.

To assess the role of each compressor in contributing to the chiller efficiency, a mKPI was calculated by performing the KPLS of all variables monitored on-board (i.e. energy and process variables). Specifically, the variables used as input of the model are: ammonia delivery pressure and temperature, oil pressure and temperature, energetic consumption and the on-off. Notably, the data series include real and integer variables, the latter representing the compressor status.

Fig. 4 shows daily mKPIs evaluated for each ammonia compressor on HP and LP sub-systems. In Fig. 4, negative values of mKPI represent days with higher efficiency, while positive peaks identify anomaly in the energy behavior. It is worth noting, that the mKPI allows to identify compressor's contribution to the system operation. In this respect, for instance, is evident how the performance of the compressor system (as given in Fig. 3) are strongly influenced by the CH1 and CL2 compressors respectively. As an additional remark, the mKPI variation permits to assess the energy performance during the weekends with mostly all the compressors set to a stand-by mode.

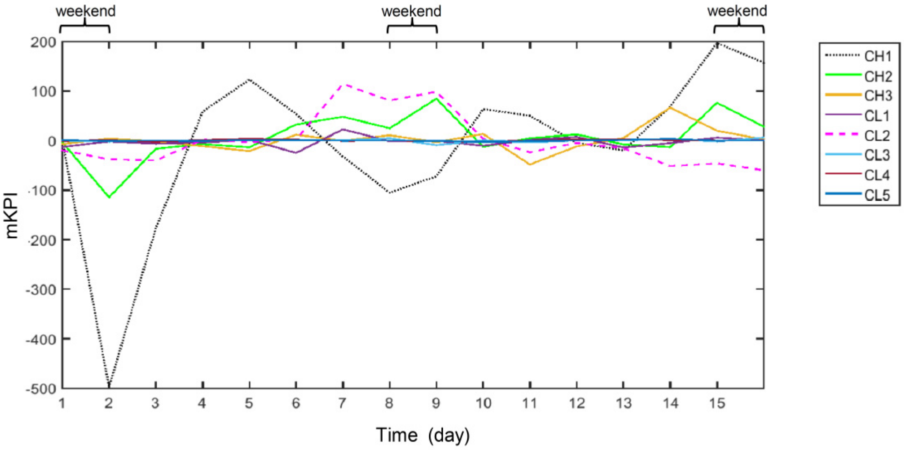

Fig. 4: MKPI for each compressor

Fig. 5 shows the comparison between MKPIs for each compressor (lines) and the sKPI (bar chart). The qualitative comparison of the mKPI against the sKPI indicates the similarity between the two trends. In particular, this is shown by CH1 mKPI and support the conclusion that the system behavior is strongly influenced by compressors of higher rated power.

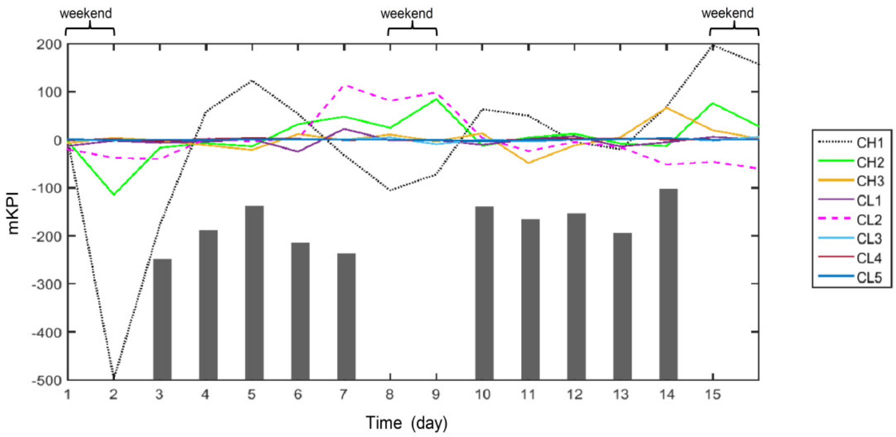

Fig. 5: Comparison between the mKPI for each compressor (lines) and the sKPI for the array (bar chart).

The use of sKPI only in the energy management can therefore result in misleading information. This is evident on day 7 (Fig. 5), for instance, when the sKPI indicates a high value of compressor system energy performance (mostly drifted by the CH1 behaviour) and is not able to account for the inefficiencies of low pressure compressors, i.e. the mKPI of the CL2 compressor (32 kW rated power). Similar but opposite situation is evident in day 14th analysis.

To give hints onto the inner working of the KPLS derivation, Fig. 6 illustrates the time evolution of the normalized monitored variables on-board CL2 compressor. In the same Figure the CL2 mKPI is also plotted.

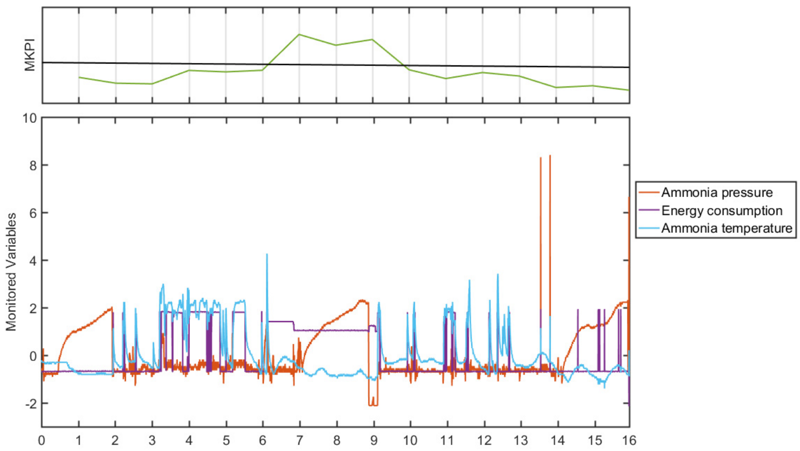

Fig. 6: Normalized monitored variables of compressor CL2

In this respect, the comparison of the trend of monitored variables against that of the CL2 mKPI (Fig. 6) suggested that the loss in component efficiency is driven by the departure of the CL2 energy demand from the ammonia pressure line. Such a circumstance demonstrates how the mKPI modeling works. The KPLS based derivation, in fact, is able to cope with the real operation and the energy behavior measuring it against the ammonia chiller demand (which is influencing the ammonia pressure or temperature levels). Operating conditions of low efficiency or anomaly than appeared whenever the inertia of the system-chiller determines ammonia pressure or temperature dynamics that differ from the compressors energy demand.

5. Conclusions

In this work a new multivariate performance indicator (mKPI) for the evaluation of energy efficiency of industrial process was proposed. The mKPI was tested on a cooling system composed by two-stage compression process. In order to highlight the potential and limits of new indicator, the mKPI was compared to the standard KPI (sKPI), specifically the specific energy consumption (SEC).

The mKPI seems to overcome the limitations shown by sKPI. Whereas, the standard indicator merely relates energy consumption to one or few process variables (e.g. production), it is does not link to the dynamic of the process. As such the sKPI does not allow to look into the energy inefficiency root-cause, providing only a metric for system energy performance.

The research shows how the mKPI is able to relate the energy consumption to different process variables, providing a more complete description of the energy behavior of the single compressor. Therefore by combining the mKPI analysis with the energy demand and the energy drivers, is possible to identify the specific variables that cause outlier in the energy performance.

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