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RESEARCH ARTICLE

Internet of Things in Energy-Sensitive Processes: Application in a Refrigerated Warehouse

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ABSTRACT This article aims to address an existing research gap in the study of the most widely used mathematical procedures in the field of automatic control of energy-sensitive industrial processes. In these types of processes, as is the case of cold storage in the food sector or the pharmaceutical industry, applying energy efficiency measures is very risky. This is because the margin of variation in the temperature of the processes is very small, since the product to be manufactured or preserved is very sensitive. This is where the developments of the Internet of the Things showcase their usefulness because they allow measurements to be taken with great accuracy and to verify the effectiveness of energy efficiency proposals. Nevertheless, there are very few studies and developments on automation measures in energetically sensitive industries. This is the research gap that the present work aims to shed light on, proposing a method for optimizing the process of automatic revision in a refrigerated food warehouse. Said method prominently employs control charts, as they allow for a relatively easy set up and require minimal intervention but can be revised manually if so desired. The analysis also includes an auxiliary variable that measures the impact of the variations in the system. Improvements are also provided to the procedures and variables, with which the most commonly used methods of efficiency control in the industry can maintain good results in energy-sensitive industries. Finally, the best selection of charts for the chosen variables is then discussed and justified.

INDEX TERMS Control charts, energy efficiency, Industrial Internet of Things, Internet of Things (IoT), IoT applications, temperature control, warehousing.

I. INTRODUCTION

The European Commission (EC), guided by the European Green Deal of 2019 and the Recovery Plan for Europe in 2021, has outlined a vision to invest 30% of its budget towards programs, projects, and initiatives aimed at addressing climate-related challenges. This commitment underscores Europe's dedication to leading the charge in becoming the world's first climate-neutral region by 2050. To accomplish this ambitious objective, the foundation of the EU's future energy strategies must continue to prioritize energy efficiency and the expansion of renewable energy sources [1]

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The pursuit of energy efficiency plays a vital role throughout the entire manufacturing process of any product, encompassing both the product's design and the procedures involved in its creation, storage, and long-term preservation [2]. In certain instances, these processes can emerge as substantial contributors to overall energy expenditure, and many of them are susceptible to variations in energy consumption.

An energy-sensitive process is one in which it is crucial to maintain an uninterrupted flow of energy during the manufacturing of a product or service. A notable example of such a process is the refrigerated storage of various goods, including pharmaceuticals, chemicals, and food products. Industrial refrigeration for preserving food alone encompasses over 550 million cubic meters of cold storage space globally, according to the International Institute of Refrigeration

(IIR, 2015). These facilities are responsible for approximately 2.5% of worldwide greenhouse gas emissions and account for 8% of global electricity consumption [3].

The substantial energy consumption in these facilities is an absolute necessity, since in refrigerated food storage installations, energy consumption is a key issue for the profitability of companies and weighs about 50% of their total expenses [4]. Furthermore, between 60% and 90% of the variations in energy consumption are a consequence of the variability in the volume of refrigerated product stored [5].

If we add that the deviations from optimal temperature, which vary for each type of food, can rapidly lead to spoilage and microbial growth, causing product loss; we have an energy-sensitive industry [6], [7]. On the one hand, energy expenditure must be optimized, considering the variety of the product, its quality and the variability of storage volume, and on the other hand, product must not be lost due to poor storage conditions.

It is estimated that roughly 300 million tons of products are discarded annually worldwide due to inadequate storage conditions [8]. In the modern world, approximately 40% of the food we consume requires refrigeration, with the refrigeration process consuming between 60% and 70% of electrical energy in cold storage facilities [9], [10].

As living standards improve, the construction of more warehouses is becoming commonplace. Therefore, advancements in the sustainability of cold storage, both in terms of energy efficiency and economic viability, are of paramount importance in today and tomorrow's society [11].

This example illustrates the intricate nature of achieving maximum efficiency in an energy-sensitive process, requiring a delicate balance between minimizing energy consumption, and ensuring the safety of the products. In the context of refrigerated buildings, various parameters must be carefully considered. Some of these parameters are common to other types of structures, such as temperature set points and insulation thickness [12]. Others are more specific to refrigerated facilities, like the unique refrigeration requirements of the stored products.

Energy efficiency measures can be adopted from various perspectives. First, there are passive measures in the design stage, such as improving insulation and optimizing cooling plants, which can be hard to adapt to the variable nature of the goods stored in a warehouse, even if they can yield significant energy savings [11].

And second, there are active measures when the facility is already in the operational stage, where cold production is trying to be adapted to the demand. This article focuses on addressing efficiency measures in this operational stage. This is a complicated balance for several reasons. Because refrigerated product warehouses are designed without knowing which food products will be stored, the interior setpoint temperature and insulation have to be estimated. But as stated previously, the nature of the specific goods stored in a warehouse can vary, so the reality is different and unique for each building. Therefore, measures need to be designed so that they are valid for the different realities these installations face and that allow customization for each stage of their operation. This applies both in terms of the variability of the product to be stored, and in potential changes in their typology, and therefore their storage conditions.

The multitude of factors at play makes the implementation of energy-efficient measures increasingly challenging in refrigerated warehouses, even when utilizing proven strategies such as enhancing insulation,

Various solutions have been proposed to address these challenges, with some studies dating back almost two decades at the time of this writing [14], [15]. Nevertheless, recent advancements in energy management technologies are now making their way into the realm of cold storage for food and other energy-sensitive processes. Among these innovations, the Internet of Things (IoT) stands out as the most notable.

The IoT has already demonstrated its advantages in non-refrigerated warehouses and many logistical operations, where numerous studies have shown its effectiveness in automating management tasks such as pickup, delivery, and record-keeping, leading to paperless and unmanned operations [16], [17], [18]. However, it's essential to acknowledge that transitioning to a smart warehouse is a time-consuming process that necessitates support from top management and substantial effort [19].

Nevertheless, the improvements are considerable, with some of the most significant benefits stemming from cloud-based programmable platforms that facilitate real-time monitoring of numerous variables simultaneously [19], [20]. This capability is invaluable for energy-sensitive processes, especially in food preservation, where it can provide meticulous control over temperature conditions.

Control charts, introduced in 1924, have remained a cornerstone of statistical process control due to their effectiveness in monitoring various processes [21]. These charts have gained popularity for several reasons, primarily their track record in enhancing productivity, preventing unnecessary process adjustments, and providing valuable insights into process capacity and diagnosis [22].

The type of charts used to deal with continuous data like the temperature or the energy consumption are known as variable control charts. These can be classified as memory-less and memory-type control charts depending on their detection ability and utilization of previous data. Both types of charts have their own sub-types and have their different uses [23].

Broadly speaking, memory-less control charts only use the current value to monitor the process, making them more accurate and serve as a direct representation, whereas the memory-type control charts combine the data with previous information, making them more sensitive to pattern changes in the analyzed data [24].

In the context of cold storage, the implementation of control charts allows to respond swiftly to significant deviations in temperature or energy consumption. While this function may seem straightforward, it possesses nuances owing to the diversity of control chart types. By proactively addressing anomalies before they lead to damage, control charts serve a pivotal role in preventing both food spoilage and unnecessary energy wastage. Notably, their simplicity and ease of setup distinguish them from more complex methods like neural networks, contributing to their widespread popularity [25].

A. CONTRIBUTIONS AND RELATED WORK

This article aims to address an existing research gap by analyzing these mathematical procedures, specifically in the context of industrial processes with high energy sensitivity. This is because, despite the utility and user-friendliness of control charts, and the notable progress in IoT technology, there appears to be a gap in research focused on energy-sensitive processes. Particularly in domains emphasizing energy consumption reduction and temperature preservation. On the one hand, many studies in the IoT and food safety industry have been primarily oriented toward logistics and transportation, with limited attention given to energy-sensitive cold storage processes. To showcase a few examples:

Pal and Kant deal with the entire logistics chain of perishable goods, and they propose an IoT solution that is very broad and layered, but with the emphasis situated mostly in transportation and packaging [18].

Fan establishes the basis of a supervision of not just the logistics chain, but the entire life cycle of the refrigerated food products using IoT. However, the focus is centered in the creation of the platform, whereas the processes of planting/culture, processing, transporting, and catering/marketing that make up the life cycle of the product are not fully elaborated on [26].

Lastly, Hu focus on the warehouse itself and the usage of a digital twin, even touching the subject of temperature monitoring, but is more focused on the implementation of the Digital twin itself and its benefits rather than analysing the energy sensitive process of temperature control itself [27].

While all these papers are well researched and constructed, the analysis of energy-sensitive processes is not the main priority in any of them.

The present work not only aims to shed light on this field but also demonstrate with real examples some adaptations of the most used mathematical models which are appropriate for the energy-sensitive industries.

The latest advances in energy management distinguish energy efficiency measures according to type, and in the operational management part they all aim at treating data in a holistic manner, given the different perspectives to consider in these treatments. A good example of this is the work of Mariano-Hernández, Deyslen, et al [28].

In the most recent works, there is clearly a trend towards developments and advances in Industry 4.0 technologies for energy management, from improving sensors and their reliability, improving sensor communications with computers and databases, to the treatment of this data for energy optimization [29].

More specific studies on warehouses in 2023 point to energy management as one of the major problems to be solved, as well as pointing to the use of Industry 4.0 technology to improve their energy management [30]. The difficulties in obtaining real data to validate procedures are one of the barriers that those studies encounter, which in this case, the authors have been able to overcome.

The main objectives can be therefore described as follows:

First is to determine which of the analyzed charts is more effective in the control of an energy sensitive process. The effectiveness of a chart will be measured in both in its ability to detect anomalies and its capacity to do it as quickly as possible. There are two types of anomalies to be detected: Operational anomalies like load shifts, caused by the behavior of the personnel in an installation; and Maintenance anomalies, which are the result of an error in the system or its equipment.

The second objective is to determine which variable would be more useful in monitoring energy-sensitive systems, both for operational and maintenance anomalies.

The third and final objective is to propose an effective method for the control of energy efficiency in energy-sensitive installations.

The authors of this study consider this objective of paramount significance for two primary reasons:

The proliferation of these procedures within the context of industrial digitalization, particularly from an energy perspective.

The global importance of energy-sensitive industries within the wider industrial landscape.

B. STRUCTURE OF THE PAPER

The remainder of this paper is organized as follows. Section II will provide an overview of the main case study of a refrigerated warehouse, alongside some of the most important specifications for the study. Section III will showcase and provide the required amount of detail for the different control charts that will be studied. Section IV will determine the time scale in which the analyses will be conducted. Section V demonstrate the conducted experiments and some of the most important and noteworthy results and graphs. Finally, Section VI will present the main conclusions of the project.

II. CASE STUDY FOR VALIDATION

The logistics center's case study encompasses a vast array of cold storage chambers, totaling over 140,000 m^3. The outside view can be seen in Figure 1. These chambers come in various types, all built with the same materials, but each of them with unique sizes, refrigeration needs, and capabilities for handling different products and storage temperatures. The temperature ranges they can accommodate span from cold to frozen.

A. EQUIPMENT

To meet the refrigeration requirements of these chambers, the center utilizes a central refrigeration system that can be seen

FIGURE 1. Outside view of the warehouse building.

FIGURE 2. Showcase of the engine room.

in Figure 2. In the interest of energy conservation, the same system is used for all types of refrigeration instead of having a separate source for each chamber. This is even though each chamber has distinct interior units that regulate the temperature to suit the stored food, considering the specific needs of the contents and the chamber volume.

The chambers obtain the cold they need from the installation by regulating the cooling flow based on the temperature measured by a sensor and the difference it has from the setpoint temperature. Since the products of the cambers are different, the setpoint temperatures are also different, which makes it difficult to adjust supply and demand. Consequently, the warehouse lacks the ability to accurately measure and adjust the energy consumption of a particular chamber or type of food.

The in-cloud platform can help alleviate this, and some progress has already been made, with additional equipment being installed in the creation of a digital twin for the logistics center. The most essential of this additional equipment are the following items:

1) An Adquio Pro programmable controller from Make Develop, which acts as a data processor and concentrator of the installed sensors and connects to the cloud platform that will create the digital twin of the logistics center. This controller receives information from the different devices connected to it, such as temperature sensors. The data received by Adquio is temporarily stored and organized to provide detailed information on environment and consumption according to several factors: The chamber to which it belongs, the location within said chamber and the exact date of recording.
2) Regeltechnik AFTF temperature sensors inside the chambers, necessary to allow the exhaustive control in real time of the environmental conditions that is one of the main objectives of this paper.
3) A Circuitor CVM-C10 network analyzer, used to monitor and control the consumption of the cooling generation equipment.

With this equipment, the data is organized and acquired in real time, and then passed to an IoT platform for control and visualization. In this case the Adquio Cloud platform was used, which has several advantages: On the one hand it allows to see data in real time, as well as historical data. On the other hand, it's also programmable, allowing the addition of control through automatic alerts. Furthermore, it has its own SCADA, which gives the system the scheduled and real-time control of the installation.

This arrangement can be observed in Figure 3 and allows for real time control of the temperatures and can even be used to program alerts with the proper software [31].

B. VARIABLES FOR ANALYSIS

The collected information can be utilized to generate a data sheet containing various variables for monitoring the status of the installation. In the case study, the data sheet will encompass a timeframe starting from the 8th of November in 2021 at 12:00 to the same date in 2022 at 10:00, with measurements taken at hourly intervals. In this research, we identify variables that can alert us as soon as possible to large deviations that can be caused by significant differences between the measured temperatures and the setpoint temperatures, or by unusual consumption values, which indicate that something is not adjusted and needs to be adjusted. The aim is to ensure that consumption is not higher than desired, nor is there product loss, greatly assisting in managing energy supply and demand during plant operation over a representative period of time where there have been different quantities of stored product, loading and unloading processes, etc

For all this reasons, the focus of this study will be on two main variables, and an auxiliary one:

On the one hand the energy consumption and the temperature of the chambers were chosen, as these variables are the most closely related to both the efficiency of the system and the safety of the stored goods. While there are other variables that could be considered in this fashion, like the humidity of the chambers, not all the analyzed chambers

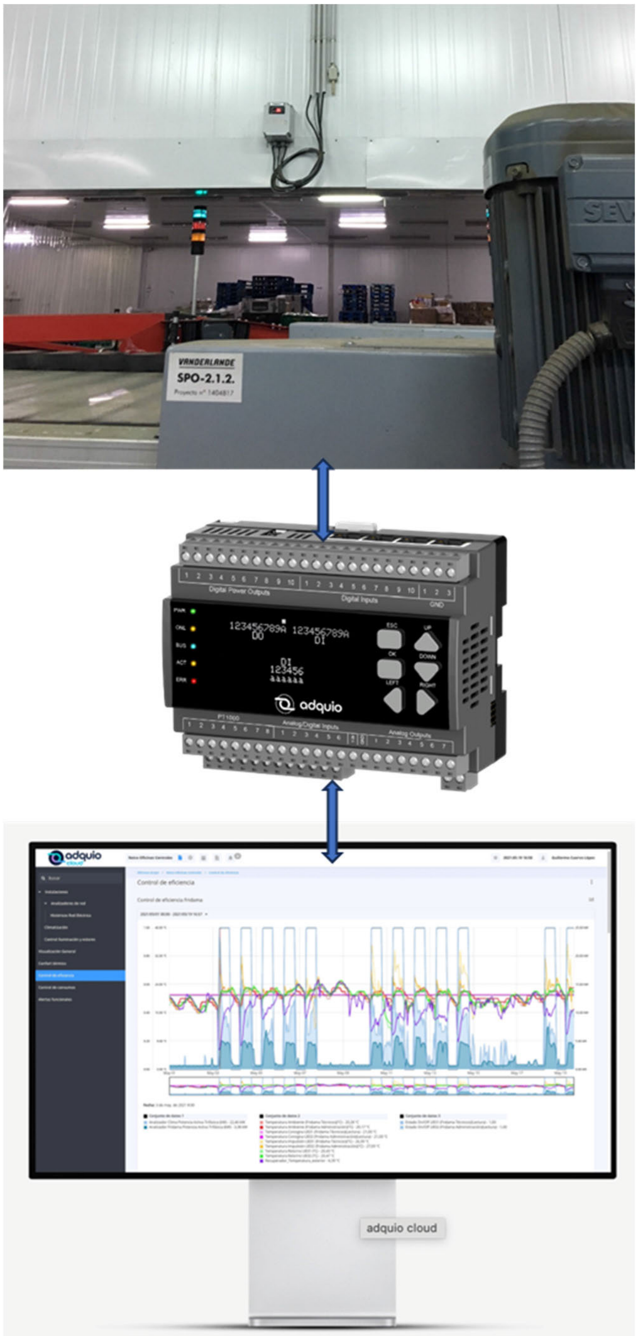

FIGURE 3. First type of sample analyzed, showcasing the entire set of data.

possess humidity sensors. Moreover, the temperature requires a more uninterrupted flow of energy to keep a stable value than the humidity. This makes the temperature a better variable to examine energy sensitive processes.

On the other hand, a selected Key Performance Indicator (KPI) was also created to aid in the analysis. Each of these three variables has its own specifications:

As previously stated, due to how the refrigeration system is designed, the energy consumption will consist of a single value that will encompass all chambers.

TABLE 1. Set temperatures of the analyzed chambers.

Chamber	Equipment	Set Temperature
Chamber A	4 coolers	4ºC
Chamber B	1 cooler	3,7ºC
Chamber C	1 cooler	-20ºC

The temperatures have a set point that can be used to check how much the system corresponds to the desired values of the chamber, and the three main set points used in the installation are represented in Table 1, each of them assigned to one specific chamber.

These chambers represent all the types of food products that are stored in the warehouse and correspond to half of the total chambers in the installation, which can be taken as a reasonable estimate of the total functionality of the system regarding the variability in temperature, since the rest of the chambers have equivalent conditions, sizes and heat transmissions to the three that have been chosen.

Lastly, a KPI is a measurable indicator used to track progress towards a desired outcome. They are often used in financial activities to measure a company's success against targets, objectives, or peers. To be effective, KPIs need to be specific, continuous, and quantifiable, so choosing the right factor is important.

In the context of energy efficiency and smart buildings, there are different types of KPIs. These include energy costs, equipment efficiency, load, and storage capacity [32], [33].

In this paper, the "Energy per analyzed magnitude" KPI is considered the most suitable. The sources suggest that in our example, this KPI should follow the formula:

$$KPI_{ij} = \frac{EC_{ij}}{T_{ij} - T_{Setj}} \tag{1}$$

where EC_{ij} represents the energy consumption of the sample i in the chamber j, with T_{ij} as the resulting temperature, and T_{Setj} represents the set point of the temperature in that chamber j.

However, there are problems with this approach.

One problem is that the consumption value EC_{ij}, which is a key component of this KPI, is a unified value despite working with multiple chambers, and cannot be easily separated for individual chamber analysis. However, this can be overcome by considering the three analyzed chambers as a reasonable estimate for the entire system.

Another problem relates to the difference in temperatures, where the ideal situation would be for the factor $T_{ij} - T_{Setj}$ to be equal to zero. But in the suggested version of the KPI it's impossible since this factor goes in the denominator and would make the values tend towards infinity.

Swapping which value goes in the denominator would solve this problem, and with both of these adjustments we could create a "Difference of temperature per unit of energy"

KPI with the formula:

$$KPI_i = \frac{\sum_{j=1} \left(T_{ij} - T_{Setj}\right)}{EC_i} \tag{2}$$

This new formula uses the same parameters, except that now it employs the sum of all analyzed chambers in the sample i, can work with the only energy consumption data available EC_i, and becomes 0 if the ideal value is reached.

Despite addressing those issues, this modification still has some clarity problems in interpreting the information displayed. In an automated and unmanned system, it's crucial to have a clear pattern that indicates when the value exceeds control limits and triggers an alarm. But in this case, when one magnitude rises, it has the opposite effects on the KPI than the other. This means that if the temperature difference increases, the value of the modified KPI also increases, whereas a rise in consumption decreases the KPI value, and vice versa. Both of these situations are undesirable but it's impossible to distinguish them from a decrease in consumption or a decrease in temperatures, respectively.

Because of this, a high value of this KPI could indicate either a very high temperature difference or very low consumption, making it difficult to know what's happening when a value surpasses control limits.

To address this problem, a different type of KPI is proposed, which is the product of the sum of temperature differences and the energy consumed by the refrigeration system. The formula for this KPI is as follows:

$$KPI_i = \sum_{j=1} \left(T_{ij} - T_{Setj}\right) \times EC_i \tag{3}$$

As in previous formulas, T_{ij} represents the temperature of the sample *i* in the chamber *j*, and T_{Setj} represents the set point of the temperature in that same chamber. Finally, EC_i showcases the energy consumption in the sample *i*.

This new KPI represents the combined impact of both variables in the system. Although there may be some ambiguity in attributing a high value to consumption or temperature difference, it's clear that exceeding a control limit is detrimental to the system. This KPI also maintains the desired value of 0, which can only be achieved if the chamber temperatures match their set values.

Another option considered is using the absolute value of the distance between the chamber temperature and the set value. This approach measures variations in temperature equally. However, knowing the sign of the temperature change in food refrigeration is essential since the consequences of a deviation in temperature from the setpoint are generally much worse than in a negative direction. Therefore, knowing the sign of the deviation is very important and would not be possible with an absolute value. For example, apples withstand a rise in temperature much worse than a drop in temperature, while green tomatoes are more vulnerable to cooling [7], [8].

Furthermore, setting 0 as the minimum value doesn't align well with the employed charts, which work better when the target value is close to the mean of the data sample. Therefore, the absolute value of the difference won't be used, as the other two variables can compensate for the limitations of the KPI.

With all these factors in mind, the next step is to evaluate the control charts that will be used in future experiments.

III. STUDY OF STATISTICAL CONTROL TOOLS

Statistical process control (SPC) is the use of statistical techniques to monitor and analyze process conditions, ensuring accurate assessment of process performance and recommending necessary corrective actions.

As stablished previously, control charts are the most widely used method for maintaining process control, allowing the monitoring of quality-related variables in production processes.

Although they have some drawbacks, such as sensitivity to shift size and in some cases suffering to small delays if not properly adjusted, their overall usefulness remains significant.. [34]. This is because of several qualities like their versatility and ease to implement [25]. But in the cases of energy sensitive processes where every moment that the process is not in control can incur losses, they have the added advantages of not only employing a relatively small amount of data per computation, but most critically; being able to provide information in real time with the correct setup. This makes them very well suited for energy sensitive procedures.

A. OVERVIEW OF THE TYPES OF CHARTS

The most basic definition of a control chart is that of a graphical representation of a quality characteristic plotted against three lines:

The Centre Line (CL), which represents the ideal value of the quality characteristic, and the Upper Control Limit (UCL), and Lower Control Limit (LCL), which showcase the acceptable range of values of the characteristic. These control limits are chosen to minimize the likelihood of in-control data points falling outside their boundaries, and act as the main parameters of the chart [35].

Other factors can influence the characteristics of the chart, like the nature of it's in-control data points, or the size of the shift in values they are most specialized to detect. It should be noted that the impact of a shift depends on the scale employed in the sample, with larger shifts having more significance in shorter time frames. With all of this considered, the key control chart types that will be explored are:

1) The Shewhart control charts, which are the most well-known examples of a memory-less control charts and are widely used because of their simplicity [21]. Memory-less control charts only use the current observation to monitor the process, and so are more accurate, if less sensitive than other charts. They are used mostly to detect larger shifts, but they can still be useful in smaller intervals [24].
2) The exponentially weighted moving average (EWMA) and the cumulative sum (CUSUM) which are the two most used memory-type control charts. These get their name for the fact that they combine the usage

of previous information with present information to make them more sensible to changes in the patterns of the analyzed data [36]. Because of this property, EWMA and CUSUM control charts are most used to detect moderate and small shifts respectively, but they could potentially remain useful even when employing the bigger intervals [24]. However, it should be noted that they generally to entail more complexity and design considerations than the relatively standardized memory-less control charts, and depending on the specific type of chart used, the calculations can become intricate, posing difficulties in their practical application [37].

While other potential charts have been considered, the three that have been selected are the most well-known and employed of all of them. This makes them easy to understand and work with, which will make the study easier to implement and increase its reach. The following sub-sections will explore each of these charts in more detail.

B. SHEWHART CHARTS

Shewhart charts are the oldest and most used control charts. The one that will be employed is the Shewhart X control chart, favored for their simplicity, ease of comprehension, and lack of complexity in calculations [38]. However, it's important to note that Shewhart control charts excel at detecting large shifts in a process but struggle with identifying small or gradual shifts, even more so than other memory-less charts.

This limitation has persisted since their inception and has led to efforts to address it using supplementary rules.

Generally, the most popular formulas of the basic characteristics of this type of charts are:

$$UCL = E\left(W\right) + 3 * \sqrt{Var\left(W\right)} \tag{4}$$

$$CL = E\left(W\right) \tag{5}$$

$$LCL = E\left(W\right) - 3 * \sqrt{Var\left(W\right)} \tag{6}$$

In which W is a function used to estimate the process mean of the data vector X, E(W) represents the mean value of W and Var(W) represents its variance. The Control limits in this context are often referred to as the three sigma limits.

The chart therefore displays the quality characteristic of a product or process against the sample number (Often denoted as "t")

This nomenclature assumes that W follows a normal distribution, implying an approximately equal chance of continuous data being above or below the mean.

Under this assumption, these two limits form an interval with a 99.73% probability of encompassing the values of W when the process is in control. Consequently, the likelihood of a false positive, or a false alarm, is quite low [25]. However, the range of this interval also presents a problem: It's the reason that the chart struggles to detect small shifts.

Other problem with this chart is that it relies on the average value and variance of the sample and, as previously stated, assumes that the data can be approximated to a normal distribution. If this is not the case, it can create problems in both small and large sample sizes. This can potentially lead to overfitting, or distortions in the mean and variance.

In the case that the mean and variance of the sample are not adequate for the analysis in a certain experiment, another set of values will be chosen.

C. EWMA CHARTS

EWMA charts offer a similar level of performance with a straightforward design, making them easily applicable in real-world scenarios [39].

One notable strength of these charts is their ability to provide a smoothed representation of the current process parameter status, rendering them valuable graphic tools [37].

Additionally, they excel at detecting small shifts in process parameters and benefit from dedicated graphical techniques, cementing their importance in identifying subtle to moderate process changes [40].

In EWMA charts, historical data is considered alongside current observations, with the weight of each measurement diminishing exponentially as it becomes less recent. This also makes it more resistant to have its control limits distorted by outlier values.

The key statistic monitored in EWMA control charts is:

$$Y_i = \lambda X_i + \left(1 - \lambda\right) Y_{i-1} \tag{7}$$

In this formula i is the sample number and λ is the smoothing parameter, which must have a predetermined value that satisfies the condition $0 < \lambda \leq 1$. A value of 1 would make the chart equal to that of a Shewhart X chart, with no memory of past data. Y_0 stands for the initial value and is typically derived from either the average of initial data or the target value if such information is available.

This monitoring statistic is then compared to the control limits and the center line, which correspond to the following values:

$$UCL = u_0 + L * \sigma\sqrt{\frac{\lambda}{2-\lambda}\left(1 - \left(1-\lambda\right)^{2i}\right)} \tag{8}$$

$$CL = u_0 \tag{9}$$

$$LCL = u_0 - L * \sigma\sqrt{\frac{\lambda}{2-\lambda}\left(1 - \left(1-\lambda\right)^{2i}\right)} \tag{10}$$

The default σ represents the standard deviation of the observations, whereas λ and L represent the two primary parameters that dictate the performance of the EWMA charts, and which must be chosen with care.

"λ" is dictates how quickly measurements lose significance over time and "L" determines the width of the control limits.

The value of λ it's crucial, as it represents the weight of the current measurement over the previous values. Making it too big will cause the EWMA chart to lose the capacity for memory, while making it too small could cause the chart to become a static value. Smaller values of λ enhance sensitivity to small shifts, whereas larger values make the chart less vulnerable to being distorted by large shifts. As a result, it's common practice to recommend values of 0.1 or 0.2 for λ.

Regarding the parameter L, the three-sigma limit applied to the Shewhart charts (Meaning L = 3) is generally used with higher levels of λ. However, in the cases of λ being lesser or equal than 0.1, there's an advantage at reducing the width of the limits for higher sensibility. In that case, employing a value of L between 2.6 and 2.8 is considered the best course of action [22], [24], [35]. Taking all of this into consideration, the main values used in the experiments will be $\lambda = 0.1$ and L = 2.7 unless stated otherwise.

It's important to note that the control limits of the EWMA are not static, unlike those in other chart types; they progressively move further from the center line. However, the control limits do eventually stabilize as the observation count "i" increases and the factor (1 - (1 - λ) ^(2i)) approaches unity.

D. CUSUM CHARTS

Cumulative Sum charts or CUSUM chart, are arguably the best at detecting small shifts in processes. Fundamentally, these charts assume that the sum of deviations from the target value, usually the mean, remains at zero if the process is in control. When the process deviates from its target, the cumulative deviation would either increase or decrease substantially, depending on the direction of shift [41].

Therefore, the chart effectively tracks the cumulative deviation from a designated point, whether said point is the mean or another target value. This does present a problem of losing some information regarding the magnitude that's being analyzed, but that can be mitigated with the correct representation. Despite the existence of other methods to represent these charts, the most common one is the Tabular method, in which the cumulative deviation is treated as a statistical function and plotted against control limits. The two main statistical functions of the tabular CUSUM are denoted as C^+ and C^- which are generally defined as:

$$C_i^+ = max[0, (X_i - u_0) - k + C_{i-1}^+] \tag{11}$$

$$C_i^- = max[0, -(X_i - u_0) - k + C_{i-1}^-] \tag{12}$$

Here, X_i represents the observation of the sample I, and u_0 is the target mean. The reference value is denoted as "k" and signifies the magnitude of the shift that the project aims to detect and is usually set to half of the standard shift (in standard units) of the process. C_{i-1}^+ and C_{i-1}^- provide the accumulation of deviations in their corresponding values that gives the name to the chart. Both C^+ and C^- are initially set to zero.

These two statistics are plotted against a control limit H and breaching this limit indicates an out-of-control situation. If the statistic C_i^+ exceeds H, the process mean is said to be shifted above the target value. Conversely if the statistic C_i^- surpasses H, it signifies a shift below the target value [23], [24], [35].

The fact that both statistics possess the same control limit despite having different meanings can make the chart both less demanding in terms of programming requirements, but also more difficult to read for a human observer. To correct this problem, it was decided that instead of having both CUSUM statistics be positive, the lower CUSUM statistic (C^-) has been adjusted so that its values fall below zero. This adjustment also involves changing the sign of the corresponding control limit.

The resulting statistic can be defined as follows.

$$C_i^- = -max[0, -(X_i - u_0) - k - C_{i-1}^-] \tag{13}$$

Regarding the size of the control limits, for a proper setup its generally recommended using a control limit between four and five times the magnitude of the shift to be detected. However, the value is considerably flexible, and in this case, to further enhance the sensibility of the chart, the value chosen was 3.5 times the shift.

Both specifications will be employed in all three variables, ensuring uniformity in the analysis unless specifically stated otherwise.

IV. EMPLOYED TIME SCALE

To achieve the goal of automatic control in energy-sensitive installations and processes, it's important to thoroughly analyze all the presented charts not only in all the featured variables but also in various time scales. This is important because energetically sensitive processes have very small ranges of variation, but those variations greatly impact the results. This makes it necessary to analyze the time scales that will be employed in the study, to verify which one is most appropriate. The steps taken in this endeavor will be showcased in the following sections:

A. SPECIFICATIONS OF THE TIME SCALE

The term "time scale" refers to the duration of the data sample examined in the current analysis. For each chart type and variable, we conducted analyses on the following sample sizes, each accompanied by their respective graphical representation:

1) The complete dataset, used to gain a comprehensive understanding of variable behavior and to assess the functionality of the graphs. Showcased in Figure 4
2) Twelve month-sized segments, which allow to pinpoint anomalous behavior with greater precision. Showcased in Figure 5
3) Four week-sized intervals, created by dividing the first month-sized segment, and providing a more detailed view of the graphs. Showcased in Figure 6
4) The daily data spanning from November 15th to December 12th, examined for an even finer analysis, and allowing to compare patterns across days of the same week and the same day across different weeks. Showcased in Figure 7

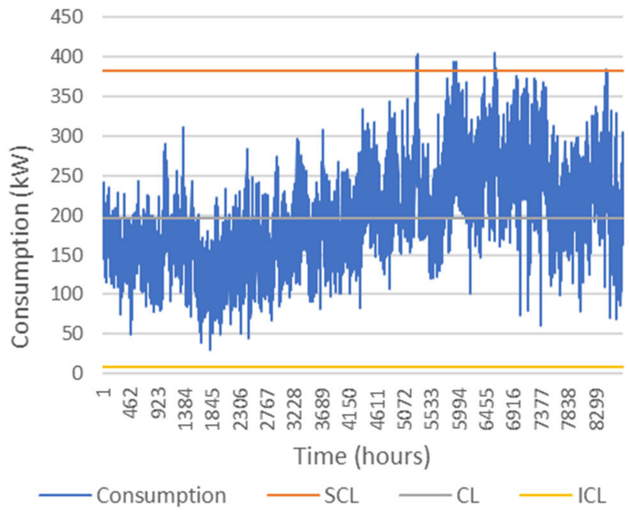

FIGURE 4. First type of sample analyzed, showcasing the entire set of data.

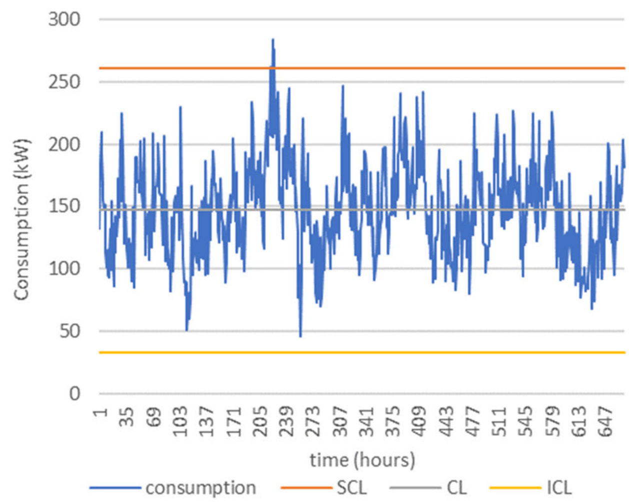

FIGURE 5. Second type of sample analyzed, employing the period from Mid-February to Mid-March.

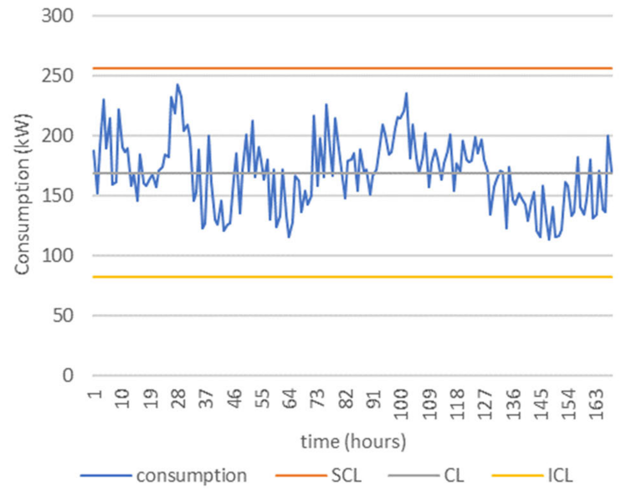

FIGURE 6. Third type of sample analyzed, showcasing the first week of the data set.

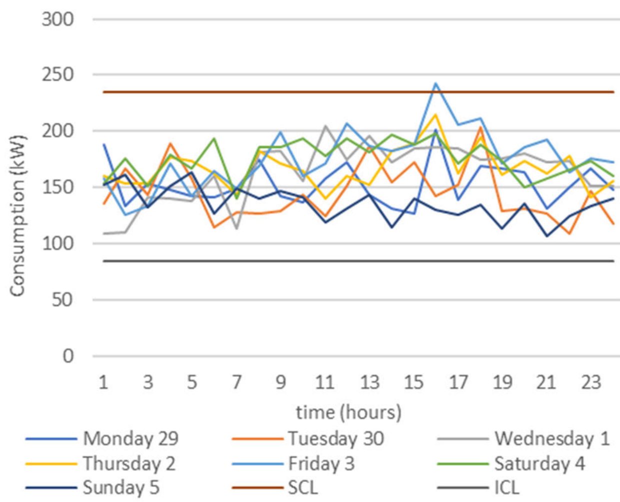

FIGURE 7. Fourth type of sample analyzed in which the comparison between all the days of the third week examined can be observed.

All the showcased graphs belong to the Shewhart analysis of the energy consumption, as this type of graph and variable requires the least amount of setup and previous adjustments.

B. SELECTION OF THE TIME SCALE

The amount of time scales analyzed is considerable, and all of them have their advantages and disadvantages. Even though it could be theoretically possible to simply employ all the different time scales simultaneously in the cloud platform, this could present problems. These problems could range from heavy computing load, to raising the risk of false alarms.

Therefore, if possible, it's helpful to select a time scale that can serve as the main representative of the analysis. This scale must strike a delicate balance by encompassing a substantial amount of data, and so preventing overfitting, while remaining manageable for analysis.

In that case, the week-sized division emerges as the primary monitoring system for automatic revision and monitorization, striking the best balance between scope and detail.

The other temporal scales, on the other hand, serve as auxiliary components, enhancing the manual revision process. Monthly and yearly analyses provide the capability of pattern recognition on a larger scale, whereas daily analysis allows for the identification of patterns on a smaller level.

Chart-specific observations related to temporal scales will be indicated in their respective sections if needed.

The upcoming sections will focus on a detailed examination of each of the charts, assessing their performance with respect to each variable.

The graphs chosen as examples were those of the third week of analysis, because of its relatively small but noticeable variations. This time frame starts on Monday 22 of November of 2021 at 12:00 and ends on Monday 29 of the same month at 11:00. In the case of temperature-related data, Chamber C has been chosen as the focal point for the graphical representation. This is because Chamber C is the most variable one, and this significantly impacts the values of the KPI.

V. RESULTS AND DISCUSSION

With all the necessary specifications presented and accounted for, the following sections will evaluate how each of the control charts perform by examining the three main variables in the selected time scale. The criterion for their evaluation is their ability to reliably detect anomalies in all three variables, along with the speed at which these anomalies are detected. If an anomaly is detected quickly, it can be fixed faster, and this minimizes the damage that they can cause and guarantees the system's efficiency. Distinguishing whether the anomaly is the result of an inefficient operation or the result of a need for maintenance would also be a desirable trait, but less fundamental to the performance of the charts.

Afterwards, the advantages and the disadvantages of each combination will be discussed, as well as the results that can be extracted from them.

A. ENERGY CONSUMPTION

This magnitude can be reasonably assumed to follow a normal distribution, and it's the least critical parameter among those analyzed. This is because the energy consumption plays a more significant role in evaluating the efficiency of the system than in security considerations. However, it must be considered in the analysis, as a higher power consumption can also be symptomatic of other problems within the system.

The following graphs showcase the behavior of the energy consumption in the three main charts, and the main points of interest of each are highlighted in the following sub-sections:

1.Analysis of the Shewhart charts: The variable benefits from the chart's accuracy regarding the data employed, since closely monitoring the variability of the energy consumption is important in energy efficiency.

Also, because of the lower level of danger for the system in the case of surpassing control limits, the benefits of having less risk of false alarms could potentially outweigh the drawbacks of a lower sensitivity.

The graph showcased in Figure 8 represents the natural values extracted from the energy consumption sensors, along with the Shawhart control limits, calculated using Formulas 4, 5, and 6 with parameters E(X) = 138.13 kW and $\sqrt{Var(X)} =$ 30.89. The values are plotted over the previously established period, measured in hours. While the values don't exceed the control limits at any point, the hour 30, corresponding to Tuesday 23 at 17:00, comes considerably close, with a value of 227 against a SCL of 230.79.

2. Analysis of the EWMA charts: The main benefit of the EWMA in the energy consumption is a higher sensibility, especially to gradual shifts, but that can be compounded by the fact that it also has a higher calculation complexity,

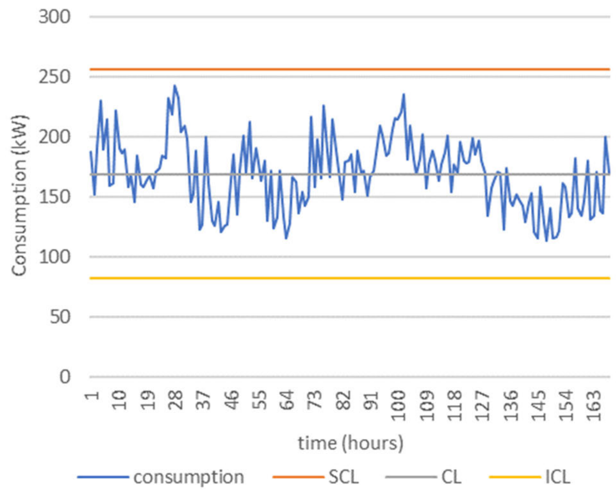

FIGURE 8. Shewhart chart of energy consumption.

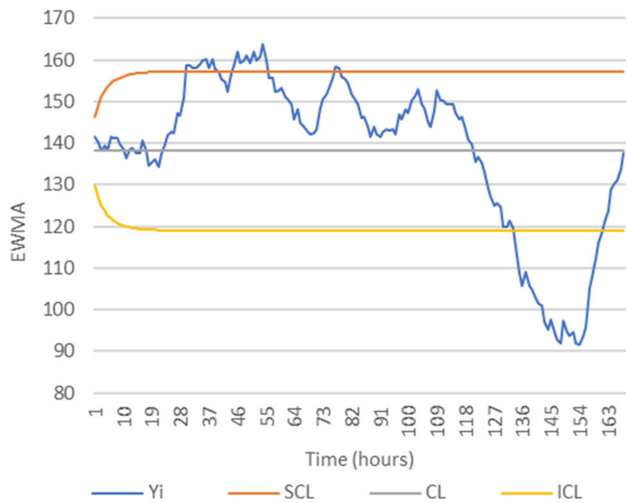

FIGURE 9. EWMA chart of energy consumption.

a slight loss of precision, and the potential increase in possibility of false alarms.

To see how much those drawbacks manifest, it's important to analyze the most meaningful values in Figure 9. This figure represents the auxiliary variable Yi shown in Formula 7, created from the values extracted from the energy consumption sensors over the previously established time period, measured in hours. This variable is represented against the EWMA control limits calculated with the Formulas 8, 9 and 10, using the values u_0 = 138.13 kW and σ = 30.89, alongside the parameters λ = 0.1 and L = 2.7.

First, there's a period between the hours 30 and 40, which correspond to Tuesday 23 at 17:00 and Wednesday 24 at 3:00 respectively, in which the chart surpasses the Superior Control Limit.

Second, there's another interval in which the value surpasses the SCL between the hour 45, which corresponds to

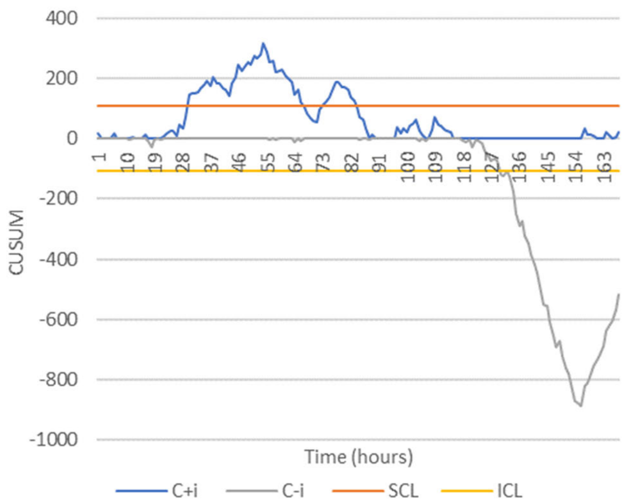

FIGURE 10. CUSUM chart of energy consumption.

Wednesday 24 at 8:00 and the hour 56, which corresponds to that same day at 19:00.

The third of interest is a small 2-hour interval between the hours 77 and 78 in which the EWMA surpasses the value of the Superior Control Limit again. These hours correspond to Thursday 25 between 16:00 and 17:00

Lastly, there's an interval between the hours 134 and 162 in which the graph goes below the Inferior Control Limit, and that interval corresponds to Sunday, 28 at 1:00 and Monday 29 at 5:00.

3. Analysis of the CUSUM charts: The nominally higher sensibility of this chart could be useful, but the drawbacks are at the most prominent in this variable, as this chart hides most of its information and only showcases the sum of the values that exceed the designed limit. This is a problem since energy consumption benefits from employing exact values to control the efficiency of the system.

Moreover, the low severity of this variable makes it so that an increased risk of false alarms is not worth the potentially higher sensitivity. To evaluate the performance of this chart, it's most significant values in the examined data, represented in Figure 10, will be analyzed. This figure represents the auxiliary variables C_i^+ and C_i^- against their respective control limits during the previously established time period, measured in hours. With a standard deviation of the period $\sigma = 30.89$, the control limits are considered equal to H = ±108,115. The auxiliary variables start from 0, with C_i^+ following formula 11 and C_i^- following formula 12. Both use the data extracted from the consumption sensors together with the values $u_0 = 138.13$ kW and k = 15.445, equal to the mean of the values of the sample and half of the value of its standard deviation respectively.

The first period that exceeds one of the control limits in either direction is the interval between the hours 30 and 67, which corresponds to Tuesday 23 at 17:00, and Thursday 25 at 6:00, in which the values surpass the Superior Control Limit.

The second period also surpasses the SCL and corresponds to the interval between the hours 73 and 84. These represent the dates of Thursday 25 at 12:00 and the same day at 23:00 respectively.

The last notable value is the hour 130, equivalent to Saturday 27 at 21:00 and is the point where the value of the chart drops below the Inferior Control Limit. Unlike other examples, it doesn't return to the control area for the duration of the analyzed period.

However, the main difference is that the CUSUM appears to take considerably longer to return to the control interval once it has exceeded the control limits in any direction. The most evident cases of this are the interval between hours 30 and 67, and the interval between hour 130 and the end of the graph.

In the first interval, two cases of product loading are grouped together with no distinction between them. In the second interval, the value doesn't return to the control limit despite the low consumption period having already passed.

However, despite this drawback, the CUSUM chart detects for the most part the same anomalies that the EWMA chart, but earlier.

4. Discussion of the energy consumption: The different properties of each chart have a considerable impact in their performance and the type of analysis that they can be used for in energy consumption. The table below shows the main anomalies detected in the sample and the interval of their detection, expressed in hours.

TABLE 2. Chart results in analyzing the energy consumption.

Anomaly	Shewhart	EWMA	CUSUM
1st Rise above SCL	Not detected	30-40	30-67
2nd Rise above SCL	Not detected	45-56	Grouped with the last one
3rd Rise above SCL	Not detected	77-78	73-84
1st Drop below ICL	Not detected	134-162	130-End of the sample.

It's very noticeable that the Shewhart doesn't manage to detect any of the anomalies the other two showcase. The hour 30 comes close but doesn't surpass the control limits. The next step is to analyze if these anomalies detected in the other charts are real or false alarms.

The first three anomalies have the same explanation: New products were being added into the installation. This caused an increase in energy consumption, as the cooling system must refrigerate an additional load of produce instead of merely keeping the temperature of the pre-existing products.

The last interval encompasses the entire day of Sunday and in the case pf the EWMA doesn't recover its original values until the early Monday hours. And this is not an isolated

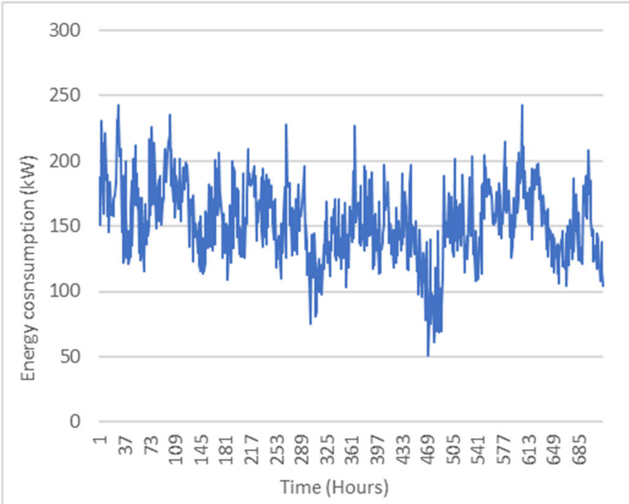

FIGURE 11. Energy consumption from early November to early December of 2021.

phenomenon. Figure 11 showcases the monthly interval that includes the analyzed week, and every single week suffers from a similar low consumption interval between the first hours of Sunday and early morning Monday. Those intervals are:

Hours 134 to 164, equivalent to the 14th of November at 1:00 and the 15th of November at 7:00

Hours 301 to 332, equivalent to the 21st of November at 0:00 and the 22nd of November at 7:00.

Hours 469 to 499, equivalent to the 28th of November at 0:00 and the 29th of November at 6:00.

Hours 639 to 666, equivalent to the 5th of December at 2:00 and the 6th of December at 5:00.

Because of this regularity in their time of emergence and their duration, it can be stated that this low consumption interval is an existing pattern in the system instead of a false alarm.

In fact, it can be stated that none of the detected anomalous values corresponds to a false alarm in the system, which highlights the sensibility of the memory type charts. However, it should be noted that none of these values corresponds to an error in the system either, they are exclusively operational alerts. With the validity of the anomalies confirmed, the results of the analysis in energy consumption are the following:

The Shewhart's accuracy might be ideal for detecting maintenance alerts in the installation since it works only with present values and uses exclusively the mean value and standard deviation. Therefore, it's useful to set up an alarm, for when it detects an anomaly, it's practically guaranteed to be an error in the system.

On the other hand, the other two charts work better from an efficiency point of view and the detection of operational errors. They help identifying overloads and drops in energy consumption, which is very useful to consider when designing energy efficiency measures.

Of these two, the EWMA doesn't exceed the values as much as the CUSUM chart and can get back to the control interval faster when the anomaly has stopped. In the case of the last anomaly, the CUSUSM doesn't return to the control values at all.

However, the CUSUM still works better for this function since it can detect the same anomalies as the EWMA, but with a couple of units of time faster. This is essential for an energy-sensitive process, since the units employed in this analysis are hours, so a small delay can make a big difference.

B. TEMPERATURE

Each analyzed chamber is assigned a specific target temperature, and the primary goal when considering temperature parameters for each chamber is to assess the deviation from this designated set point.

In case the standard deviation proves inadequate for the sampled data, it's possible to estimate the acceptable temperature variation necessary to maintain optimal storage conditions [10]. In this instance, the chosen level of tolerance is between 1 and 2.5°C from the set point.

The temperature benefits from close monitorization. However, given its critical role in food storage, the potential trade-off between heightened sensitivity, potential information loss, and an increased risk of false alarms may be justified if the advantages outweigh these concerns.

The following graphs showcase the behavior of the temperature in the three main charts, from which the main results can be reached:

1. **Analysis of the Shewhart charts**: The biggest problem with this chart is that it cannot simply be assumed that the data follows a normal distribution. It's possible for a chamber to stay at a temperature slightly higher or lower than the set value for a long time. This generates a small standard deviation, but it might not be harmful to the food if the difference is very low.

Despite this, some modifications can be made on the employed values so that they are more compatible with the Shewhart chart. In this analysis, the modifications chosen were the following ones:

First, using the set temperatures as an alternative control line instead of the mean value.

Second, substituting the standard deviation for another value that could serve a similar function. To synergize with the first modification, the chosen value was the square root of the Mean Squared Error (MSE). The MSE corresponds to the average of the squared difference between the estimated value of an experiment (In this case, the set point of the temperature) and the actual measured values. This translates into a value of 0.73, which turns into control limits with a value of around 2.1 degrees Celsius from the set point. This falls within the limits chosen earlier.

It was deemed that in with those modifications, the high accuracy of this chart could become useful. The results of this

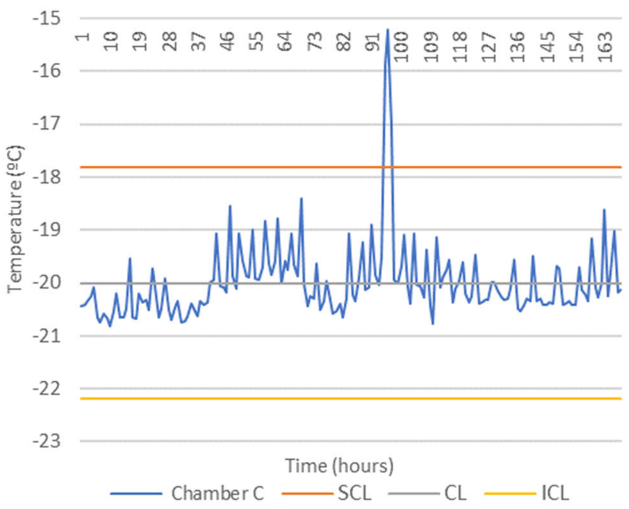

FIGURE 12. Shewhart chart of the Chamber C temperature.

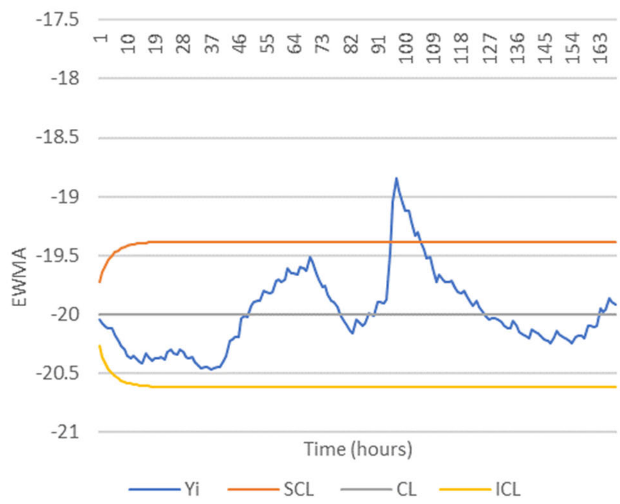

FIGURE 13. EWMA chart of the Chamber C temperature.

analysis are showcased in Figure 12. This figure represents the natural values extracted from the temperature sensors of chamber C, together with the Shawhart limits calculated by Formulas 4, 5 and 6, with the values E(X) $= -20°$C (The set value of the Temperature in chamber C) and the value $\sqrt{Var\ (X)}$ equal to 0.73 (Result of the previously calculated MSE) The values are represented over the established period of time, measured in hours.

Its most noticeable value is the huge spike in temperature that surpasses the Superior Control Limit from the hours 95 to 97, which are equivalent to Friday 26 from 10:00 to 12:00.

2. **Analysis of the EWMA charts**: The higher flexibility of the EWMA provides a considerable advantage in the analysis of temperature. The presence of fixed values for both the control line and the weighting factor has the added effect of making it much easier to detect larger and slower shifts instead of being absorbed into the graphs. This factor is a huge advantage that complements the higher sensibility of the chart. Also, the chart still provides a comparatively accurate, if smoothed, graph of the variable. In that case, the loss of information isn't very significant.

The graph showcased on Figure 13 represents the auxiliary variable Yi shown in Formula 7, created from the values extracted from the temperature sensors of chamber C during the previously established period, measured in hours. This variable is represented against the EWMA limits calculated by Formulas 8, 9 and 10, using the values $u_0 = -20°$C and $\sigma = 1$, which are equivalent to the set temperature of Chamber C and an acceptable temperature deviation of 1°C respectively. The other parameters of the functions correspond to the standardized values $\lambda = 0.1$ and L = 2.7.

Some minor noteworthy points of interest are the hour 69, when there's a minor peak in the temperature that nevertheless doesn't manage to reach the Superior Control Limit, corresponding to Thursday, 25 at 8:00.

Lastly, there's a considerable interval between the start of the sample on Monday 22 at 12:00 and the hour 42, Wednesday 24 at 5:00 in which the temperature is noticeably lower than normal, while also not managing to drop below the Inferior Control Limit at any point.

The most notable interval of interest, however, is between the hour 96, where the value surpasses the superior control limit, and hour 106, there the value goes back to the control interval. These hours correspond to the day Friday 26 at 11:00, and the same day at 21:00 respectively. This value is equivalent to the same spike in temperatures detected in the Shewhart chart but detected an hour later.

3. **Analysis of the CUSUM charts**: The higher sensibility of the chart is a very tempting prospect for a variable so essential for the security of the warehouse, not to mention that the chart can be made to easily fit the specifications of the set value and standard 1°C variation that was also employed in the EWMA chart. The resulting graph is showcased in Figure 14 which represents the auxiliary variables C_i^+ and C_i^- against their respective control limits during the previously established period, measured in hours. With an acceptable difference value $\sigma = 1$, the control limits are considered equal to H $= \pm 3.5$. The auxiliary variables start from 0, with C_i^+ following formula 11 and C_i^- following formula 12. Both use the data extracted from the temperature sensors of Chamber C together with the values $u_0 = -20$ °C and k $= 0.5$, which are equivalent to the chamber setpoint temperature and half of the accepted deviation respectively.

Its main distinctive feature is the massive spike in values that surpasses the Superior control limit in hour 95, equivalent to Friday 26 at 10:00, and the process does not go back to being in control until hour 116, equivalent to Saturday 27 at 7:00.

4. Discussion of the Temperature: The temperature presents some unique challenges regarding the monitorization. All the charts have been able to detect the sudden rise in the temperature of chamber C, but their performance is influenced by other factors. The following table showcases the intervals in which each chart detected the main anomaly.

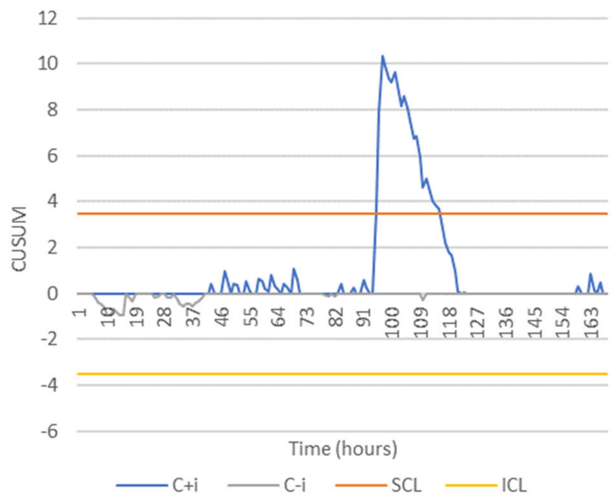

FIGURE 14. CUSUM chart of the Chamber C temperature.

TABLE 3. Chart results in analyzing the temperature.

Anomaly	Shewhart	EWMA	CUSUM
Rise above SCL	95-97	96-106	95-116

There are two criteria to consider this a real alert and not a false alarm: Either this point entails a noticeable fluctuation in energy consumption, or it causes a risk to the stored goods.

Since the increase in temperature is considerable (Over 4.5 degrees in its highest point) this poses a noticeable danger to the product and therefore is considered a maintenance alert instead of a false alarm.

With the validity of the anomaly confirmed, the performance of the charts will be analyzed:

One the one hand, while the Shewhart chart can employ alternate values to help it with the development of the graphs, and the results have been adequate on the experiment, those are still ultimately dependent of the values of the sample. So, even though it detected the anomaly in time, it can't be considered reliable in the monitorization of temperature. While it still could potentially be useful for detecting malfunctions quickly, it's inefficient and not a good fit for this kind of variable.

On the other hand, the EWMA chart has the advantage of being able to fit better with the needs of this variable. Moreover, the sensibility of the chart can be adjusted more ergonomically than with the Shewhart chart, and still helps showing several tendencies within the graph that can help with the selection of efficiency measures. However, by far the biggest problem with the chart is the fact that it detects the anomaly one hour later than the Shewhart chart. This happens because of the weight of the memory in the EWMA chart. It's not overwhelming, but it makes it more difficult for the chart to detect strong sudden shifts, and it takes it slightly longer to return to the control area.

While this point it's also closer to where the auxiliary cooling equipment starts functioning, this delay is a massive problem for an energy sensitive system. In this example, a whole hour could be the difference between a product being lost or salvageable.

The CUSUM chart, meanwhile, has the advantages of being able to be easily adjusted to the parameters of the analyzed chamber, while at the same time managing to detect the rise in temperatures at the same time as the Shewhart chart. The biggest drawback of the CUSUM chart is that when it surpasses the control limits, it takes considerably longer time to return to the control values, even more than the EWMA chart. This could be a problem, especially when it hides other potential alarms when being outside the control limits, or like this example when the anomaly is very brief, but the chart doesn't reflect it.

Despite these drawbacks, the CUSUM has the best of both other charts and is the best to use to set up alarms in the temperature.

It should be noted that all these charts require that their formulas use of the set temperature in the place of the mean and an assigned acceptable value instead of the standard deviation to be functional. Using the unmodified formulas leads to the analysis being performed around the sample instead of the characteristics of the installation, which can lead to distorted values and false alarms.

As an example of this phenomenon, let's compare the examination of the Chamber B with the CUSUM charts. Both of the following graphs in Figure 15 cover the same week and use the same parameters. However, the first one employs all the modifications used on the previous graphs, while the second one uses the standard formula without any changes. This includes the adjusted lower CUSUM statistic (C_i^-) that was made for easier observation.

It's possible to see that with the modifications, the CUSUM stays not just within limits, but without any variations big enough to be noticeable. However, in the version without the changes, not only surpasses the control limit multiple times and with both statistics, said statistics overlap visually with each other and their values are also noticeably lower.

This happens because the mean value of the chamber in the sample is 3.5°C and the standard deviation is 0.076°C compared to the set value of 3.7°C and the assigned accepted deviation of 1°C. Which means the sample stays with very little variation at a temperature slightly lower than the set point, but at no point is this temperature a danger to the stored goods. Therefore, in the second graph all the instances of a statistic surpassing the control limit can be considered false alarms, created because the chart is reacting very strongly to very small changes to the temperature.

The proposed modifications help avoid these mistakes, centering the set value of the installation as the point around which the variations are considered, setting an acceptable deviation that takes into account the needs of the specific

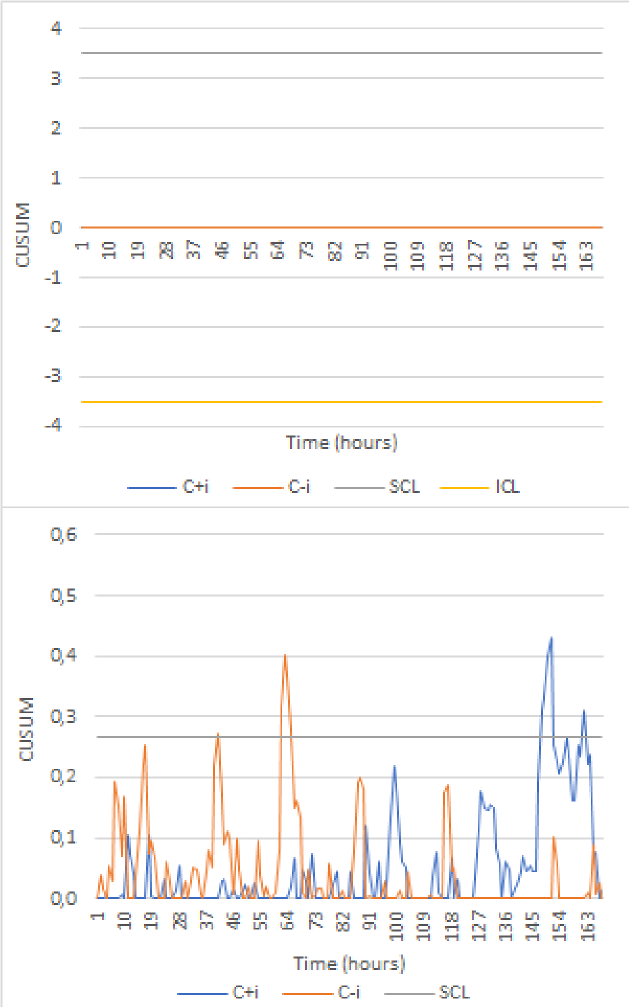

FIGURE 15. **CUSUM chart of the Chamber C temperature.**

stored goods, and making it so more information is conveyed visually in case of need.

C. KEY PERFORMANCE INDICATOR

One advantage that this magnitude has is that operates similarly to temperature, with an ideal value that can be targeted, in this case 0. As stated previously, this would correspond to all the analyzed chambers being at their designated set temperatures.

Accepting a variance of 1°C for each chamber, the cumulative sum of variations across the three analyzed chambers results in an accepted variance of approximately 3°C.

Conversely, the selected variance for consumption is based on the standard deviation of the entire year's dataset, approximately 62.43 kW. This choice minimizes risk of overfitting and ensures applicability across experiments.

The product of these two variances, totaling 187.3, is used as a substitute for the standard deviation of the KPI in all the experiments.

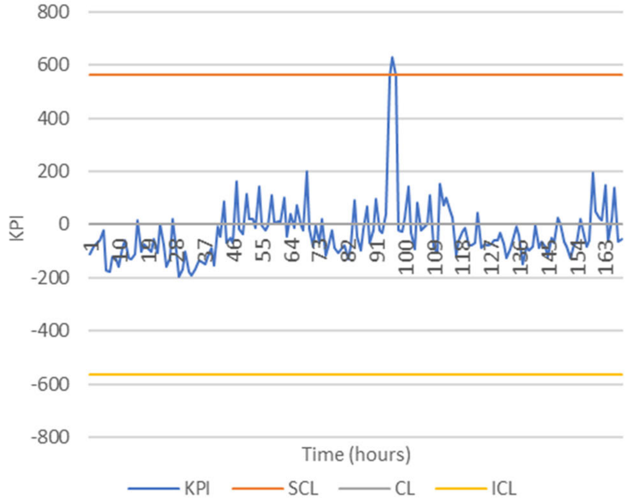

FIGURE 16. **Shewhart chart of the KPI variable.**

The following graphs will analyze the behavior of the KPI in the three main charts:

1. **Analysis of the Shewhart charts**: The fact that the chosen KPI is a compound of two other values gives it flexibility regarding the utility of the chart and the values used in it.

However, this parameter faces a similar problem than the temperatures: The most important factor for the monitorization is the distance of the values to a set point, when this chart specializes more in keeping the said values stable. Despite this, the chart has been analyzed, using the value of $E(X) = 0$ and $\sqrt{Var(X)}$ equal to 187.3 to (the previously mentioned product of the variances) to create the Shewhart control limits shown in Formulas 4, 5 and 6, and the results can be observed in the Figure 16:

The only notable point of interest is hour 96, when the graph surpasses the Superior Control Line. This corresponds to Friday 26 at 11:00, and it's the only point on the entire chart in which the graph surpasses any of the control limits.

2. **Analysis of the EWMA charts**: The EWMA chart employs the same standardized values for the construction of the graph as the Shewhart chart. The results of this analysis can be seen in Figure 17. It represents the auxiliary variable Yi shown in Formula 7, created from the composite KPI values over the previously established time period, measured in hours. This variable is represented against the EWMA limits calculated through Formulas 8, 9 and 10, using the values $u_0 = 0$ and $\sigma = 187.3$, which are equivalent to the ideal value of the KPI and the deviation that was previously designated as acceptable, respectively. The other parameters of the functions correspond to the standardized values $\lambda = 0.1$ and $L = 2.7$.

There are two main points of interest in the chart. The first one is from hour 34, where the graph drops below the Inferior Control Line, to hour 41, when it goes back to the control interval again. These are equivalent to Tuesday 23 at 21:00 and to Wednesday 24 at 4:00 respectively.

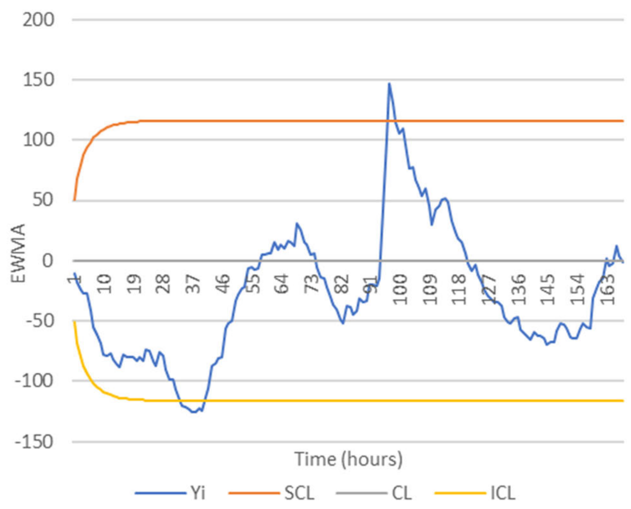

FIGURE 17. EWMA chart of the KPI variable.

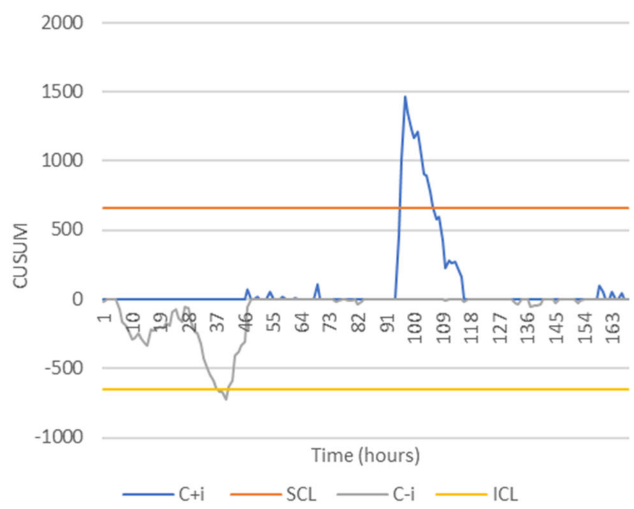

FIGURE 18. CUSUM chart of the KPI variable.

The second one is from hour 97, where it surpasses the Superior Control Line, to hour 99, where it goes below it again. The are equivalent to Friday 26 at 12:00 and at 14:00 respectively.

3. **Analysis of the CUSUM charts**: The KPI has a couple of advantage over the others regarding the compatibility with this chart: A high enough magnitude it's warranted to be harmful to the installation, and it's not as crucial to know the specific values. This means that the biggest drawback of this chart is not as big of a problem for the KPI than for the rest of the variables. The resulting graph can be observed in Figure 18, which represents the auxiliary variables C_i^+ and C_i^- against their respective control limits during the previously established time period, measured in hours. With an acceptable difference value $\sigma = 187.3$, the control limits are considered equal to H $= \pm 655.55$. The auxiliary variables start from 0, with C_i^+ following formula 11 and C_i^- following formula 12. Both use the composite data generated for the KPI with the information from the temperature and energy consumption sensors, together with the values u_0 = 0 and k=93.65 These are equivalent to the ideal value of the KPI and half of the accepted deviation respectively..

The most notable points of interest are the following:

First, the interval between hours 38 and 40, when the graph drops below the Inferior Control Limit. These hours correspond to Wednesday 23 at 2:00 and the same day at 4:00 respectively.

Second, the interval between hours 96 and 107, when it surpasses the Superior Control Limit. These hours correspond to Friday 26 at 11:00 and at 22:00 respectively.

4. Discussion of the KPI: In the analysis of this variable all the charts have employed the same values of mean and deviation, so they operate on a somewhat leveled playing field. This helps emphasize the differences in performance between the three of them. The results of the experiments can be seen in the following table.

TABLE 4. Chart results in analyzing the KPI.

Anomaly	Shewhart	EWMA	CUSUM
Drop below ICL	Not detected	34-41	38-40
Rise above SCL	96	97-99	96-107

The KPI should prove its usefulness in two areas: when there is a threat to the quality of the product or when excessive energy consumption poses a risk to the installation.

The first point of interest is not detected by the Shewhart chart, and it reflects an interval with a high level of consumption happening around the same time as a period where the temperature of the chambers was lower than normal.

The second point of interest is equivalent to the temperature spike seen around that time, which had already been identified as a danger to the quality of the products within the installation.

Both anomalies can be considered genuine problems within the system. Because the raise in consumption occurred because a change in loads within the installation, first anomaly can be considered an operational alert. The second is a maintenance alert, as in the temperature analysis.

Knowing that both anomalies are valid, the next step will be to analyze the performance of the charts:

First, the Shewhart's precision proves itself to be mostly inadequate. There isn't a big advantage to the accuracy of the showcased data given the ambiguity of the intermediate values, and its low sensitivity becomes a problem since there's an anomaly that it doesn't manage to detect.

The memory-type charts do manage to detect both anomalies but differ when they detect each one and how long does the detection last.

The EWMA detects the drop below the ICL significantly earlier and takes a while for the process to return to control values, while it detects the rise above the SCL one hour later, even if it doesn't stay out of control for very long.

In the CUSUM, the drop below the ICL is detected several hours later and it's only a brief incidence, while the rise in temperatures is detected quickly and takes a considerable amount of time to return to its control values.

Of the two anomalies, the rise over the SCL represents a brief phenomenon, while the drop below the ICL is symptomatic of a problem that happens over a period. Therefore, the EWMA chart's representation of the anomalies is more in-line with the behavior of their root causes and manages to detect the operational alert considerably faster than the CUSUM chart. However, the CUSUM still manages to detect the maintenance alert an hour earlier than the EWMA.

So, while both charts are useful, there doesn't seem to be one clearly superior to the other.

For the most part, the KPI appears to fulfill its function correctly within the EWMA and the CUSUM charts, surpassing the control values when the energy consumption is so high that it signals something harmful to the system (As in the first anomaly) or when the quality of the product is being compromised. (As in the second anomaly)

It should be noted, however, that for this to be the case, both charts need to employ the setup and modifications that were described in the previous sections. It might be possible to select another deviation for the energy consumption rather than the standard deviation of the entire year's dataset, but as shown with Figure 15 regarding the temperatures, using the mean and deviation of the sample can easily lead to false alarms and overfitting the chart to the sample. Employing the set points of the temperatures and the acceptable deviation in all the chambers helps avoid this problem, and this also applies to the KPI as it's a compound variable of the temperatures.

D. LIMITS AND FUTURE WORK

It should be noted that study examined only a specific type of energy-sensitive process, the control of temperature in refrigerated food storage. Future studies could investigate the needs of more types of foods, analyze other variables like the humidity, or apply the methods discussed in this paper to other energy sensitive industries like pharmaceutics.

E. OVERALL DISCUSSION

The control charts are an extremely useful analysis feature, but they need to be implemented with care. The characteristics of the variable dictate how much the qualities of a certain chart can benefit them, and in some cases, the theoretical advantages offered by a chart can't be observed in the studied examples.

The following section will have two main functions:

Showcase notable situations in which more than one variable is affected at once.

Evaluate the performance of the charts after having used them to analyze all the variables.

TABLE 5. Comparison of the early anomaly between the different variables.

Variable	Time of the anomaly	Behavior in the EWMA chart
Energy Consumption	30-40	Surpassed limits
Temperature	32-42	Not surpassed limits
KPI	34-41	Surpassed limits

1. **Notable situations**: There are a few instances where an anomaly that doesn't seem relevant enough in its own chart has a higher significance in the whole system. The main example of this is the valley that was observed in the EWMA chart of the temperature from the start of the sample to around hour 42, but it's especially notable starting from hour 32.

This anomaly doesn't surpass the established control limits, and therefore doesn't cause an alert, but it's significant when compared with the values of the EWMA chart in energy consumption and in the KPI around the same time.

The fact that this temperature is so low while there's an unusual amount of energy consumption is what causes the anomaly in the KPI variable.

This anomaly represents one of the problems with having a single unified refrigeration system for all chambers. The anomaly in energy consumption occurred because of the extra load added to a different chamber at that time and forcing the equipment to consume more energy to cool down the added load instead of just keeping the existing goods refrigerated.

But because the whole system is connected, it also had the unintended side effect of slightly decreasing the already low temperature of the rest of the chambers for a few hours. This is the reason the KPI surpasses the control limits, and notably no other point in which the energy consumption surpasses the control limits in its charts has an equivalent in the KPI.

2. **Performance of the charts in energy sensitive industries**: These are the main observations made on the three employed charts and their usefulness:

The Shewhart chart seems perfectly capable to detect the maintenance alerts quickly. However, it has been unable to detect a single operational alert in all the experiments. Because of this, the chart is only useful in certain situations where the operational concerns don't pose a huge risk to the safety of the installation, like the monitoring of energy consumption.

The EWMA can detect all the operational and maintenance alerts, but it suffers from a major problem: Every alert with every variable is detected at least an hour later than the rest of the charts. The only exceptions are the operational alert in the KPI, in which is faster than the CUSUM; and the first operational alert in the energy consumption, which is detected at the same time as the CUSUM. These delays are very damaging for energy sensitive processes, especially in the case study since the smallest unit of time employed is an hour. Therefore, the EWMA chart is extremely situational, only surpassing other charts on operational alerts in the KPI variable. It would only be useful as an auxiliary measure in that specific variable, or as a smoothing graphic tool to evaluate tendencies, like in the previous section.

The CUSUM is also able to detect both operational and maintenance alerts in all variables. The maintenance alerts detect them at the same time as the Shewhart, and both types of alerts faster than the EWMA chart. The only exception is the operational alert in the KPI, in which is slower and is barely able to detect the anomaly. Its biggest drawback is that once the value surpasses the control limits, it takes a considerable amount of time to get back. While that could be remedied by making it less sensitive, that could also prevent it from detecting some anomalies at all, and the drawback is not as big of a problem in this type of process.

3. Contributions of the analysis: While not perfect, the CUSUM emerges as the optimal and most useful chart for the control of variables in energy sensitive processes. However, as it was pointed out in the discussion of the temperature and the KPI, the chart requires some modifications to function effectively in these conditions. Using the standard formula with only the values of the specific samples leads to false alarms, the overfitting of the sample, and less visual information in the case that a manual revision is desired. Therefore, these modifications are essential for the employment of this chart in any energy sensitive industries.

In all variables, the two main statistics are as follows.

$$C_i^+ = max[0, (X_i - u_0) - k + C_{i-1}^+] \tag{14}$$
$$C_i^- = -max[0, -(X_i - u_0) - k - C_{i-1}^-] \tag{15}$$

Both statistics are plotted against a control limit with the same absolute value, and in all cases, X_i represents the observation of the sample I and both C_{i-1}^+ and C_{i-1}^- represent the previous value of the statistic, which is initially set to zero.

However, in each of the variables, both the control limits and the parameters u_0 and k have different values.

In the Energy Consumption, both u_0 and k have their standard values. u_0 is the mean of the sample, lacking a precise target value. The reference value k corresponds to half of the standard deviation of the sample, and the control limits are considered 3.5 times the standard deviation. Using the chart to monitor the energy consumption with these values helps analyze the energy efficiency of the system.

In the Temperature, the value of u_0 is equal to the set point of the corresponding chamber, which serves as the target mean. And instead of using the standard deviation, both k and the control limits use the assigned accepted deviation of 1°C. Control of the temperature is essential for the safety of the refrigerated system, and these values allow the CUSUM chart to fit the needs of the stored goods.

In the KPI, the value of u_0 is equal to 0, which signifies that all the analyzed chambers are at their set temperatures. And instead of the standard deviation of the sample, the reference value k and the control limits employ a compound value. This value is equal to the standard deviation of the energy consumption along entire year's dataset, multiplied by the sum of the assigned accepted deviations of all the chambers.

With these parameters the analysis of the KPI with the CUSUM chart serves to measure the impact of the deviations in the system, making it useful in determining if any given alert in the energy consumption also constitutes a potential danger to the safety of the stored goods, as it was the case with its operational alert explained above. The KPI can also be used to monitor other variables with desired set points, like the humidity, which makes it a versatile and useful monitoring tool to increase the safety in energy sensitive industries.

VI. CONCLUSION

This article aims to serve as a steppingstone in the analysis of efficiency in energy-sensitive processes, which are vital elements in many industries. In these processes, there are many variables that need to be kept in control simultaneously, in this case the most notable are the energy consumption and the temperature to which the energy consumption is meant to regulate. In these variables, there are some minor variations that are not the result of a system failure, but merely a result of changes in the operational modes in the installation. The control charts allow to keep control of these variables while helping filter these regular variations out but some modifications and specific values to help them detect the real errors as quickly as possible without being so sensitive as to create false alarms. This makes this study valuable because it indicates not only which charts are better for the analysis, but also the required adaptations of the charts so that they can be used more efficiently.

In this case, the chart that performed better in all the analyzed variables was the CUSUM chart. This chart was able to detect all the operational alerts as well as the maintenance alerts, and the detection happens faster than with other analyzed charts in most cases, which is crucial in energy sensitive industries. The adaptations suggested in this article help the chart in various ways. By turning the statistic C- into a negative function and making it more obvious which of the functions corresponds to the shifts below the target value, the chart convey more visual information for manual revision. Most critically, by setting the parameters of u0 and k to the previously discussed values in each variable, it's possible to minimize the risk of false alarms in all variables, while maximizing sensitivity.

Additionally, said variables are very important for the analysis of the industry. All the variables examined have demonstrated their usefulness in different areas:

First, the monitorization of energy consumption is crucial for the analysis of the efficiency of the system, being able to detect processes like the overloads resulting from the refrigeration of extra added load, or drops like the one detected on Sundays. This makes it easier to assign proper energy efficiency measures to the installation.

Second, the control of the temperature is essential for the safety of the installation, being the main factor that determines the quality of the stored goods, and the main reason that the refrigeration process is energy-sensitive to begin with.

Lastly, this study also introduces an additional Key Performance Indicator or KPI. This variable helps measure the impact of anomalies within the system and can be used to measure the severity of some alerts. For example, in the analyzed cases the KPI helps distinguish that a certain alert that was also detected in the energy consumption possesses a problem for the safety of the system rather than only its efficiency. and allows to analyze the temperatures of the whole installation rather than only chamber by chamber. Additionally, this parameter is flexible and can be easily customized to analyze other variables of interest.

Overall, practically any energy sensitive industry will benefit from close monitorization. But choosing the optimal tools and procedures for the monitoring process can make it considerably more efficient, safe, and accessible.

REFERENCES

[1] C. Jones and A. Piebalgs, *The Role of CCUS on the EU Road to Climate Neutrality*. Fiesole, Italy: European University Institute, 2022.

[2] R. Neugebauer, M. Putz, A. Schlegel, T. Langer, E. Franz, and S. Lorenz, "Energy-sensitive production control in mixed model manufacturing processes," in *Proc. Leveraging Technol. Sustain. World, 19th CIRP Conf. Life Cycle Eng.*, Berkeley, USA, May 2012, pp. 399–404.

[3] K. Fikiin, B. Stankov, J. Evans, G. Maidment, A. Foster, T. Brown, J. Radcliffe, M. Youbi-Idrissi, A. Alford, L. Varga, G. Alvarez, I. E. Ivanov, C. Bond, I. Colombo, G. Garcia-Naveda, I. Ivanov, K. Hattori, D. Umeki, T. Bojkov, and N. Kaloyanov, "Refrigerated warehouses as intelligent hubs to integrate renewable energy in industrial food refrigeration and to enhance power grid sustainability," *Trends Food Sci. Technol.*, vol. 60, pp. 96–103, Feb. 2017.

[4] Meteor Space. (2022). *25+ Warehouse Energy Consumption Statistics You Need to Know*. Accessed: May 2, 2024. [Online]. Available: https://www.meteorspace.com/25-warehouse-energy-consumption-statistics-you-need-to-know/

[5] J. A. Evans, A. M. Foster, J.-M. Huet, L. Reinholdt, K. Fikiin, C. Zilio, M. Houska, A. Landfeld, C. Bond, M. Scheurs, and T. W. M. van Sambeeck, "Specific energy consumption values for various refrigerated food cold stores," *Energy Buildings*, vol. 74, pp. 141–151, May 2014.

[6] I. M. Marklinder, M. Lindblad, L. M. Eriksson, A. M. Finnson, and R. Lindqvist, "Home storage temperatures and consumer handling of refrigerated foods in Sweden," *J. Food Protection*, vol. 67, no. 11, pp. 2570–2577, Nov. 2004.

[7] W. R. Kim, M. M. Aung, Y. S. Chang, and C. Makatsoris, "Freshness gauge based cold storage management: A method for adjusting temperature and humidity levels for food quality," *Food Control*, vol. 47, pp. 510–519, Jan. 2015.

[8] M. M. Aung and Y. S. Chang, "Temperature management for the quality assurance of a perishable food supply chain," *Food Control*, vol. 40, pp. 198–207, Jun. 2014.

[9] J. A. Evans, E. C. Hammond, A. J. Gigiel, A. M. Fostera, L. Reinholdt, K. Fikiin, and C. Zilio, "Assessment of methods to reduce the energy consumption of food cold stores," *Appl. Thermal Eng.*, vol. 62, no. 2, pp. 697–705, Jan. 2014.

[10] J. Sun, P. Im, Y. Bae, J. Munk, T. Kuruganti, and B. Fricke, "Fault detection of low global warming potential refrigerant supermarket refrigeration system: Experimental investigation," *Case Stud. Thermal Eng.*, vol. 26, Aug. 2021, Art. no. 101200.

[11] S. Tong, B. Nie, Z. Li, C. Li, B. Zou, L. Jiang, Y. Jin, and Y. Ding, "A phase change material (PCM) based passively cooled container for integrated road-rail cold chain transportation—An experimental study," *Appl. Thermal Eng.*, vol. 195, Aug. 2021, Art. no. 117204.

[12] D. Pudleiner and J. Colton, "Using sensitivity analysis to improve the efficiency of a net-zero energy vaccine warehouse design," *Building Environ.*, vol. 87, pp. 302–314, May 2015.

[13] I. C. Yilmaz and D. Yilmaz, "Optimal capacity for sustainable refrigerated storage buildings," *Case Stud. Thermal Eng.*, vol. 22, Dec. 2020, Art. no. 100751.

[14] B. Hackett, S. Chow, and G. AR, "Energy efficiency opportunities in fresh fruit and vegetable processing/cold storage facilities," in *Proc. ACEEE Summer Study Energy Efficiency Industry, Amer. Council Energy-Efficient Economy*, Washington, DC, USA, Jul. 2005, pp. 1–10.

[15] W. B. Ekman, "Innovation in cold storage technologies," *Stewart Postharvest Rev.*, vol. 1, no. 3, pp. 1–14, 2005.

[16] K. Zhao, M. Zhu, B. Xiao, X. Yang, C. Gong, and J. Wu, "Joint RFID and UWB technologies in intelligent warehousing management system," *IEEE Internet Things J.*, vol. 7, no. 12, pp. 11640–11655, Dec. 2020.

[17] Y. Song, F. R. Yu, L. Zhou, X. Yang, and Z. He, "Applications of the Internet of Things (IoT) in smart logistics: A comprehensive survey," *IEEE Internet Things J.*, vol. 8, no. 6, pp. 4250–4274, Mar. 2021.

[18] A. Pal and K. Kant, "Internet of perishable logistics: Building smart fresh food supply chain networks," *IEEE Access*, vol. 7, pp. 17675–17695, 2019.

[19] M. van Geest, B. Tekinerdogan, and C. Catal, "Smart warehouses: Rationale, challenges and solution directions," *Appl. Sci.*, vol. 12, no. 1, p. 219, Dec. 2021.

[20] Z. Mao, F. Li, Q. Su, Z. Fang, X. Xu, and Y. Ding, "Application of energy-saving control strategy in air conditioning terminal equipment based on constant temperature difference of chilled water," *Case Studies Thermal Eng.*, vol. 28, Art. no. 2021, p. 101409.

[21] A. Mukherjee and R. Sen, "Comparisons of shewhart-type rank based control charts for monitoring location parameters of univariate processes," *Int. J. Prod. Res.*, vol. 53, no. 14, pp. 4414–4445, Jul. 2015.

[22] V. D. C. C. de Vargas, L. F. Dias Lopes, and A. Mendonça Souza, "Comparative study of the performance of the CuSum and EWMA control charts," *Comput. Ind. Eng.*, vol. 46, no. 4, pp. 707–724, Jul. 2004.

[23] M. Faisal, R. F. Zafar, N. Abbas, M. Riaz, and T. Mahmood, "A modified CUSUM control chart for monitoring industrial processes," *Qual. Rel. Eng. Int.*, vol. 34, no. 6, pp. 1045–1058, Oct. 2018.

[24] N. Abbas, M. Riaz, and R. J. Does, "Mixed exponentially weighted moving average-cumulative sum charts for process monitoring," *Mixed Exponentially Weighted Moving Average-Cumulative Sum Charts Process Monitor.*, vol. 29, no. 3, pp. 345–356, 2013.

[25] M. V. Koutras, S. Bersimis, and P. E. Maravelakis, "Statistical process control using shewhart control charts with supplementary runs rules," *Methodology Comput. Appl. Probab.*, vol. 9, no. 2, pp. 207–224, Jun. 2007.

[26] H. Fan, "Theoretical basis and system establishment of China food safety intelligent supervision in the perspective of Internet of Things," *IEEE Access*, vol. 7, pp. 71686–71695, 2019.

[27] B. Hu, H. Guo, X. Tao, and Y. Zhang, "Construction of digital twin system for cold chain logistics stereo warehouse," *IEEE Access*, vol. 11, pp. 73850–73862, 2023.

[28] D. Mariano-Hernández, L. Hernández-Callejo, A. Zorita-Lamadrid, O. Duque-Pérez, and F. Santos García, "A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis," *J. Building Eng.*, vol. 33, Jan. 2021, Art. no. 101692.

[29] S. Sivakumar, J. Logeshwaran, R. Kannadasan, M. Faheem, and D. Ravikumar, "A novel energy optimization framework to enhance the performance of sensor nodes in Industry 4.0," *Energy Sci. Eng.*, vol. 12, no. 3, pp. 835–859, Mar. 2024.

[30] O. Oloruntobi, K. Mokhtar, N. M. Rozar, A. Gohari, S. Asif, and L. F. Chuah, "Effective technologies and practices for reducing pollution in warehouses—A review," *Cleaner Eng. Technol.*, vol. 13, Apr. 2023, Art. no. 100622.

[31] S. Z. Fernandez, S. Gomez Vazquez, J. B. Montes, and S. C. Oliveira, "Digital twin modeling of refrigerated warehouses," *Dyna*, vol. 98, no. 3, pp. 234–439, May 2023.

[32] C. Schmidt, W. Li, S. Thiede, B. Kornfeld, S. Kara, and C. Herrmann, "Implementing key performance indicators for energy efficiency in manufacturing," *Proc. CIRP*, vol. 57, pp. 758–763, Jan. 2016.

[33] J. Al Dakheel, C. Del Pero, N. Aste, and F. Leonforte, "Smart buildings features and key performance indicators: A review," *Sustain. Cities Soc.*, vol. 61, Oct. 2020, Art. no. 102328.

[34] E. T. Volodarsky and I. O. Pototskiy, "Theoretical substantiation and application of CUSUM-charts," in *Proc. IEEE 8th Int. Conf. Adv. Optoelectronics Lasers (CAOL)*, Sep. 2019, pp. 636–639.

[35] R. A. Sanusi, N. Abbas, and M. Riaz, ''On efficient CUSUM-type location control charts using auxiliary information,'' *Qual. Technol. Quant. Manage.*, vol. 15, no. 1, pp. 87–105, Jan. 2018.
[36] R. A. Sanusi, ''An EWMA monitoring scheme with a single auxiliary variable for industrial processes,'' *Comput. Ind. Eng.*, vol. 114, pp. 1–10, Jan. 2017.
[37] S. V. Crowder, ''Process control and statistical inference,'' *J. Qual. Technol.*, vol. 29, no. 2, pp. 134–139, 1997.
[38] Y. J. Ou, J. Hu, X. Li, and T. Le, ''MIMO EWMA-CUSUM condition-based statistical process control in manufacturing processes,'' in *Proc. IEEE Emerg. Technol. Factory Autom. (ETFA)*, Barcelona, Spain, Sep. 2014, pp. 1–8.
[39] S. Ali, Z. Abbas, H. Z. Nazir, M. Riaz, X. Zhang, and Y. Li, ''On designing non-parametric EWMA sign chart under ranked set sampling scheme with application to industrial process,'' *Mathematics*, vol. 8, no. 9, p. 1497, Sep. 2020.
[40] N. Khan, M. Aslam, and C. Jun, ''Design of a control chart using a modified EWMA statistic,'' *Qual. Rel. Eng. Int.*, vol. 33, no. 5, pp. 1095–1104, Jul. 2017.
[41] N. Abbas, R. F. Zafar, M. Riaz, and Z. Hussain, ''Progressive mean control chart for monitoring process location parameter,'' *Qual. Rel. Eng. Int.*, vol. 29, no. 3, pp. 357–367, Apr. 2013.

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