An Intelligent Procedure for the Methodology of Energy Consumption in Industrial Environments

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Abstract. The concern of the industrial sector about the increase of energy costs has stimulated the development of new strategies for the effective management of energy consumption in industrial setups. Along with this growth, the irruption and continuous development of digital technologies have generated increasingly complex industrial ecosystems. These ecosystems are supported by a large number of variables and procedures for the operation and control of industrial processes and assets.This heterogeneous technological scenario has made industries difficult to manage by traditional means. In this context, the disruptive potential of cyber physical systems is beginning to be considered in the automation and improvement of industrial services. Particularly, intelligent data-driven approaches relying on the combination of Energy Management Systems (EMS), Manufacturing Execution Systems (MES), Internet of Things (IoT) and Data Analytics provide the intelligence needed to optimally operate these complex industrial environments. The work presented in this manuscript contributes to the definition of the aforementioned intelligent data-driven approaches, defining a systematic, intelligent procedure for the energy efficiency diagnosis and improvement of industrial plants. This data-based diagnostic procedure hinges on the analysis of data collected from industrial plants, aimed at minimizing energy costs through the continuous assessment of the production-consumption ratio of the plant (i.e. energy per piece or kg produced). The proposed methodology aims to support managers and energy-efficiency technicians to minimize the plant's energy consumption without affecting the production and therefore, increase its competitiveness. The data used in the design of this methodology are real data from a company dedicated to the design and manufacture of automotive components and one of the main manufacturers in the automotive sector worldwide. The present methodology is under the pending patent application EU19382002.4-120.

Keywords: Energy efficiency, Smart Manufacturing, Intelligent Systems, Industry 4.0, Big Data, Cyber Physical Systems

1 Introduction

The progressive increase in energy costs is a growing concern in the industrial sector, with electricity prices for non-household consumers achieving unprecedented values in 2019 (i.e. more than 0.15 EUR per kWh (including taxes) for the European Union in 2019 [4]). Besides this rising trend, another problem stems when comparing the cost of electricity to the value of industrial production, which is starting to have an impact on the competitiveness of manufacturing companies as their production costs become higher over time. Although renewable energies are becoming increasingly important to counteract this issue, the vulnerability derived from the consumption of fossil fuels and the dependence on oil-exporting countries in recent years has spawned the search and development of alternative strategies for the efficient management of energy consumption in the industrial sector.

In this context, the concept of energy efficiency involves the efficient allocation of the amount of energy required to produce products and services with a given set of industrial assets. Improvements in energy efficiency are generally achieved through the adoption of new technologies, upgrades in the production chain to make it more efficient, or through the application of commonly accepted methods to reduce energy losses. Beyond the industrial sectors, there are many motivations for businesses to improve their energy efficiency, the main one is that by keeping the energy use to its minimum, electricity costs can be reduced, without affecting their production entailing larger economic savings. This profitability holds as long as energy savings offset any additional costs of implementing an energy-efficient technology. Reducing energy use is also considered essential for the global reduction of greenhouse gas and due to regulations like ISO 50.001 .

Energy efficiency lies at the core of Industry 4.0 [7], which refers to a new industrial paradigm that defines the transition from *traditional* – i.e., based on industrial machinery – to the concept of digital manufacturing [10]. The concept of Industry 4.0 covers a range of industrial developments, including Cyberphysical Systems (CPS), Internet of Things (IoT), Internet of Services (IoS), Robotics, Big Data, Cloud Manufacturing and Augmented Reality [11]. Most of these technologies under the Industry 4.0 influence already existed years ago. However, their successful deployment over industrial environments has not been a reality until such technologies have evolved mature enough and have encountered a rich digital, interconnected industrial ecosystem, as provided by massive monitoring sensors, manufacturing databases and the end-to-end traceability of products and services. This digital transformation process is driven by an abrupt increase in the volume of data, the power of computer systems and connectivity, and their storage capacity that has increased at an exponential pace in recent decades [15]. Industrial machines can now operate with each other in a symbiotic way. As a result, the development and improvement of each technology contributes to the advance of the rest of technologies. These changes allow the different industrial sectors to adapt, evolve and create synergies to become stronger and more competitive [1]. Having greater interconnection capacity, greater adaptability and greater speed of information exchange has a huge competitive advantage potential for all types of industries, either for their internal functioning or for the services they offer to their customers for their products and services [14].

Modelling of industrial and manufacturing processes is very important in an environment where production processes must be digitally supported by new technologies [16]. Raw data do not provide significant value for decision making in a cyber-physical system, unless these data are effectively processed and analyzed [8]. In order to analyze massive amounts of data generated by both IoT applications and existing ICT systems, data science and analysis techniques must be developed and employed [2, 13, 3]. It is necessary to collect, analyze and optimize all details of a manufacturing process related to the desired process results. The real goal of Industry 4.0 is to create a seamless integration of processes to the intelligent cyberphysical factory [6] [17].

Energy efficiency is not an exception in the need of data-based modelling pipelines suited for manufacturing processes noted above. The contribution of the present work is framed within this statement: specifically, we define a procedure for the diagnosis of energy (in)efficiencies in industrial plants. Our proposal reponds to machine learning algorithms that allow examining the production-consumption ratio (i.e. energy per piece or kg produced), internalizing the operation with a global vision of the plant, process and machine, and inferring abnormal or unknown operational patterns from the collected data. The ultimate aim of the procedure is to develop new methodologies endowed with Machine Learning functionalities that guarantee a sustained industrial production while minimizing energy costs. To the best of our knowledge, in the current literature there is no prior work dealing with global solutions that integrate the data at plant, process and machine level. Effectively, existing approaches are considered at plant level due to lack of measures at lower levels, or they only optimize the individual behavior of certain machines, without considering their integration and interaction with the rest of the plant machinery. A case study will be presented and discussed in order to support the novelty of our procedure with empirical evidence based on real data obtained from several industrial plants.

2 Background and Motivation

Classical industrial control systems are not able to adequately cope with the essential problems of today's connected world in industrial environments, mainly due to issues with data types, information modelling and the relationships between data providers and control systems. This article proposes an intelligent procedure that, based on the interpretation of historical data, analyzes different behaviors with the aim of supporting decision making processes. In order to carry out this methodology of energy consumption in an industrial plant, the proposed approach includes advanced data-based models capable of inferring knowledge not only at the plant level, but also at the machine level. In the state of the art, there are no global solutions that integrate data at plant, process and machine levels. Instead, they are either considered at the plant level (due to lack of measures at lower levels), or they only optimize the individual behavior of certain machines, without considering their integration and interaction with the rest of the plant. The use of the proposed solution yields an overall vision of the system data, disregarding the level at which they are produced. This approach introduces the concept of plant, line, process, machine and piece's reference models for a better adaptation to the needs of modern industrial applications.

In the field of manufacturing, information technologies must be integrated with process control engineering. To do this, systems must be interoperable, which requires the exchange of information throughout the production process. On one hand, an EMS (Energy Management System) is used to collect data on the production equipment energy consumption. EMS systems provide in-depth knowledge of the energy consumption mode of the industrial plant, either through high-level measurements of its transformers and/or electrical connections, or through individual measurements of the equipment installed in the plant. On the other hand, an MES (Manufacturing Execution System) is used for production control, being its ultimate goal to increase the efficiency of the production plant (OEE, Overall Equipment Effectiveness) and thereby, to reduce costs and improve productivity. Thus, while EMS is focused on the energy control of the plant, an MES system is focused on the information of the production itself.

From an energy point of view, the industrial plant can be considered as a collection of loads grouped at different submetering levels. Thanks to the deployment of IoT, equipment like meters and gateways enable the measurement of a variety of physical magnitudes, as well as the connection of different industrial assets, enabling the collection of data at diverse submetering levels. Throughout the analysis of patterns emerging from production data, energy behaviors can be interpreted. Energy inefficiencies in a production process can also be detected, and the root cause for those inefficiencies can be identified. Therefore, our methodology allows to discern whether the discovered energy behaviors are due to production changes.

The challenge of this intelligent procedure, proposed in this article, is not only to merge the energy consumption and production data, but also to analyze the information collected by these subsystems. This information is provided to the plant manager through a set of tools that allow him to implement the necessary actions to maximize the energy efficiency of the industrial ecosystem thanks to the supervision, management of alarms and reports, consultation of indicators, control panels and so on.

3 Proposed Methodology

As has been mentioned in preceding sections, a new methodology is proposed for the analysis and integral evaluation of energy consumption in industrial plants. Figure 1 illustrates this methodology, which responds to a typical CPS architecture [9]. Each of the processing layers are explained in the following sections::

3.1 Physical-Energy Layer

The physical layer is responsible, through sensors of different nature, of capturing information over time. We assume that data captured by sensors over time are deployed over different assets of the industrial plant. In particular, each of such sensors captures and conveys energy measurements [kWh] to the MES module, yielding a collection of daily energy consumption curves $\mathbf{x}^{s,d} \doteq [x_t^{s,d}]_{t=1}^{T^s}$, wherein $s \in \{1, \ldots, S\}$ indicates the index of the sensor, and $d \in \{1, \ldots, D^s\}$ denotes the day index out of a total of D^s days for sensor s. We assume that curves are registered at a rate of 1 measurement every Δ^s units of time, which yields the exact number of daily measurements T^s collected for sensor s.

The set of consumption loads are divided into (i) productive loads, those loads associated with production processes (i.e. hot-stamping, cold-stamping). (ii) auxiliary loads, those loads not directly associated with production (i.e. lighting, air compressors), and (iii) unmonitored loads (processes not associated with any energy measurement equipment). Preferably, all loads should have the same temporal discretization, for which a time homogenization function is implemented for the sake of an uniformized sampling of loads. Separating energy measurements of different nature allows not processing them together, which would cause uncertainty when detecting energy inefficiencies. An energy consumption curve $\mathbf{x}^{s,d}$ represents a profile of energy consumption measured at a rate of 1 sample every Δ^s seconds, where the superindex d denotes a specific energy consumption curve.

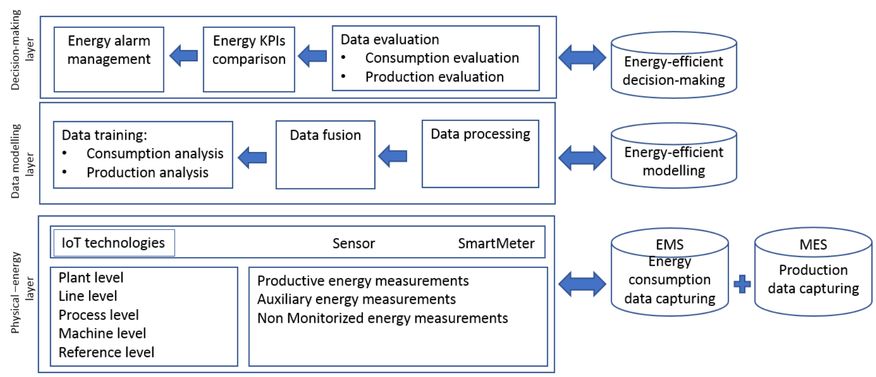

Fig. 1: Architecture for the proposed methodology for energy consumption monitoring and evaluation of industrial plants.

As mentioned above, energy consumption measurements are collected from the loads at four different levels: plant level, production line level, process level and machine level. Production level measurement sensors, or information captured by MES and measured in kg, allow production to be represented as a daily value aggregated at a plant level. From the information of energy consumption and production, this methodology allows to evaluate and consider other type of indirect metrics. For example, if the principle of energy conservation is met, the value of the unmonitored loads can be computed as the difference between the sum of the total loads at the transformer level, and the sum of the total monitored plant curves.

3.2 Data Modelling Layer

Basically the Data Modelling Layer is responsible for merging the information on energy consumption and production, and for identifying the normal mode in which the plant operates, based on similar behavioral patterns inferred from historical information. Initially, this information is divided into several groups of different behaviors. Loads from the same group have similar shapes and consumption levels, and therefore are declared to imprint similar effects on the energy consumption/production ratio. The grouping of loads and their relation with the daily production are the most important concepts of this methodology. The data layer is divided into the following modules:

Data Processing For each of the consumption curves $\mathbf{x}^{s,d}$ of the plant, this module verifies first their quality in terms of data completion. In case of missing measurements in any of the load curves (due to sensor connection failure or any other reason), the missing entries are imputed whenever the time interval of missing data does not exceed a predefined threshold. Different techniques for missing time series data imputation are used to interpolate missing points in the energy consumption curves. For example, missing data can be imputed with the mean value at the involved time instants of the energy consumption curves belonging to a same cluster or pattern (which is the output of the module explained in Subsection 3.2). This example, however, comes at no loss in generality for the proposed methodology: other imputation strategies can be chosen.

Data Fusion This module homogenizes data collected from EMS and MES in terms of information content in time, and transforms it into useful information for subsequent modeling. The module also comprises a generic database for integrating such data at all levels (plant, line, process, machine).

Data Clustering Once energy consumption curves have been collected for the S sensors over the plant, this module utilizes a clustering algorithm to infer K daily energy consumption patterns $\mathcal{C}_k^s$, where $k = 1, \ldots, K$. Each energy consumption pattern $\mathcal{C}_k^s$ represents a subset of the daily energy consumption curves of sensor s grouped together according to a similarity metric. Let us denote as $x_t^{s,d}$ the energy consumption measurement collected at time slot $t \in \{1, \ldots, T^s\}$ for sensor s and day $d \in \{1, \ldots, D^s\}$, where T^s denotes the number of daily slots, and D^s accounts for the number of daily consumption traces for sensor s. The representative $\mathbf{c}_k^s = [c_{t,k}^s]_{t=1}^{T^s}$ of each energy consumption pattern

$\mathcal{C}_k^s$ is calculated as the mean value of each component $x_t^{s,d}$ of each daily energy consumption curve $\mathbf{x}^{s,d} \in \mathcal{C}_k^s$ belonging to that pattern:

$$c_{t,k}^s = \frac{1}{|\mathcal{C}_k^s|} \sum_{d:\mathbf{x}^{s,d} \in \mathcal{C}_k} x_t^{s,d}, \tag{1}$$

where $|\mathcal{C}_k^s|$ denotes cardinality of a set. Thus, an energy consumption pattern represents an energy behavior that characterizes a set of similar daily energy consumption curves.

The inference of the above consumption patterns is done by applying a clustering technique. Without loss of generality we resort to the well-known K-Means clustering algorithm. Considering the notation introduced in this section, the clustering algorithm used to compute these energy consumption patterns implements an iterative process for minimizing the distance between elements forming a cluster and its representative:

$$\arg\min_{\mathcal{C}_1,\ldots,\mathcal{C}_K} \sum_{k=1}^{K} \sum_{d:\mathbf{x}^{s,d} \in \mathcal{C}_k} \left\| \mathbf{x}^{s,d} - \mathbf{c}_k^s \right\|^2, \tag{2}$$

where $||\mathbf{x}^{s,d} - \mathbf{c}_k^s||$ denotes the squared Frobenius norm. It is well-known that for the K-Means algorithm, the number K of clusters to be sought is a parameter that must be set beforehand. Many criteria can be followed for this purpose [5, 12]; in our system we adopt the so-called Elbow method, which draws the value of K from the point of maximum deflection in the representation of the variance between groups divided by the total variance of the selection from the set of curves.

Once the K patterns have been computed, for a new energy consumption curve obtained from sensor s, its degree of similarity/dissimilarity with respect to current patterns is evaluated by comparing the new energy consumption curve with the K patterns already defined. Depending on whether the new energy consumption curve is close to one of such patterns in terms of a threshold imposed on the similarity measure, it is declared that the new energy consumption curve belongs to that pattern. The new energy consumption curve is associated to the group of curves represented by the pattern, and the pattern is updated taking into account the new curve. The treatment of the new curve comprises the following steps:

1. When the new curve fails to match any of the prevailing set of energy consumption patterns, we retrieve from the MES production data corresponding to the same time span of the energy consumption curve under analysis.

2. Considering this information, two quantities are computed: 1) the total energy consumed by the asset monitored by sensor s over the time span of the curve under analysis; and 2) the production rate of the asset over the same period of time.

3. A comparison is made to historical data in terms of the relationship between the above two parameters, yielding a quantitative tool to assess the energy efficiency of monitored asset as per its contribution to the overall productivity of the plant.

Data Regression As stated above, the analysis performed every time a new energy consumption curve is obtained from data captured from the industrial plant, is explained based on this statistical inferred behavior. Once several K patterns are obtained during a training stage using data collected for a certain time horizon, every time a new energy consumption curve is obtained, for example on a daily basis, it is determined to which pattern the new curve belongs. This is done by comparing the new curve with the K patterns. A new energy consumption curve belongs to a certain pattern if the distance to the centroid of that certain pattern is smaller than the distance to any other centroid (centroid of any other pattern) and the distance to it is smaller than the maximum distance from the rest of energy consumption curves set in the training stage. The new energy consumption curve is compared with the day of maximum energy consumption.

Figure 2 represents an example of pattern calculation performed with the above mentioned procedure from a collection of energy consumption curves. The energy consumption curves were defined by electricity consumption data collected at the electric distribution grid connection point of an industrial plant, where daily energy consumption patterns were measured every $\Delta^s = 15$ minutes and measured in kWh. We note that further details on the particularities of the use case cannot be provided for confidentiality reasons. The plot clearly shows three different energy patterns, whose corresponding energy consumption curves are perfectly discriminable from each other. In each pattern, the representative is computed as per Expression (1).

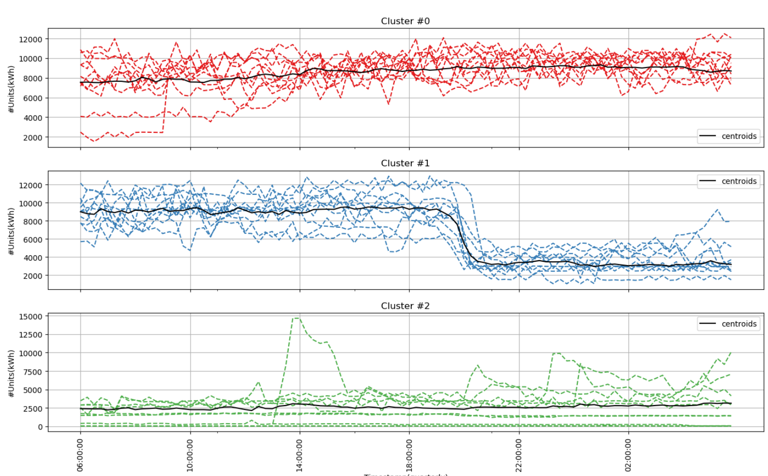

Fig. 2: Consumption curves and inferred representative patterns of a monitored asset of a real-world industrial plant.

Departing from these centroids, we continue with the exemplifying case by depicting in Figure 3 the production (in kg) versus the aggregated energy consumption (in kWh) corresponding to the real-world industrial asset under consideration. In this graphical representation, there are as many points as historic days are used in the analysis for obtaining energy consumption patterns. The continuous line is a straight line obtained by means of an adjustment for least squares. This line permits to represent the relationship between energy and production.

In the case of an adjustment for least squares, this adjustment is characterized by a χ^2 statistical test. This statistic is used to determine whether a new daily consumption trace belongs to the distribution spanned by the historical consumption curves. If this hypothesis fails to hold, a production alarm may be triggered. This involves starting with all days as candidate variables, testing the deletion of each day using a chosen model criterion, deleting the day whose loss gives the most statistically insignificant deterioration of the model fit, and repeating this process until no further days can be deleted without a statistically significant loss of fit. In this way it is possible to understand the contribution of each day.

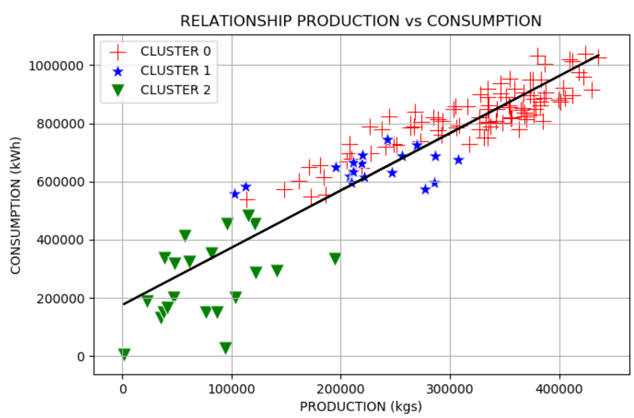

Fig. 3: Relationship between production and energy consumption of the monitored asset.

Thus, if for example production data is available every 24 hours, the aggregated energy consumption for 24 hours is obtained for each curve forming each pattern. Later, in the evaluation stage, during for example daily execution of the methodology by comparing the relationship of the energy consumption versus production with the relation of all the curves forming the K patterns, it is possible to detect energy efficiency alarms. In other words, if an increase in energy consumption is caused by an increase in production, no alarm should be triggered. On the contrary, if an increase in energy consumption is not associated to an increase in production, an alarm should be triggered. Therefore, production is extremely important in order to prevent false alarms. The goal is to detect intensive energy consumption, higher than expected, not associated with production increases.

3.3 Decision-making Layer

This layer of the proposed methodology resorts to visualization analytics towards explaining the outcome of the Machine Learning algorithm so as to make it more understandable to plant managers. The ultimate aim is to render the whole logic of the methodology transparent to the manager, and to allow expediting the best possible operational choice. The functionalities of this decision-making layer include the identification of anomalous trends, automatic notification of control alarms, centralization of forensic data on consumption and production, definition of control Key Performance Indicators (KPIs), and the generation of customized reports about production processes, including visual comparisons between processes of the plant.

4 Conclusions and Outlook

Within the industrial sector, process and auxiliary equipment is a source of energy expenditure that results in a variable operating cost in the income statement of the industry. For a plant with an energy expenditure of 1M euros/year, the company, a manufacturer of automotive parts, spends in the order of 100 KEuros to 250 KEuros per year. It is a priority for the industry to have optimized equipment not only in regard to its operation, but also in terms of its energy consumption. The optimized management of this equipment, as well as the detection of inefficiencies in its operation and the consequent reprogramming of its operation entails great energy savings (it can reach up to 5% of the total plant consumption in certain sectors - based on Gestamp's EE experts).

This work has presented a simple and effective methodology that not only allows for an energy-efficient management of production processes and equipment, but also provides a solution to automate the detection of energy inefficiencies at the plant level through the inspection of production-consumption ratio. In fact, this is methodology is being implemented in several real plants around the world. It implements descriptive analytic methodologies (i.e., clustering and regression techniques). The proposed methodology is based on the study of real data from different production plants and different processes. The production processes are planned/controlled (EMS) and their production monitored/quantified by external systems (MES). In the same way and under the ISO 50.001 standard, more and more energy management systems are implemented, which measure consumption at plant, process and machine level.

We envisage several promising research directions rooted on this work:

– The methodology herein described is focused on the descriptive analysis of plant operation. In the future, these descriptive models should be able to predict future moments in order to anticipate the occurrence of certain events that reflect on a degradation of their energy efficiency. This is crucial in order to establish preemptive strategies for optimizing energy-efficient systems.
– The presented methodology and further descriptive capacities to be developed will prevent faults from happening by virtue of early predictions and proactive decision making. In this regard, an interesting research path aims at making production plants resilient to plausible occurrence patterns that might have never occurred before, thereby hindering any chance to learn from them. For this purpose, we plan to investigate generative models which, in addition, might help plant managers understand unseen insights within the complexity of real-world production systems.
– New technologies for distributed and efficient data processing such as fog computing and edge computing can be incorporated to the proposed methodology towards deploying part of the data processing and mining on sensors themselves. These paradigms, however, bring about issues related to latency, reliability and the distribution of algorithmic components over the network. A closer look will be taken at how to redesign each layer to make their modules compliant with Fog and Edge computing, as well as new functionalities emerging therefrom (e.g. correlation between alarms triggered at different sensors).

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