Development of an energy monitoring and control interface for the forest products industry

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Abstract

The transition to advanced data analysis systems that rely on Industry 4.0 approaches is driving energy management practices across all industrial sectors, creating more energy efficient and sustainable production systems. Hence, by implementing energy monitoring and control systems based on these principles, it is possible to identify potential energy improvement opportunities at all organizational levels and to analyze any variation in the energy behavior of manufacturing processes using energy performance indicators. With this in mind, this article proposes an energy dashboard interface that integrates various energy performance indicators and statistical control methods, to monitor, control, and evaluate electricity consumption in sawmill manufacturing processes. Through a case study and synthetic datasets, the electricity consumption of the main manufacturing processes of a Canadian sawmill was evaluated using this interactive interface. With this energy dashboard, it was possible to develop a more fluid and intuitive decision-making process for all organizational levels, evaluate energy costs, establish relationships between production outputs and energy consumed, map energy savings, make energy predictions, and set energy targets for future improvements. This is a practical tool that shows in detail the operational energy profile of an organization.

Keywords
Energy management, Forest products industry, Energy control systems, Business intelligence, Energy performance indicators.

1. Introduction
Over the last few years, the fight against global warming, mainly caused by the increase in greenhouse gas emissions, has grown in importance among governments and organizations around the world. In this global emergency, according to the Intergovernmental Panel on Climate Change [IPCC] (2014), a more efficient use of energy is one of the key factors for mitigating global warming. In this context, the industrial sector plays a highly important role since it represents between 25% and 50% of the world's final energy consumption (Thollander et al., 2020). Fortunately, industry 4.0 foundations lie in digital transformation and the creation of more intelligent and interconnected production systems (Müller et al., 2019). Currently, these are an avenue that is not only allowing companies to be more efficient and agile in their manufacturing planning processes, but it is also allowing them to have better energy control systems, focused on drawing the real picture of their energy consumption profiles (Shrouf et al., 2014). Therefore, the energy management (EM) approaches and the concepts and technologies that are driving the fourth industrial revolution, such as the use of smarter energy meters, engineering analysis methods and control tools, enable manufacturing plants to improve their energy efficiency and reduce their CO_2 emissions (Campo et al., 2018; Shrouf et al., 2014).

From this perspective, in the forestry sector, industry 4.0 has been approached in a heterogeneous way since, in the last decades, sensor and remote sensing technologies have been discussed, investigated, and developed more deeply than any other 4.0 dimension in this industry (Müller et al., 2019). Consequently, advanced data analysis to facilitate decision-making appears to be an area with little progress in this sector, which makes it difficult to interpret energy consumption patterns and implement efficient EM practices. Regarding the energy profile of this sector, the energy trend around the world has changed since biomass and electricity have been predominant sources of energy in recent years. Hence, considering that the development of new technologies based on bioenergy has been growing progressively (e.g. boilers, kiln drying, cogeneration systems, etc.), the forest products sector must now focus its attention on reducing and managing its electricity consumption through the implementation of efficient energy strategies, as it represents about 25% of its total energy use (Quesada-Pineda et al., 2015). In turn, the first action that this sector should take to deploy energy initiatives that allow it to have a more accurate picture of its energy profile, is to understand historical electricity consumption (Quesada-Pineda et al., 2015). Nevertheless, it seems that companies in this sector are not aware of it since in a study carried out in Serbia by Rajić et al. (2019), on 104 companies belonging to the forest products industry, the authors observed that energy managers lack the knowledge needed to implement techniques and tools for collecting information, processing data, and monitoring energy consumption trends. Besides, the second action to deploy energy strategies in this industry is to define energy performance indicators (EnPIs) (Johnsson et al., 2019), especially at the process level (Andersson and Thollander, 2019; Bunse et al., 2011). In addition, according to Benedetti et al. (2017), even when these indicators are defined, an adequate energy control and monitoring system focusing on analyzing its evolution over time is often ignored or not considered, despite the fact that these energy information systems can be designed to provide the supporting information required to monitor the energy consumption patterns of a company and to track the performance of EM projects (Van Gorp, 2005).

Thus, in order to address the aforementioned wood industry gaps, the aim of this article is to develop a user-friendly energy dashboard interface that allows sawmills from the forest products sector to manage and control the electricity data of their manufacturing processes at different organizational levels, to clearly identify their major energy efficiency issues, and to have a more efficient decision-making process. To achieve this goal, a literature review first made it possible to identify the main EnPIs used at different organizational levels in this sector, and then, to determine the statistical control tools necessary to analyze their behavior. Subsequently, using a synthetic dataset based on the real monthly electricity and production data of a Canadian sawmill, these indicators and statistical control methods were tested on a simulated energy control system created for this study. Finally, through the use of Microsoft Power BI software, it was possible to design and build the energy dashboard and to apply it to a case study in which its functionality and user interface were evaluated. Hence, this dashboard interface allows decision makers from this industry to integrate EM approaches with new ways of processing and analyzing information in an industry 4.0 environment. It also offers a wide variety of control tools to evaluate the energy performance in sawmill production processes in great detail. Its interactive design makes it easy to use and its implementation is simple if sawmills possess the information required to exploit it. The structure of the article is as follows. Section 2 outlines the literature review. The research methodology is then detailed in section 3. Section 4 presents the energy dashboard interface and its applicability through a case study. The article ends with a brief conclusion.

2. Literature Review

Considering that the energy dashboard interface presented in this research was developed specifically for the forest products sector, the following sections describe the fundamental EM concepts and tools associated with this study.

2.1 EM practices in the forest products industry

Overall, efficient energy use in the manufacturing industry allows companies to remain competitive and sustainable as it reduces their economic and environmental impacts related to energy consumption (Thollander et al., 2020). However, as stated by Johnsson et al. (2019) and Quesada-Pineda et al. (2015), only a few studies have evaluated energy efficiency measures in the forest products industry even if in some works, such as Gopalakrishnan et al. (2005), their development and implementation were proven crucial to reduce wood processing costs and improve the company's competitiveness. Johnsson et al. (2019) also emphasized that the lack of information related to the specific energy use in sawmill operations makes it difficult for decision makers to determine which processes have the highest energy efficiency potential. On the other hand, regarding the use of energy control systems and EnPIs in this sector, in a survey conducted by Espinoza et al. (2011) on 188 American sawmills, 63 percent of the sawmills surveyed claimed to have been working on energy efficiency improvements, while only 8.6 percent declared to have energy baselines and EnPIs to effectively monitor and control energy performance in operations on a continual basis. More recently, guided by their interest in determining the current situation regarding the application of EM practices in the Serbian wood industry, Rajić et al. (2019) were able to highlight that only 15.38% of the 104 companies they interviewed were involved in finding opportunities for energy improvement. They found that in general, within this industry, the appropriate decision support mechanisms to control energy consumption were unknown. Contributing to the development of these control systems and based on lean principles, Gopalakrishnan et al. (2012) developed an analysis tool that allows sawmills to compare their electricity consumption against an energy benchmark indicating the optimal energy consumption required in operations. In this way, companies could better understand their energy consumption patterns and the intrinsic relationship between energy use and production parameters. For their part, Johnsson et al. (2019) recently investigated the currently applied and potentially viable key EnPIs in the Swedish forest products industry, highlighting that to estimate the energy efficiency potential of this industry and deploy strategic energy measures, their development is first necessary. Hence, energy efficiency must be measured, monitored, and frequently evaluated using EnPIs in order to have a successful EM system (Bunse et al., 2011).

2.2 EnPIs and its application to the forest products industry

In recent years, the great concern to reduce carbon emissions and improve energy efficiency in manufacturing processes prompted industrial companies to become more engaged in understanding their energy issues and created the need to develop EnPIs capable of showing them an extensive picture of their current energy performance (Bunse et al., 2011) at a given time. Thus, these indicators are essential to successfully implement effective energy saving measures, track their progress, and define future energy performance targets (Johnsson et al., 2019) which represent what an organization hopes to attain when managing its energy consumption (Van Gorp, 2005). In the same way, these EnPIs can be classified according to the scale (work unit, work center, plant) and organizational decisional level at which they will be used (May et al., 2013). Likewise, the EnPIs calculated and analyzed in the work units are used to analyze in detail the energy behavior of the manufacturing processes and their subsystems, while the EnPIs employed at a strategic level are mostly used by top management in order to understand the overall financial performance of the entire EM system (Benedetti et al., 2017). So, as established by Bunse et al. (2011), the nature of these indicators can be physical (process level) or economical (aggregated level). Figure 1 shows the way in which the nature of these indicators is integrated into the different decisional levels of an organization.

Figure 1. Distribution of EnPIs at different decisional levels of an organization

On the other hand, before conceiving these EnPIs, it is necessary to consider the boundaries in which they will operate, in other words, the areas of the organization requiring energy performance control. Morvay and Gvozdenac (2008) defined them as Energy Costs Centers (ECC) which are according to their definition « business segments (i.e. departments, areas, units of equipment or single equipment) where activities or production volume are quantifiable and where a significant amount of energy is used ». Therefore, EnPIs have to be defined according to the different ECC established in each organization and their deployment will depend on the access to information, organizational structure configuration, and particular needs of each company (Benedetti et al., 2017). In this context, given that throughout the company, there are different users who require different information, it is necessary to determine how this information has to be organized (Tokola et al., 2016), how much detail it should have, and how it will be used, since the EnPIs for top management are different than those used in production. Thus, once the ECC and users have been defined, the next step is to choose the type of indicator for each level of the organization. In this context, the EnPIs can be very diverse since they will be used for different purposes and by different users. In their simplest form, these can be measurements or ratios between two values while in their most complex form, these can be engineering models (Andersson and Thollander, 2019). At the strategic level, the energy cost ($), the specific energy cost ($ / kWh), and the total electricity consumption (kWh) are examples of simple values that are relatively easy to obtain with the electricity bill. Energy Intensity (EI) is an economic indicator also used at an aggregated level (Andersson and Thollander, 2019) and for the accountable ECCs, this is simply the ratio of energy consumption to a monetary value, such as the cost of energy in a given period of time (Bunse et al., 2011). At the operational level, for managers it is also useful to know the maximum energy consumption in a certain period of time since it gives them a graphical representation of the critical energy consumption patterns in the processes. Similarly, for production processes, the Specific Energy Consumption (SEC) is a physical indicator that is expressed as the ratio between the number of units produced and the corresponding amount of energy consumed over a defined period of time (Morvay and Gvozdenac, 2008). For the forest products industry, SEC is commonly expressed as the amount of energy consumed per m^3 of sawn goods for an entire sawmill (kWh/m^3). For companies in this sector, as mentioned by Johnsson et al. (2019), it is an easy indicator to manage since the amount of energy supplied to the sawmill and the production volumes are usually readily available. In their study, the authors also provide a comprehensive list of performance indicators for monitoring the energy efficiency of an entire sawmill and its two most energy-intensive processes (sawing and drying of wood). In other studies such as the one carried out by Gopalakrishnan et al. (2012), SEC can also be expressed as the ratio between the electrical energy consumption and the production volume in thousand board feet (kWh/Mbf). Thus, SEC can be a very practical indicator since it is easy to understand. However, it is also approximate (Gordic et al., 2014) as it does not reveal the intrinsic relationship between energy use and production level variations. Statistical models and control tools have to be used for this purpose.

2.3 Statistical control tools

As previously discussed, the indicator typology becomes more complex, going from the strategic level (where ratios are commonly used) to the operational level (where statistical control tools are required to determine with greater precision the true energy behavior in operations). However, before employing these analysis methods, system data must be measured and collected. It should be of high quality and ideally obtained on a continuous basis to ensure accurate and reliable analysis (Gordic et al., 2014). This information can be obtained from utility bills, measuring instruments, sub-meters, information systems (e.g. ERP), historical data, etc. (Gordic et al., 2014; Morvay and Gvozdenac, 2008; Van Gorp, 2005). Likewise, collected data can be acquired from the whole plant or each ECC. Subsequently, a mathematical model could use this information to establish an energy baseline against which the collected data will be compared (Van Gorp, 2005). Therefore, to provide continuous control and better management of all the collected data, companies need an energy control system to analyze and detect changes in their energy and economic performance over a given period. Currently, various data analysis tools can be integrated into the energy control system, such as graphical methods, statistical tools, regression analysis, residual analysis, CUSUM analysis (cumulative sum of differences), control charts, etc. (see Benedetti et al., 2017; Gordic et al., 2014; Morvay and Gvozdenac, 2008; Van Gorp, 2005). The following subsections will explain in more detail some of the most important statistical tools that were used in this study for different users and levels.

2.3.1 Regression analysis

This tool evaluates how a dependent variable (energy) is related to the independent one (production) within the system. According to Morvay and Gvozdenac (2008), the relationship between these two variables for most industries is represented linearly, which means that energy plotted against production will generate a straight line that will be represented by the following equation:

$$E = a * P + b$$

where E represents the dependent variable (energy), P is the independent one (production), and a and b are constants that have to be calculated for each data set using the “least square method”. As mentioned by the authors, once this linear equation is calculated with a spreadsheet software, it can be used to calculate the energy baseline against which the current measured values will be compared. The baseline equation’s correlation coefficient indicates the strength of association that exists between production and energy with a value above 0.7 being an acceptable confidence level (Greenwald and Wallace, 2007). If the correlation coefficient is lower, data from another period should be chosen to find the baseline equation. Thus, in terms of analysis, it is more advisable to create a baseline through a mathematical model that emphasizes the true energy behavior in operations (obtained from the collected data) instead of using a baseline that is just a constant value such as the SEC (Benedetti et al., 2017). Furthermore, by substituting the production values in the regression equation, it will be possible to forecast how much energy would have been used in the period being evaluated according to the equation obtained. As mentioned by Morvay and Gvozdenac (2008), if the difference between the current measured values and the predicted ones is calculated, a residual value will be obtained (commonly known as energy savings). Then, by calculating the cumulative sum of these differences through the “CUSUM method”, it will be possible to obtain the total amount of energy savings over an observed period of time (Benedetti et al., 2017).

2.3.2 Target line equation and residual analysis

As explained above, the baseline equation represents the relationship between energy and production over the evaluated data set. However, to draw the target equation for future improvements, data from periods with the best energy performance should be used to set the desired energy efficiency (Greenwald and Wallace, 2007). Therefore, a new regression equation is obtained from the chosen target period and used to calculate the difference between the measured values (E_i) and the new predicted ones (E_i’). With the residual values obtained, according to Morvay and Gvozdenac (2008), a standard error of estimate (control limits) can be calculated with the following equation:

$$S_{EE} = \pm \sqrt{\frac{\sum_{i=1}^{n}(E_i - E_i')^2}{n-2}}$$

where S_{EE} represents the upper and lower limits and n represents the number of periods being analyzed. Thus, through a scatter diagram, the residual values can be plotted against their respective production levels, and then the lower and upper limits can be drawn in order to identify periods with excessive variation that are not meeting the target. Given that, with the new target line, the correlation values will be very close to 1, it is recommended by Morvay and Gvozdenac (2008) to set the upper and lower limit to 3 x S_{EE}. An application of this tool will be shown in the case study section.

2.3.3 CUSUM Map and Energy control matrix

At the strategic and tactical levels, the energy performance and energy savings progress can be assessed on a monthly basis through a CUSUM map for each ECC integrated into the company's energy analysis. This tool will show the areas or ECC's that are contributing to the energy objectives and those that are negatively impacting the energy performance of the plant. According to Greenwald and Wallace (2007), this is a way to collectively analyze the positive and negative energy trends of the whole company. On the other hand, the Energy control matrix tool proposed by Benedetti et al. (2017) reports energy and economic performances at a strategic level on a monthly basis. Basically, the columns of this table show the monthly percent variation of the total current energy costs of the whole plant with respect to its baseline values of the previous year. It also exhibits two secondary indicators that help determine how the energy performance of each ECC and general variations in energy costs affect the total performance of the whole company in a given period. Thus, the first one shows the percent variation of the current energy consumption of all ECCs with respect to their baseline values (CDI) and the second one refers to the percent variation of current energy costs against those of the previous year (cDI). This tool was adapted and used in this study and all its variables, nomenclature, equations, and specific details can be consulted in the work carried out by Benedetti et al. (2017). Therefore, to achieve a more fluid decision-making process at all organizational levels, all of these energy indicators and energy control tools should be integrated into a dashboard (Tokola et al., 2016) that allows each user to effectively monitor variations in energy consumption, set energy goals or analyze energy savings. In the next section, the research methodology will be described.

3. Methodology

In order to develop an energy dashboard interface that integrates various EnPIs and statistical control methods to allow sawmills to monitor and control their electrical energy consumption at various organizational levels, this work was divided into four main steps. In terms of literature, the bibliographic databases that served as support to identify the main concepts linked to this work were Engineering Village, Web of Science, ScienceDirect, SpringerLink and IEEE Xplore. Regarding the data collection phase, the study considered articles published from 2010 to 2020. However, because the research was conducted following the hermeneutical circle analysis criteria, relevant references obtained from these articles and other papers older than the established limit were also considered. In relation with the research boundaries, it is important to emphasize that the dashboard developed in this work is completely focused on analyzing and monitoring the electrical energy consumption in a sawmill. However, it could be adapted to analyse other energy sources as well. That being said, the first step focused on conducting a literature review of the forest products sector's energy context in order to identify its EM practices and the way in which this sector controls and monitors its energy consumption. In the second phase, the scientific literature was explored again in order to identify the main types of EnPIs and statistical models used in the manufacturing industry and in the forest products sector to monitor energy performance. For each bibliographic database consulted, the research equation established to identify the EnPIs and statistical tools used in the manufacturing industry was the following: "energy performance indicators" and "energy management" and "manufacturing", while for the forest products sector it was defined as follows: ("energy performance indicators" or "energy management" or "energy savings") and forest products industry. Afterwards, the most relevant articles for the study were identified and inductively, after analyzing the selected articles, the EnPIs and statistical models employed in the present work were defined one by one. Once identified, these were classified according to their nature and the different organizational levels at which they will be deployed to control energy performance. Therefore, based on the work carried out by Benedetti et al. (2017), Gordic et al. (2014), Morvay and Gvozdenac (2008), Van Gorp (2005), as well as Greenwald and Wallace (2007), it was possible to determine five widely used statistical control tools to monitor the energy performance in manufacturing processes at different organizational levels: regression analysis, CUSUM method for evaluating energy savings, residual analysis, CUSUM map, and energy control matrix. Furthermore, the indicator typology chosen in this study becomes more complex when progressing from the strategic level to the operational level (going from simple values or ratios to statistical control tools). The methodology proposed by Benedetti et al. (2017) helped identify the most important criteria when deploying an energy control system within an organization. In the third phase, the real monthly electricity and production data of a Canadian sawmill were analysed, organised, processed, and later transformed into a synthetic dataset with similar statistical properties, but different values, in order to protect the company's private information. After having generated the synthetic data and having organized and classified them according to the different end users and organizational levels that were going to use them, these were stored in Excel databases. Finally, in the fourth and last phase, with the use of Microsoft Power BI software, this information was integrated with the statistical methods and EnPIs found in the scientific literature, their corresponding measures and calculations were established and, as a result, it was possible to build the energy dashboard interface for the Canadian sawmill and validate its application through a case study that will be presented in detail in the following section.

4. Case study

The methodology described above made it possible to gather all of the necessary elements to evaluate and test the energy dashboard interface functionality through a case study applied to a Canadian sawmill. As mentioned earlier, the data presented in this section are only illustrative and serve as a support for the development of the research, since they were synthetically created from the real information of the studied sawmill. Therefore, to protect the company's identity and respect its privacy, no further details of its organizational structure or its business model will be given. Similarly, as already discussed, the study only focused on analyzing the electricity consumption in the main sawmill's production processes. Hence, according to Gopalakrishnan et al. (2012), a typical sawmill configuration includes debarking, sawing, edging, trimming, drying, planing and waste chipping processes. The manufacturing operations start with the debarking process where the bark is removed from the wooden logs that come from the forest. Then, in the sawing process, the debarked logs are sawn and transformed into lumber according to different dimensions and specifications. The edging process consists of eliminating the irregular edges and imperfections on the sawn pieces, while the trimming process consists of squaring the ends of the lumber to form uniform flat ends. For its part, the drying process is responsible for reducing the moisture content of the lumber. Subsequently, in the planing process, the required lumber thickness is obtained and its surface is smoothed. Finally, the chipping process takes advantage of all the wood waste from the production processes to produce wood chips, considered a valuable byproduct for this sector. As for the energy profile of the forest products industry in Canada, according to the Government of Canada (2021), from 2015 to 2019 this sector consumed on average 139,677,827 GJ, which makes it an important energy consumer. In relation to its total energy consumption, biomass represents 54.4% of the total energy used, while electricity represents 25.6% and natural gas 14.2% (Nyboer, J., and Bennett cited in Quesada-Pineda et al., 2015). Regarding the case study boundaries, according to the energy and production data obtained from the Canadian sawmill, only the debarking, sawing, drying, and planing processes were used in order to assess the functionality of the energy dashboard interface, and together with the whole plant, these were defined as the main ECCs of the case study. Thus, since operations in a sawmill require the use of large electric motors which are used to run the equipment from the aforementioned processes and since these are the largest energy consumers in a typical sawmill according to Gopalakrishnan et al. (2012), an energy dashboard interface is key for evaluating energy efficiency and energy consumption patterns in wood processing operations.

With respect to the information used to develop the energy dashboard interface, energy and production data were obtained for the month of February, 2020. The electricity consumption data were obtained through the sawmill's energy meters for all of the evaluated ECCs. However, for the production information, the company's global production volume was not available but they had data from the sawing and planing processes. Therefore, the energy data for the debarking and drying processes only served to calculate the percentage they represent in relation to the total electricity consumption of the sawmill, but not to determine the SEC or to perform statistical analyses that are more complex and that require production variables. On the other hand, to calculate the total monthly electricity consumption of the whole plant, the energy values of the four processes were added. Over a period of 29 days, the sum included only 25 days since the monthly measurements began on day 3 and there were 2 days in which the energy data for all the processes were incomplete. For the debarking and drying processes, the total monthly energy consumption was found over 25 days as well. However, all the energy analyses carried out in the sawing and planing processes were based on 18 days since there was no production in these areas on 9 days and 2 days had incomplete energy data, as mentioned above. Therefore, on the energy dashboard interface for these two processes, the monthly analyses begin on February 3. In addition to the information obtained, in order to extend the analysis of the study and demonstrate the functionalities of the CUSUM map and energy control matrix, it was necessary to generate additional fictitious values that no longer correspond to the Canadian sawmill, but that maintain the same statistical properties. The method used to generate this additional data will be explained in the next section. However, in practice, the baseline values have to be calculated through statistical models that interrelate electricity consumption with production levels or other variables that affect the way in which electricity is consumed.

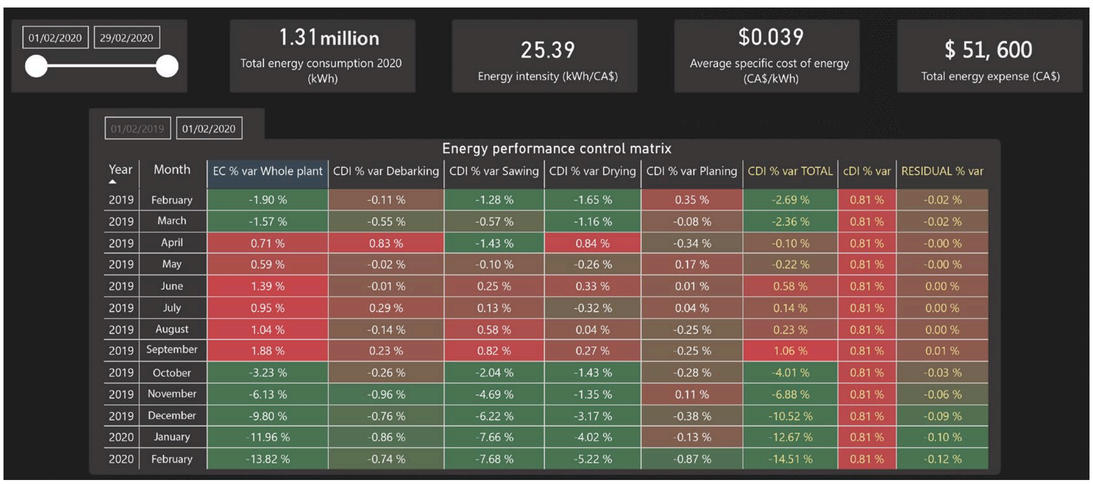
The EnPIs created for the case study were the same as those found in the scientific literature and their level of application, their corresponding ECC, the users linked to them, their control modalities, the information related to these (e.g. production volumes), and the sources of information from which they can be obtained are presented in Table 1. Likewise, of all the indicators shown, only the first three are of an economic nature and the rest are physical indicators to use in the sawmill operations. Similarly, as the global production volumes of the Canadian sawmill were not available and only the total electricity consumption of the whole plant was known, the possible energy indicators at the tactical level were not represented in Table 1. Ultimately, once the synthetic data were integrated with the EnPIs and statistical control tools, it was possible to build the energy dashboard interface for the case study. Regarding the construction of the energy dashboard interface, it was built with Microsoft Power BI software and its development was carried out in multiple phases. In the first place, the synthetic data that had already been organized in Excel databases were integrated with the EnPIs and the different selected statistical control methods. Then, their corresponding calculations were made according to the equations of each mathematical model. In parallel, while the measurements and mathematical relationships were being created, the most relevant visualizations and dynamic graphics such as pie charts, scatter charts, area charts, visualization cards, date slicers, dynamic tables, and KPI indicators were used to facilitate the analysis of the information and to highlight changes and anomalies in the energy performance of operations. Once the mathematical relationships were developed, templates were created to design the way in which the information was going to be presented and distributed at each organisational level. In total, an interface with 2 pages was created for the strategic level (energy control matrix, CUSUM map) while for the operational level, more specifically for the sawing and planing processes, another interface was created with 4 pages (general monthly results, regression analysis, CUSUM analysis, and creation of energy targets).

Table 1. Overview of EnPIs created to evaluate energy performance in a sawmill at different organizational levels together with their main characteristics.

<table>
<tr><th>Indicator</th><th>Decisional level</th><th>ECC</th><th>Indicator users</th><th>Control tools</th><th>Related data</th><th>Information source</th></tr>
<tr><td>Total energy cost ($)</td><td rowspan="3">Strategic</td><td rowspan="3">Whole plant</td><td rowspan="3">Top management / Energy manager</td><td rowspan="3">Energy dashboard interface / Energy control matrix</td><td rowspan="2">Total energy consumption</td><td rowspan="3">Electricity bill / Energy metering systems / sub-meters</td></tr>
<tr><td>Specific cost of energy ($/kWh)</td></tr>
<tr><td>Energy intensity (kWh/$)</td><td>Total energy cost</td></tr>
<tr><td>Total energy consumption (kWh)</td><td>Tactical</td><td>Whole plant</td><td>Energy manager</td><td>Energy dashboard interface / Energy control matrix / Regression analysis / CUSUM analysis / Residual analysis / CUSUM map</td><td>Global production volume / External temperature</td><td>Electricity bill / Energy metering systems / sub-meters</td></tr>
<tr><td>Debarking process energy consumption (kWh)</td><td rowspan="10">Operational</td><td>Debarking process</td><td rowspan="10">Energy manager / Production manager</td><td rowspan="4">Energy dashboard interface / Energy control matrix / Regression analysis / CUSUM analysis / Residual analysis / CUSUM map</td><td rowspan="10">Production volumes</td><td rowspan="10">Energy metering systems / sub-meters</td></tr>
<tr><td>Sawing process energy consumption (kWh)</td><td>Sawing process</td></tr>
<tr><td>Drying process energy consumption (kWh)</td><td>Drying process</td></tr>
<tr><td>Planing process energy consumption(kWh)</td><td>Planing process</td></tr>
<tr><td>Maximum daily energy consumption (kWh)</td><td rowspan="6">Sawmill production processes</td><td rowspan="2">Energy dashboard interface</td></tr>
<tr><td>SEC (kWh/m3) or (kWh/Mbf)</td></tr>
<tr><td>Predicted energy consumption "Baseline" (kWh)</td><td>Energy dashboard interface / Regression analysis / CUSUM analysis / CUSUM map</td></tr>
<tr><td>Energy savings (kWh)</td><td>Energy dashboard interface / CUSUM analysis / CUSUM map</td></tr>
<tr><td>Predicted energy consumption "Target" (kWh)</td><td rowspan="2">Energy dashboard interface / Residual analysis</td></tr>
<tr><td>Energy target (kWh)</td></tr>
</table>

4.1 Strategic level analysis

To determine how the energy control matrix could be used at the strategic level on a monthly basis, additional monthly values were generated for the 4 processes and the whole plant. Since the data for February 2020 and 2019 had already been calculated for the operational level, the generated data covered from March 2019 to January 2020. It was also necessary to create values for the total monthly consumptions from February 2018 to January 2019 to calculate baseline values. Finally, since confidentiality reasons prevented access to the sawmill's electricity bills, the EnPIs used to analyze the current economic performance of the whole plant for the February 2020 period were calculated from the synthetic energy data of the Canadian sawmill and the current tariff of its energy provider. This tariff specifies that the first 210,000 kWh consumed in the month must be billed at \$CA 0.0503/kWh and what is consumed after this limit must be billed at \$CA 0.0373/kWh. Power costs are also stipulated in the tariff but they were not considered in this study. For the case study, all of these costs had to be calculated, but in reality, these could easily be obtained from the electricity bill. Therefore, to exemplify the use of the energy dashboard interface, the upper part of Figure 2 shows the plant's total electricity consumption and the three strategic economic indicators shown in Table 1 (simple values and ratios) that give a global perspective of the total energy costs in the evaluated period. The energy control matrix is shown below and the third column (EC % var Whole plant indicator) shows the monthly percent variation of the plant's current total energy costs with respect to its baseline values of the previous year. Dynamic conditional formatting allows the user to understand at first glance where the percent variations are above zero (in red) indicating a decrease in performance and those below (in green) showing improvement. In this example, the general economic performance of the sawmill improved considerably between the periods of October 2019 and February 2020, but between April 2019 and September 2019, the company's energy performance decreased continuously due to the sawing and drying processes. From columns 4 to 8, the CDI % var indicator shows the monthly percent variation of the current energy consumption for each sawmill process with respect to the baseline values of the previous year, and CDI % var TOTAL represents the sum of the percent variations of the 4 processes. The cDI % var indicator shows the percent variation of current energy costs of all the ECCs versus those of the previous year. In this case, this indicator remains constant with a value of 0.81% in all periods because energy tariffs did not change in the periods that were evaluated. Finally, as mentioned by Benedetti et al. (2017), on the same row, the sum of the percent variations of all the CDIs being analyzed and the cDI will not give the exact value of the EC % var Whole plant indicator since all these values interact with each other. Therefore, as suggested by the authors, it is necessary to create another indicator (RESIDUAL % var) that measures this interaction.



Year	Month	EC % var Whole plant	CDI % var Debarking	CDI % var Sawing	CDI % var Drying	CDI % var Planing	CDI % var TOTAL	cDI % var	RESIDUAL % var
2019	February	-1.90 %	-0.11 %	-1.28 %	-1.65 %	0.35 %	-2.69 %	0.81 %	-0.02 %
2019	March	-1.57 %	-0.55 %	-0.57 %	-1.16 %	-0.08 %	-2.36 %	0.81 %	-0.02 %
2019	April	0.71 %	0.83 %	-1.43 %	0.84 %	-0.34 %	-0.10 %	0.81 %	-0.00 %
2019	May	0.59 %	-0.02 %	-0.10 %	-0.26 %	0.17 %	-0.22 %	0.81 %	-0.00 %
2019	June	1.39 %	-0.01 %	0.25 %	0.33 %	0.01 %	0.58 %	0.81 %	0.00 %
2019	July	0.95 %	0.29 %	0.13 %	-0.32 %	0.04 %	0.14 %	0.81 %	0.00 %
2019	August	1.04 %	-0.14 %	0.58 %	0.04 %	-0.25 %	0.23 %	0.81 %	0.00 %
2019	September	1.88 %	0.23 %	0.82 %	0.27 %	-0.25 %	1.06 %	0.81 %	0.01 %
2019	October	-3.23 %	-0.26 %	-2.04 %	-1.43 %	-0.28 %	-4.01 %	0.81 %	-0.03 %
2019	November	-6.13 %	-0.96 %	-4.69 %	-1.35 %	0.11 %	-6.88 %	0.81 %	-0.06 %
2019	December	-9.80 %	-0.76 %	-6.22 %	-3.17 %	-0.38 %	-10.52 %	0.81 %	-0.09 %
2020	January	-11.96 %	-0.86 %	-7.66 %	-4.02 %	-0.13 %	-12.67 %	0.81 %	-0.10 %
2020	February	-13.82 %	-0.74 %	-7.68 %	-5.22 %	-0.87 %	-14.51 %	0.81 %	-0.12 %

Figure 2. Economic EnPIs and Energy control matrix

For the CUSUM map shown in Figure 3, the same generated data for 2018, 2019, and 2020 created for the energy control matrix were used to find the differences between actual values and baseline values and determine the monthly energy savings. Figure 3 reveals that, for this case study, the cumulative energy savings of the sawmill from February 2019 to October 2019 were 121,315.31 kWh. Each visualization card is conditionally formatted to highlight negative values in green (energy savings) and positive values in red (electricity consumption higher than the forecasted baseline values). Figure 3 shows that the cumulative sum of the electricity consumption of the debarking process was 3774.52 kWh more than predicted, which indicates a poor energy performance in this process. However, the sawing and drying processes had significant improvements in October 2019, which is easily visible when analyzing their respective area graphs. For all area charts, a date slicer that dynamically changes the analysis dates can be found at the top, which makes it easier to interpret the results. Thus, the CUSUM map is a tool that automatically relates the energy savings of each ECC and allows to quickly analyze the general energy performance trends of the sawmill.

Figure 3. CUSUM map for the whole plant and related ECCs

4.2 Operational level analysis

As mentioned before, additional generic total values had to be created for the 4 processes and the whole plant for the month of February 2019 in order to make an annual comparison against the 2020 values that were synthetically obtained from the real data of the Canadian sawmill. Figure 4 shows the general energy portrait of the sawmill. In the upper part, the first two indicators show the total electricity consumption of the whole plant for the periods of February 2019 and 2020, while on the right two indicators measure the difference between these two values in kWh and percent variation, to analyze if energy performance improved or worsened. All the energy indicators in this interface are simple, easy to read, and dynamic. The total electricity consumption in kWh for each process is on the left side. A pie chart shows the main energy consumers in the sawmill together with their corresponding electricity consumption percentages. Here, the sawing process is the most energy intensive process with 54.21% of the total electricity use in the whole plant.

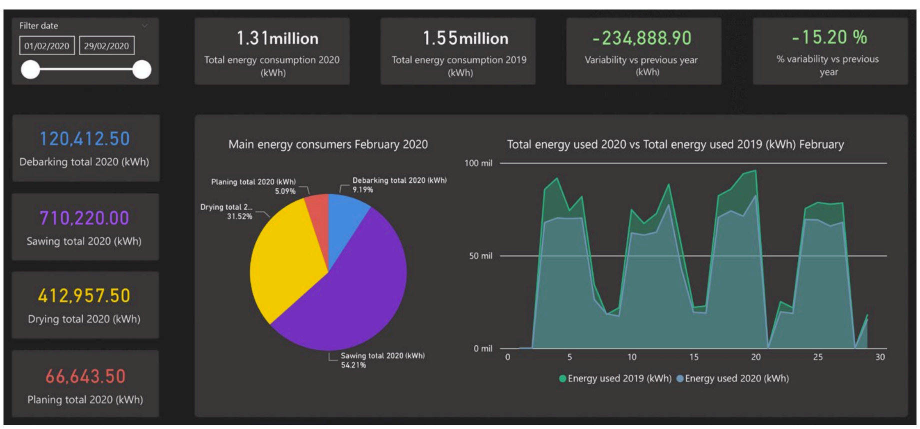


Figure 4. Sawmill energy portrait (operational level)

Hence, to analyze the energy behavior of this process in detail, based on a period of 18 days, the regression analysis (Figure 5) associated the production volumes (m^3 of sawn products) with the electricity consumption (kWh) that were recorded during February 2020, to determine the linearity that exists between both variables. Therefore, the scatter diagram shows the production volumes plotted against electricity consumption in a rather straight line, represented by the baseline equation shown at the top of Figure 5. Because the correlation coefficient between both variables is highly reliable (R^2= 0.86), this equation was employed as a baseline to predict how much energy should have been used during the evaluated period. With Microsoft Power BI, it was possible to optimize the way in which this baseline equation is calculated, since it is much easier to determine the appropriate scenarios to predict energy consumption and set energy targets. In addition, the calculations are done automatically just by moving the date slicer or by selecting the desired points on the scatter plot. This interface also shows the SEC and the maximum electricity consumption, where it is possible to see that February 20 was the most energy-intensive day.

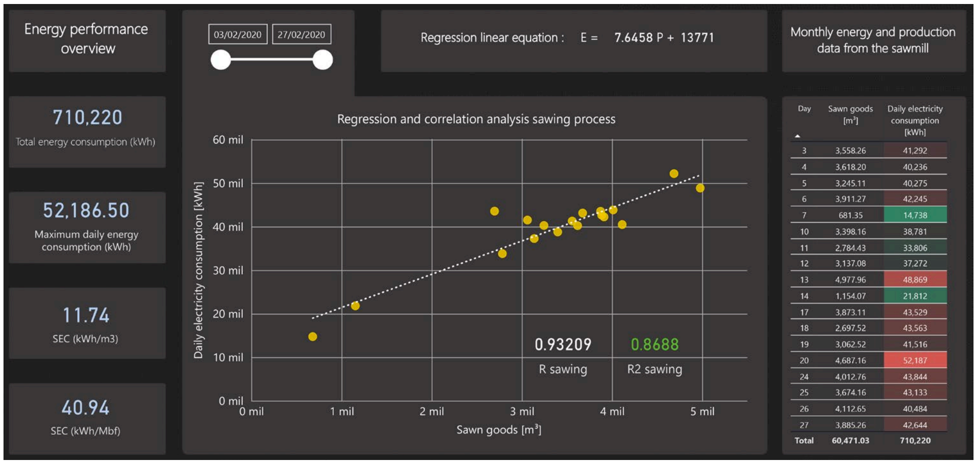


Figure 5. Regression analysis of the sawing process

Figure 6 shows the results of the CUSUM analysis obtained from the baseline equation which simply represents the cumulative sum of the differences between what was actually consumed and what was predicted with the baseline equation during the evaluated period. It shows that the energy behavior of the sawing process was very unstable. From February 18 to February 25, energy consumption was much higher than the predicted one which resulted in the loss of the energy savings that had been accumulated from February 3 to February 17. The CUSUM tool is very useful to verify energy performance improvements, detect energy anomalies, and validate energy savings.

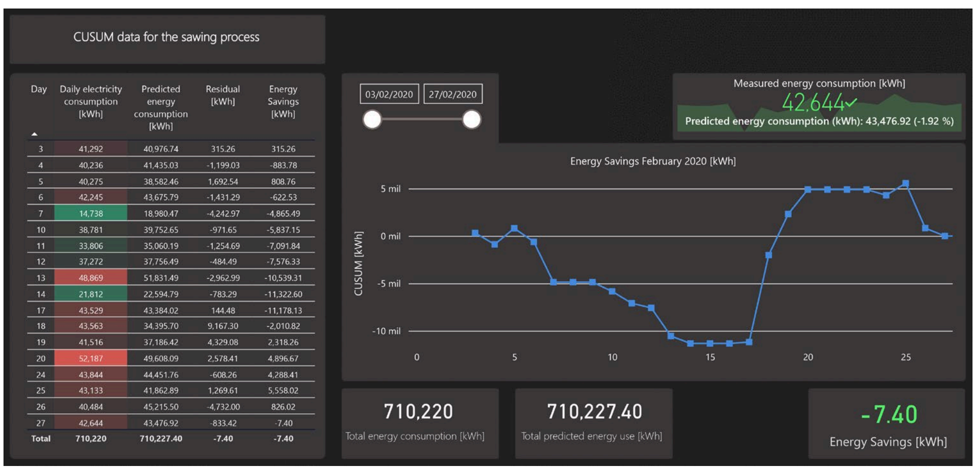


Figure 6. CUSUM analysis of the sawing process

Finally, in the residual analysis (Figure 7), a target equation that contains the three best energy performances of the month was defined. Then, the differences between the actual consumption and the new predicted ones were calculated (Energy target) and the S_{EE} value was estimated according to the equation established by Morvay and Gvozdenac (2008) to define the upper and lower control limits of the scatter diagram. The control limits were set at 3 x S_{EE} since the target line correlation was very close to 1. The table to the right in the figure highlights the difference between the total monthly energy use (daily electricity consumption) and the predicted one and gives the targeted monthly amount of energy that must be saved, which in the case of the sawmill example is 71,305.25 kWh. Likewise, the scatter diagram with the limits plotted reveals that the variations in energy use above the upper limit are quite high for 7 of the 18 days observed, and that the largest difference between measured values and predicted ones occurred on February 18, where the variation between the two was 13,243.44 kWh. Hence, this case study gives a specific example of what could be done when an energy dashboard interface is combined with appropriate statistical analysis tools and EnPIs.

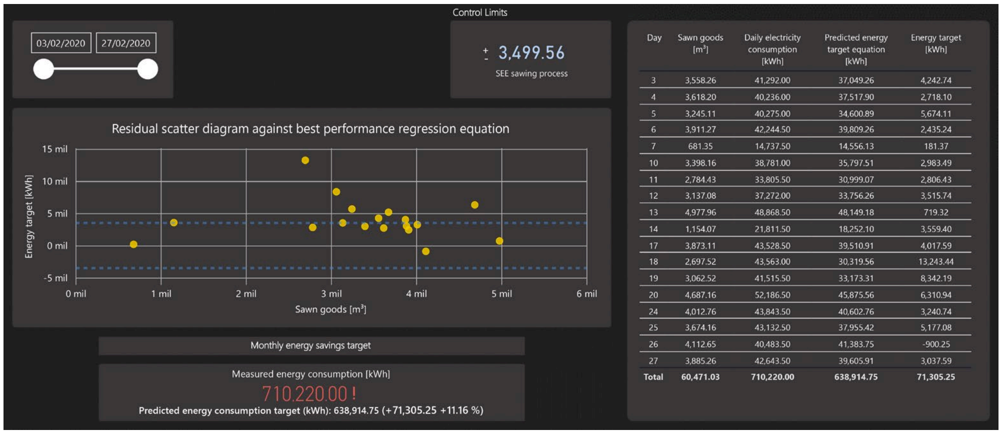


Figure 7. Residual analysis and target equation of the sawing process

5. Conclusion

Industry 4.0 approaches relying on intelligent and advanced data analytics environments are driving EM practices across all manufacturing sectors. A better understanding of the energy behavior in industrial operations is a key success factor to have energy efficient and sustainable production systems. Therefore, energy control systems are important to identify potential energy efficiency improvements and unexpected changes in energy performance that can be quantitatively analyzed at all organizational levels with EnPIs and statistical control tools. From this perspective, the work carried out in this article focused on developing an energy dashboard interface to analyze, with synthetic data sets, the electricity consumption patterns of the main manufacturing processes of a Canadian sawmill, through various integrated EnPIs and statistical control methods. The results obtained after applying this energy dashboard interface to the case study of the Canadian sawmill revealed that the operational controls and energy strategies to be deployed at all organizational levels will depend entirely on the type of information that can be accessed. Indeed, when numerical information systems feed the energy dashboard interface, it is possible to monitor and control electricity consumption patterns, identify excessive variations in energy use, detect anomalies, develop better decision-making, map processes energy savings, establish relationships between production outputs and consumed electricity, make predictions, and define energy targets for future improvements. However, when only the electricity bill is used, the analysis possibilities become limited and only rely on the analysis of simple and approximate EnPIs, which makes it difficult to understand the true nature of energy problems. Ultimately, the energy dashboard interface is an operational guide that supports decision-making with dynamic graphics and visualizations that make it easier to interact with information. However, only through deductive reasoning, knowledge of processes, and field experience will it be possible to draw effective conclusions for operational energy improvements. This energy interface can also be easily adapted and applied to other industrial sectors as long as they have the necessary information to exploit it. The application of this tool should continue to be validated in more sawmills and case studies to further improve its interface. In future research, other types of energy sources could be added to the interface to provide a complete picture of a sawmill's energy profile. It would also be pertinent to fully integrate the interface with the information systems to automate data processing and be easily shared through cloud systems at all organizational levels.

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