A case study on the analysis of an injection moulding machine energy data sets for improving energy and production management

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Abstract

Energy consumption is a concern worldwide, and energy efficiency approaches are among the pillars of Sustainable Manufacturing nowadays. Additionally, the industrial sector accounts for the largest share of energy use, being responsible for roughly 30 % of all energy consumption worldwide. Due to developing and more restrict regulations towards energy efficiency, investing in this area presents big opportunities for industry such as reducing costs, increasing productivity and a significant reduction in environmental impact. Unfortunately, this engagement is still far from the desired level of development in many companies, especially small to medium enterprises (SMEs), who usually do not have the in-house expertise or the correct resources for applying such techniques.

However, with the developing technologies in industrial sector and the growth in the processing and storage capacity of IT equipment, industry has entered the age of "Big Data", where data collection and analysis play a major role in this scenario to acquire further knowledges towards energy efficiency and a better understanding of the production processes.

A study was carried out on a Thermoplastic Injection Moulding company, which segment is known for having an intense electrical energy usage given the nature of its production stages. In order to determine the productive and non-productive electrical energy embodied in manufacturing operations and get a better understanding of the production processes, an analysis based on the Machines' time series data streams and some extra information about the processes was made. The outputs result in a better understanding of the machine's electrical consumption, and provide insights regarding potential saving strategies and improvements on the production side such as better scheduling, improved production tracking, operator engagement and equipment efficiency.

Introduction

ENERGY IN INDUSTRY

Energy consumption is a big concern among the industrial sector, which in 2016 was responsible for approximately 30 % of the share of global energy use (EIA 2017). Although the electricity generation from renewable sources (hydro, wind, solar and others) has been increasing along the past few years and the adoption of these sources may well be the long-term solution, the demand for energy is also increasing and the share of fossil fuels is the same as it was 25 years ago (EIA 2017). This source of energy supply is still dominant, accounting for 84.5 % of the overall energy sources, and intensively contributes to the Greenhouse Gases (GHG) emissions (DECC 2015).

Based on this, energy savings and efficiency strategies have been hardly pursued in the recent years by enterprises that aim to achieve Sustainable Manufacturing and contribute to a greener environment (Cosgrove et al. 2016). Some studies (Jollands, Tanaka and Gasc 2009; Granade et al. 2009; Herrmann, Thiede, and Heinemann 2011; Trianni, Cagno, and Farné 2016) have been focused on identifying where, when and how energy is being consumed along industrial processes, and show that potential reductions in energy and Green House Gases (GHG) emissions can be achieved on manufacturing sites where the energy consumption is well understood and there is a certain level of management and behavioural engagement. However, several studies (Christoffersen, Larsen, and Togeby 2006; Palm and Thollander 2010; Thollander and Ottosson 2010; Backlund et al. 2012; Paramonova and Thollander 2016) show that only a limited number of companies actually focus on managing energy and that cost-efficient energy efficiency measures are not always implemented, explained by the existence of knowledge gaps and barriers of different categories such as behavioural, economic, technology-related, competence-related or, in most cases, just the lack of awareness and information or a prioritisation of more urgent business issues.

THERMOPLASTIC INJECTION MOULDING PROCESSES

As a sector that mainly relies on thermal processes, the Thermoplastic Injection Moulding Industry has critical concerns with respect to the cost of energy consumption. The typical injection moulding process consists of a few highly energy demanding steps which are performed in a single machine in a consistent power consumption profile (Takahashi et al. 2010). Since the characteristics and quality parameters of the final products have a direct link to the temperature and pressure during production, nearly constant heating of large amounts of material and the use of high pressure clamping tools are necessary.

Given the importance of production costs related to electricity consumption, several studies have been conducted in the injection moulding sector. Mattis et al. (1996) proposed a framework for the design of components and moulds with the goal of minimising energy consumption and environmental impacts for the entire product lifecycle. Takahashi et al. (2010) investigated the implementation of an energy recovery system for electric motors in injection moulding machines, achieving savings of up to 49 % in simulation. A number of studies (Chee et al. 2011; Pang and Le 2014; Geramifard et al. 2016) have also focused on the analysis and classification of energy measurements to achieve a better understanding of the energy usage in each of the stages of production.

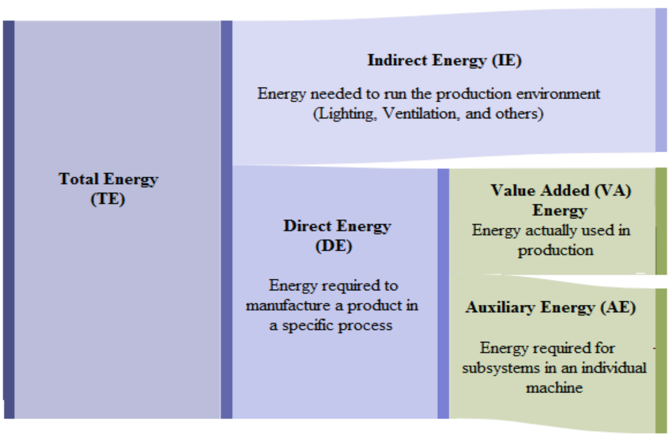

Figure 1. Energy Flow Breakdown (adapted from (Rahimifard, Seow, and Childs 2010)).

INDUSTRY 4.0 AND INDUSTRIAL PROCESS DATA

The opportunities provided by the increase on the demand for data, the price drop of IT devices and the adoption of Industry 4.0 technologies in the industrial sector such as Cyber-Physical Systems (CPS) (Doyle, Duarte, and Cosgrove 2015) are changing this scenario. Industry has acknowledged the potential in exploiting data-driven strategies to reduce those gaps and acquire a better understanding related to their electricity flows (Duarte, Cosgrove, and Hardiman 2015). To include sustainability methodologies into their processes, keep up with regulations on manufacturing and understand the energy requirements and the way it is consumed has become an important field for manufacturing companies to invest in the recent years (Trianni, Cagno, and Farné 2016).

Due to the large amount of information available, data-driven strategies based on real-time and historical information holds incredible potential for helping companies to better understand their business and for optimizing performance (GE Intelligent Platforms 2012). Manufacturing generates more data than any other sector and all the information generated by machines and devices, cloud-based solutions, business management, etc., has been reaching volumes that go beyond one thousand Exabytes annually and is expected to increase even more in the next years (Yin and Kaynak 2015).

Data in the industrial sector are usually recorded in a temporal and sequential order. This type of information is referred to as Time Series Datasets (TSDs) and the current values generally have some relationship with the values recorded in the past. Therefore, storing the value and the instant in which the measurement is made adds great value to the information and the chronological order of events play a relevant role in the analysis solutions (Wooldridge 2011).

ENERGY DATA ANALYSIS

An approach to collect and exploit industrial processes energy data in a useful way, helping with the decision making for production engineers to verify machine efficiency in relation to electricity consumption and determine the electricity embodied in manufacturing operations is a field to be investigated. To understand the energy consumption in a production environment, it is necessary to outline the energy flow within an industrial facility along with the classification of energy usage and its relationship to processes and production outputs. An approach proposed by Rahimifard, Seow, and Childs (2010) and referred to in (Mousavi 2015), (Duarte, Cosgrove, and Hardiman 2015) and (Cosgrove et al. 2016) describes a way of modelling the energy flows within a manufacturing system using a production-based point of view and provides a breakdown of the energy used during production. The energy consumed by different processes can be categorized into two groups: direct and indirect energy.

Direct Energy (DE), defined as the energy consumed by processes to manufacture a product, includes the Value Added (VA) and Auxiliary Energy (AE). Indirect Energy (IE), on the other hand, is related to the energy needed to provide the environmental conditions required for running the business, such as lighting, ventilation and heating. VA is the energy actually needed for production in a direct way such as drilling and milling operations, while AE is the energy required to support activities and auxiliary equipment of the machine for processing,

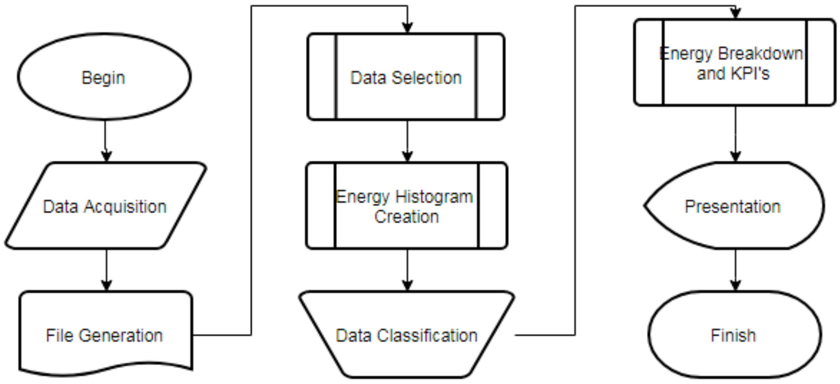

Figure 2. Methodology Flow chart.

such as cooling, lubrication and pumping systems (Mousavi 2015).

The better understanding regarding energy flows also enables fuel consumption and Greenhouse Gasses emission reduction, and energy monitoring and analysis allow organisations to develop and build the necessary knowledge regarding their energy needs and enable the development of crucial energy management plans (O'Rielly and Jeswiet 2015). By analysing the direct and indirect energy and their relationship to production activities, it is possible to derive the detailed energy consumption breakdown, identify the auxiliary (non-value added) energy embedded in the production process and explore its potential for energy reduction and/or production enhancement (Seow and Rahimifard 2011).

Methodology Overview

The analysis of data collected over time allows one to discover the exact time events occur, as well as extract different information from datasets that are not directly related. One example is data related to electricity consumption at machine level, which can provide production figures and other Key Performance Indicators (KPI's) based on the energy profiles when a product is made.

The proposed methodology consists on the collection of empirical energy data from a machine through independent root-mean-square (RMS) current readings on the three phases of the electrical supply to the machine. This data is then analysed through a sequence of steps, where the data points collected by the acquisition device are classified based on the process behaviour and extra information collected during the process.

The flowchart in Figure 2 exemplifies, in a higher level, the methodology.

POWER LEVEL PROFILES AND HISTOGRAM ANALYSIS

This approach consists of a histogram analysis of the different energy levels performed by the machine along the period. Based on the 3-phase RMS current readings and the reference voltage, the power values, expressed in kilowatt (kW), are obtained for every single record in the data set, as described by Equation 1 where 'Iavg' corresponds to the arithmetical average between the 3 currents in Amperes, 'V' represents the Voltage in volts and the 'PF' stands for Power Factor, which in this case was considered as 1.

$$P_{(kW)} = \frac{(I_{avg} * V * PF * \sqrt{3})}{1000}$$

Equation 1. 3-Phase power calculation.

The next step is to summarize all the occurrences of each power value, representing them in a histogram. By this analysis, it is possible to recognize recurrent patterns of energy values and identify the different range of energy intensity required by each product created by the machine. This information helps to better understand the embodied energy in the manufacturing process. Also, an insight of the value for the idle and stand-by power levels can be analysed, since it is expected that values close to these levels will be the most frequent in the histogram.

ENERGY BREAKDOWN

The energy breakdown proposed by Seow and Rahimifard (2011) draws particular attention to the auxiliary energy usage, and the potential areas in the factory where energy efficiency measures can be introduced. This enables decision makers to get a better understanding of the overall energy usage in an industrial facility, with a bigger focus on the potential for savings.

This approach tries to establish the energy breakdown in order to quantify the amount of energy spent on the actual production and the auxiliary energy which, if possible, can be reduced. Besides the energy consumption, some production information is extracted from this analysis, and the times of production and non-production activities, in a way to support or corroborate the insights regarding energy efficiency measures to be possibly taken through changes in the company scheduling routines, operator engagement and other metrics.

Case Study

FACILITY DESCRIPTION

The case study was carried out at a subcontract manufacturer based in County Clare, Ireland, since 1979, which was given the name "Company X". The company has expertise in the production of plastic parts using Injection Moulding, Gas Assisted Injection Moulding, Silicone Moulding, Product Expansion and Printing processes.

Many of the production operations performed by the company are currently being planned, scheduled, managed and reported by operators in a paper-based way. As an error-prone approach, this strategy can be a source of inaccuracies and unreliability for the whole process, besides being a bottleneck towards the generation of important Key Performance Indicators (KPIs) for the plant.

Given the actual scenario, the company has an interest in migrating into a more digitised and integrated shop floor environment, with focus in obtaining improved performance or further clarification on the following aspects:

- Reliable information on overall energy consumption;
- Reliable information on machine-specific energy consumption;
- Identification of machines with most significant energy spending;
- Overall Equipment Efficiency (OEE) analysis;
- Automatic production counting.

MONITORED EQUIPMENT

The proposed experiment was developed and validated on a real process performed on a 110T Sandretto 430/110 injection moulding machine from 1999. Weighing 5.7 tons, the machine can apply a clamping force of 110T in its closing unit and a pressure of 1,500 bars in its injection unit. To get those numbers, it drives a total of 29 kW of power, with 18.5 being dedicated to the motor and pump power.

MEASUREMENT EQUIPMENT

A Chauvin-Arnoux AL-843, a commercially available off-the-shelf data logger which records the current flowing in conductors using four flexible current inductive sensors (Chauvin-Arnoux 2012) was used to capture the current data on the referred machine. Given some restrictions applied by the company, no extra wiring was allowed in the cell, so power connectivity was also restricted. Therefore, the possibility of powering the Chauvin-Arnoux device with batteries and the flexibility of their connections made it the chosen equipment.

DATA COLLECTION

The AL-843 data logger was plugged to each phase of the power supply to the machine on 14th of February, 2017, at 8am and monitored it during eighteen hours, recording the 3-phase current data until 2am of the following day. Given the nature of the process (a short cycle time of 25 seconds) and the fact that the acquisition device would be used to capture the samples during a short period, the sampling rate was set to record at a rate of one reading at every second. The AL-843 also captured the timestamps for each 3-phase current record.

The file with the raw current information about for the referred machine was then put in a folder to be read and imported into a database. Once in the database, the data analysis was performed through the execution of an algorithm that classified the data points based on set operations the extra contextual information about the process held by company. The results were analysed and presented with a visualisation tool.

During the period of data collection, the company production department reported the production of 450 parts, which records were made by operators in a manual basis.

Results

TIME SERIES VISUALISATION

Figure 3 shows the data captured by the AL-843 data logger during the period in which it was attached to the Sandretto machine. It was clear to see, besides the condensed amount of data, that the production shift was captured from 8am to 4pm resulting in 8 hours of data that in which the energy levels were considerably higher than the following hours.

It was also spotted that, during the moments in which the machine appeared to be in idle state, it was still consuming a baseline of 15 kilowatts. Those values are related to the nature of the process, which involves heating elements to melt the plastic and the pumps to provide the necessary force for the injection moulding process.

When analysed in a big scale, it was possible to identify the periods of production and idle by the difference in energy intensity levels. However, when zooming into the dataset to get

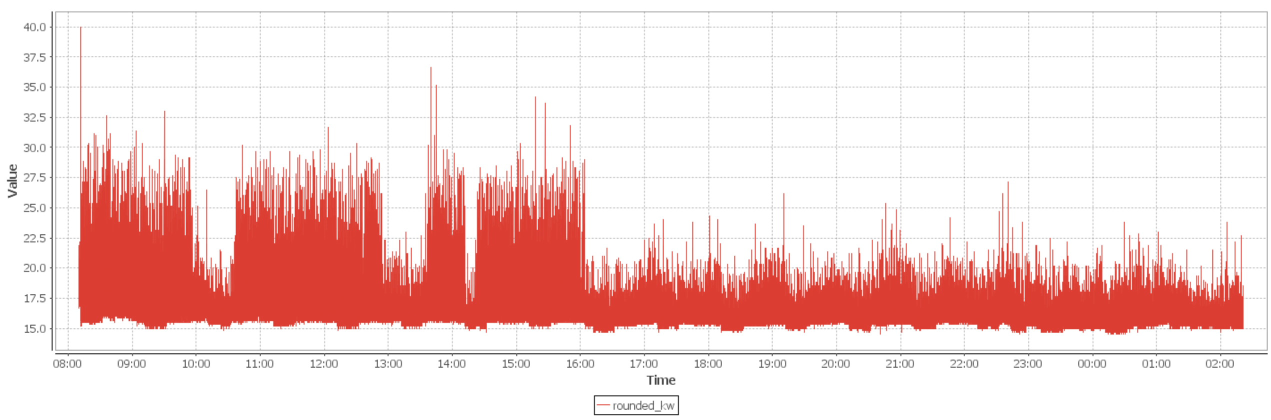

Figure 3. Power consumption on Sandretto machine under Time Series format.

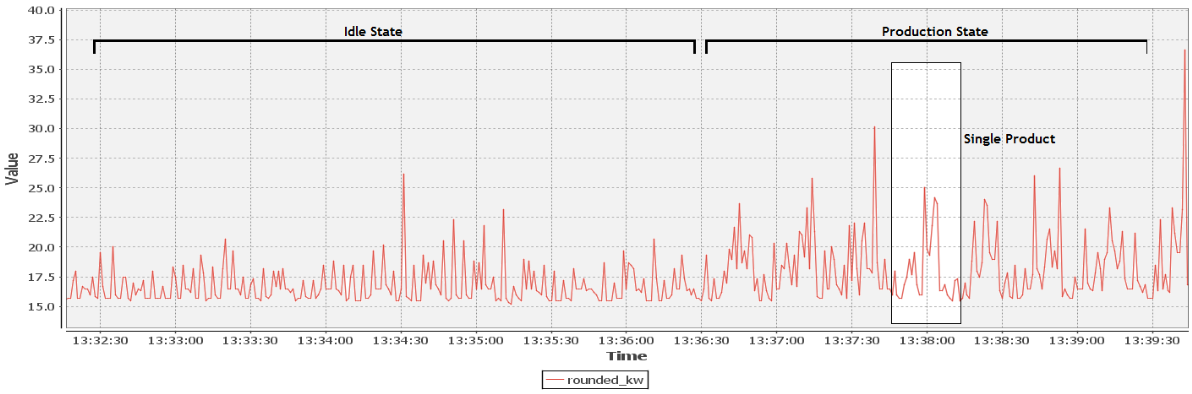

Figure 4. Detailed zoom and Highlight on a product at Sandretto power signature.

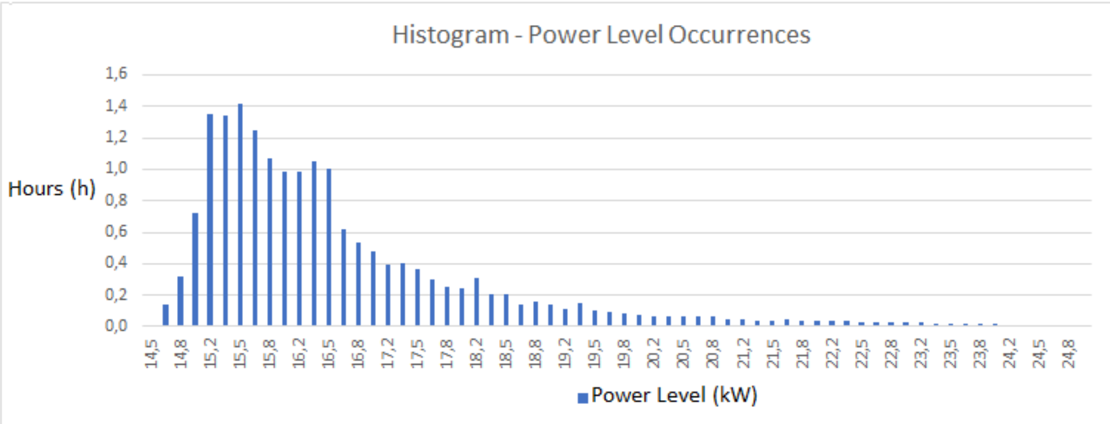

Figure 5. Histogram with Sandretto Machine power levels.

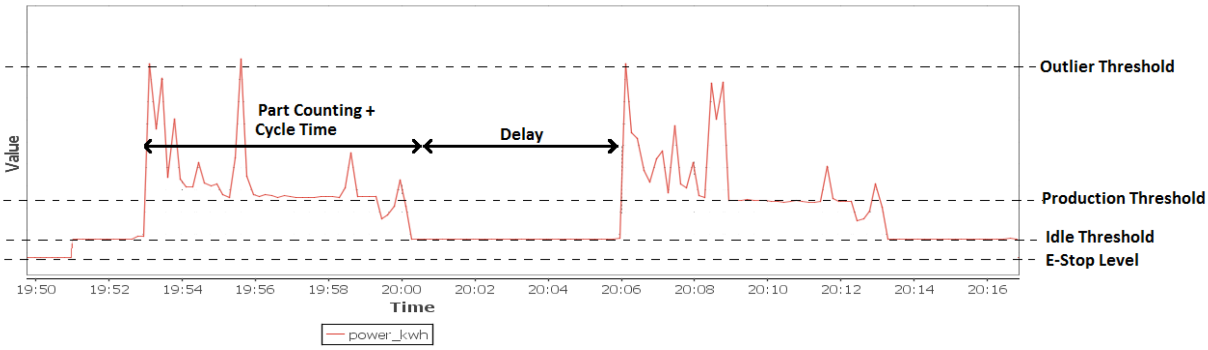

Figure 6. Zoom into a single product, showing production indicators.

a clearer image as shown in Figure 4, it was showed that the threshold that separates idle from production states are very close, which can give misleading information if just a small sample of data is captured.

HISTOGRAM RESULTS

Figure 5 presents the histogram of power levels for the Sandretto machine. As spotted on the time series output analysis, the definition of thresholds on injection moulding machines is not visually clear as in the previous studies done by the authors with precision engineering machines. The nature of the process consists on a high baseline of auxiliary energy to keep the heating element and pumps running, so the numbers for idling and production are not easily classified.

ANALYSIS KPI RESULTS

Figure 6 presents some of the outputs from the analysis over a real product being made and Table 1 summarises the outputs from the analysis over the 18 hours' dataset of the Sandretto machine, which discussion follows below.

Table 1. Production and Process Indicators returned by Analysis on Sandretto data.

Indicator	Value
Idle Threshold	15.0 kW
Production Threshold	15.3 kW
Outlier Cut-off	24.8 kW
Parts Made	912
Real Cycle Time	24.7 s
Total Energy Consumption	304.56 kWh
Productive Energy Consumption	112.23 kWh
Non-Productive Energy Consumption	192.33 kWh
Total Working Time	18.1 hours
Productive Time	6.2 hours
Non-Productive Time	11.9 hours

The part counting output returned by the analysis algorithm received a special attention during the analysis on this study, given the information from the production department was that during the period the machine had produced 450 parts, while the algorithm returned almost exactly the double, 912.

When confronted with the company, the production team were considerably satisfied with the number, and the number being close to double the amount recorded by them was due the fact that the product being made during that day was composed of two symmetrical parts, and 912 would result in 456 parts (against 450 reported by operators), which they confirmed to be a great benefit at using the analysis algorithm, as a way of corroborate what is recorded by operators during their shifts in a manual and paper-based process.

The energy consumption and time breakdown, as presented by Figure 7, also raised the company's awareness that periods without production correspond to an expressive amount of wasted energy. This led the company to consider an investigation regarding optimal operation of injection moulding machines, and since the process uses heating elements and material that cannot be left inside the machines, saving energy by just turning machines off is not as easy as for other types of process.

With the presented outputs, the company was able to identify the energy embodied in each part made, by dividing the energy used for production by the number of pieces, and then be able to address this information to their costs and sales planning.

TIME SERIES RESULTS

Figure 8 shows the outputs under the time series format on the Sandretto data points. From the picture, it was possible to check that the production threshold was also reached during all the idle periods, given the small difference between the production and idle levels. However, the periods in which the production occurred were correctly captured by the Real Production vector, and the with the zoom feature was possible to visualise the parts being identified and the vector that captures the full production cycles.

Conclusions

The use of the solution developed in this research in the monitored machine granted the company a better understanding of its energy consumption profile, which can lead it to an optimised work scheduling and higher efficiency numbers, improving productivity and enabling smarter maintenance strategies.

A more accurate cost addressing regarding the electrical energy spent on each product can also lead to energy savings and therefore to price reductions to the final customer, bringing a competitive advantage to the company. As one of the main concerns of the company, its total emissions and overall environmental impact of the plant could also be significantly reduced by the completion of the planned improvements.

Energy efficiency management in manufacturing SMEs is still an undeveloped field due to different factors such as competing priorities or barriers related to lack of resources, expertise and awareness. However, more than in any other sector, Industry has developed a strong interest in reducing energy costs. Although the detailed breakdown of energy consumption and the total energy required for manufacturing a product is still not well understood by industry members, the rise in energy costs and the increasing number of environmental re-

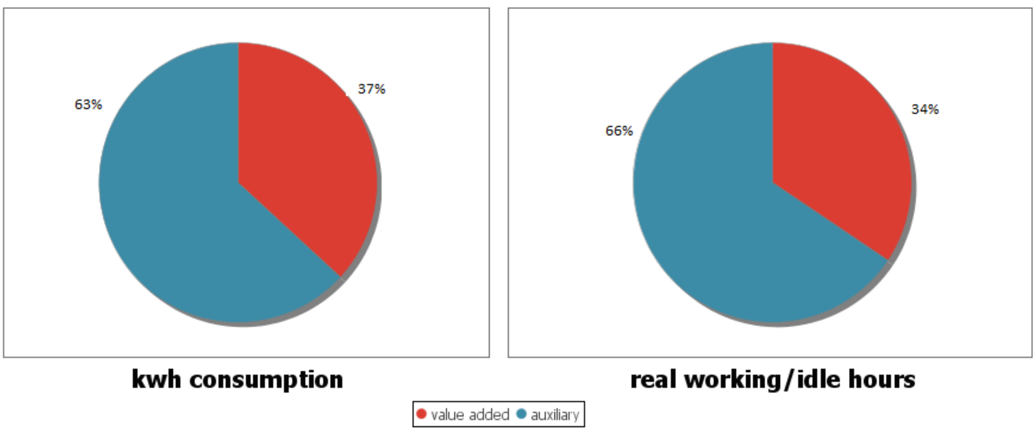

Figure 7. Energy and Time Breakdown on Sandretto Machine.

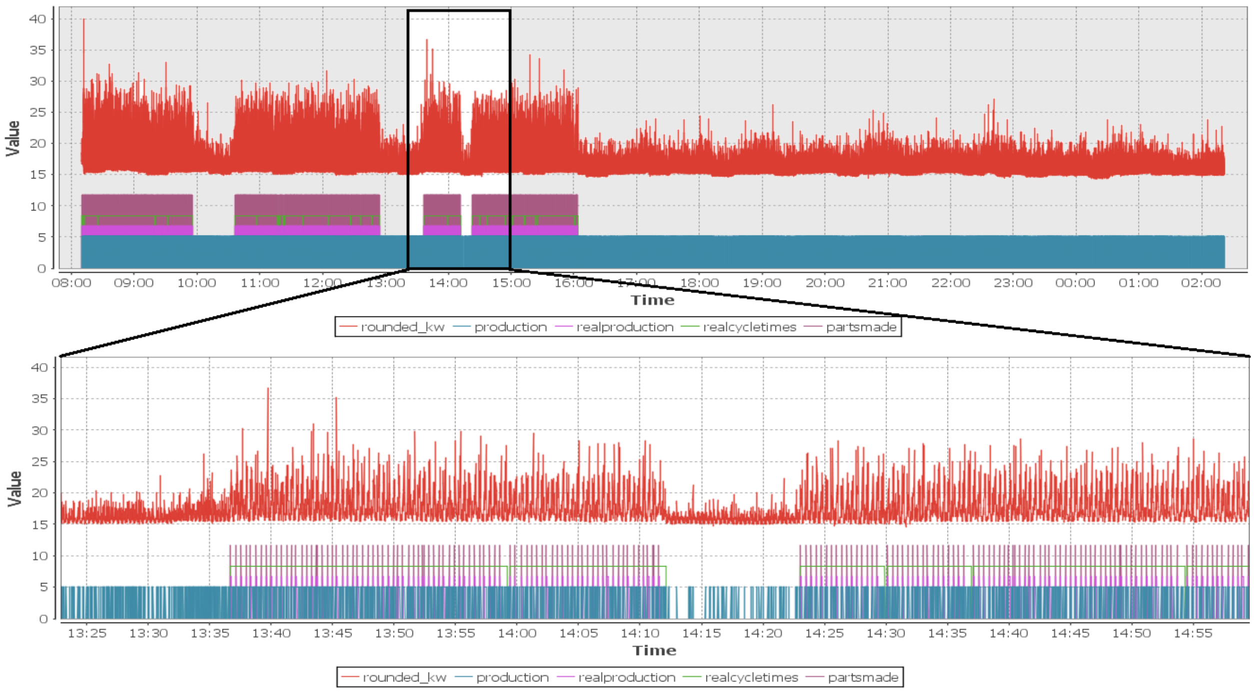

Figure 8. Progressive Zoom on Sandretto Machine data and algorithm outputs.

quirements have become key economic drivers and highlight the importance of efforts towards the adoption of an Energy Efficient Management (EEM) approach in manufacturing applications.

The study has proved there is merit in a system that uses the electrical power consumed by a machine to give production related information. Besides production relevant information within the electrical power profile, it may also reveal issues relating to machines' operation modes, such as machines left in idle for long periods, consuming large amounts of electricity, causing a negative effect on production capacity. There are few machine productivity monitoring system on the market that will give this level of information.

The solution has also proven to be a good option for legacy machines, since the analysis is completely based on electricity readings and some extra information about the processes which are usually held by companies, while the use of energy data provides a flexible and standardized way of extracting and analysing the information for potential benefits. For companies that do not have consolidated metrics for their processes, estimated values can be used and with visual iterations on the data classification and a fine tuning in the parameters, a better mapping of their energy consumption can be achieved.

Further Work

This work can be further developed in different ways. The discussion with the analysed data with production engineers has indicated possible functional expansions of the system.

- Operators' performance analysis

With the power profiles analysis, it is possible to extract information about operators' performance and behaviour, becoming a monitoring solution for best practices and times for the activities. This topic, however, needs further attention with respect to ethical implications it might cause. During this research, no operator data was recorded, but with the correct set of inputs and parameters, an analysis of operators' monitoring and feedback could have been done.

- Full Integrated Ambient

In this case study, only an independent data acquisition module was put in place due to restrictions imposed by the company. All the analysis was made in an external machine that was not related to Company X. The ability to work with files that are imported to a separate database grants great flexibility to the methodology. However, including the database inside the company systems, in a way that the algorithm has access to historical data streams without the need of a file importing process, would add value to the solution and companies could do their own analysis according to demand, both with historical and real time data. Finding a company willing to implement the full solution might be a challenge, but the results presented by the case study may help on getting companies more interested in this type of analysis.

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