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STATISTICAL MONITORING OF MASS VARIABILITY IN GYPSUM PACKAGES

MONITORAMENTO ESTATÍSTICO DA VARIABILIDADE DE MASSA EM EMBALAGENS DE GESSO

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ABSTRACT: This study presents a case analysis of statistical process control and process capability in gypsum powder packaging at a manufacturing company located in the Araripe Gypsum Production Cluster, Pernambuco, Brazil. Its originality lies in applying and jointly interpreting descriptive statistics, normality testing, Individuals and Moving Range (I-MR) control charts, and process capability indices to examine package-mass variation in an industrial context that has received limited attention in the literature. Based on 150 consecutive package-mass measurements collected during a single production shift, the study provides a structured assessment of process behavior in relation to the company's internal packaging specifications. The proposed analytical approach offers practical support for identifying process improvement priorities, monitoring variation, and guiding decisions regarding equipment adjustment, measurement systems, and operating procedures. The findings also illustrate the value of distinguishing process stability from the ability to meet specification limits, helping managers avoid relying on a single statistical indicator when evaluating packaging performance. This case study contributes to the application of statistical quality tools in gypsum manufacturing and provides a methodological reference for future investigations of packaging processes in mineral-based industries.

KEYWORDS: Gypsum; Statistical Process Control; Process Capability; Package Mass; Quality Management.

RESUMO: Este estudo apresenta uma análise de caso sobre o controle estatístico de processos e a capacidade do processo de empacotamento de gesso em pó em uma empresa localizada no Polo Gesseiro do Araripe, Pernambuco, Brasil. A originalidade do trabalho está na aplicação conjunta de estatística descritiva, teste de normalidade, gráficos de controle de valores individuais e amplitude móvel (I-MR) e índices de capacidade do processo para avaliar a variabilidade da massa das embalagens em um contexto industrial específico. A análise foi baseada em 150 medições consecutivas da massa das embalagens, coletadas durante um único turno de produção, considerando os limites

internos de especificação adotados pela empresa. A abordagem proposta oferece suporte à identificação de prioridades de melhoria, ao monitoramento da variabilidade e à tomada de decisões relacionadas aos equipamentos, aos sistemas de medição e aos procedimentos operacionais. O estudo também evidencia a importância de distinguir a estabilidade estatística da capacidade de atender aos limites de especificação, contribuindo para uma avaliação mais abrangente do desempenho do processo. Dessa forma, a pesquisa amplia a aplicação de ferramentas estatísticas da qualidade ao setor gesseiro e oferece uma referência metodológica para futuras investigações sobre processos de empacotamento em indústrias de base mineral.
PALAVRAS-CHAVE: Gesso; Controle Estatístico de Processo; Capacidade do Processo; Massa de Embalagens; Gestão da Qualidade.

1. INTRODUCTION

Strategic management plays a crucial role in determining an organization's position and long-term sustainability in the marketplace (Ritzman & Krajewski, 2004). This is essential for companies seeking to gain competitive advantages and meet the demands of increasingly discerning consumers, driven primarily by the wide availability of competing products. According to Dantas et al. (2025), organizations must continuously redefine and reorganize their production systems to respond effectively to the competitiveness imposed by current market challenges. In this context, companies need to explore new management approaches to achieve success in an increasingly competitive environment. The primary objective should be to improve the control of production processes and the activities and resources involved in these processes. Such improvements contribute to greater production efficiency, maximize the utilization of available resources, and reduce activities that do not add value to the final product (Moreira, 2011).

Gypsum-producing companies, for example, have continuously sought to add value to their products through innovation as part of an ongoing process of technological advancement (Santos, Ferraz, Silva, 2019). Therefore, to remain competitive and expand their market share, industries must continuously evaluate and improve their management practices and business strategies.

The industries operating within this sector, characterized by high production volumes as evidenced by the amount of gypsum ore extracted and processed in the region, represent a segment of significant economic importance and require studies that assess the effectiveness of their production systems. The Araripe Gypsum Production Cluster is one of the main economic hubs in the interior of Pernambuco. Located in the far hinterland of the state, in an area considered the epicenter of the northeastern Brazilian semi-arid region, it is situated on crystalline bedrock and comprises the municipalities of Araripina, Trindade, Ipubi, Ouricuri, and Bodocó. According to data from the Sindicato das Indústrias do Gesso do Estado de Pernambuco (SINDUSGESSO), the cluster is responsible for approximately 95% of Brazil's national production of gypsum ore, plaster, and related products.

Within this dynamic context, organizations strive to enhance their productive and operational systems through the implementation of control tools encompassing all stages of the production chain. As a result, reductions in waste generation and process inefficiencies are expected throughout the manufacturing process (Fernandes et al., 2021; Oliveira, Silva, Santos, 2022).

Among the various tools available for evaluating process quality and control in manufacturing industries, Statistical Process Control (SPC) stands out as one of the most widely adopted approaches. This methodology enables the monitoring and control of production quality, ensuring that manufacturing processes operate within established standards and specifications (Valença, Oliveira, 2023).

One of the critical stages in gypsum manufacturing is the packaging process. Consequently, the research problem addressed in this study is: Does the packaging process maintain package weights within statistical control limits and established specification requirements? To answer this question, the objective of this study was to analyze the variability of gypsum powder package weights using control charts, assessing whether the process is statistically stable and compliant with the specified requirements.

2. LITERATURE REVIEW

2.1 STATISTICAL PROCESS CONTROL

Quality control and continuous improvement have become fundamental strategies for enhancing organizational competitiveness (Montgomery, 2017). According to Crosby (1984), quality can be defined as the degree to which a product or service conforms to predetermined specifications. From this perspective, quality has become one of the primary factors influencing consumers' purchasing decisions, directly affecting the selection of products and services (Montgomery, 2017). Consequently, continuous process monitoring is essential to ensure that products and services consistently meet established quality standards, making process control a fundamental requirement for effective quality management (Costa, Epprecht, Carpinetti, 2018).

Within this context, Statistical Process Control (SPC) has become one of the most important methodologies for monitoring and controlling quality in manufacturing processes by applying statistical techniques to evaluate process variability. Originally developed by Walter A. Shewhart in the 1920s, SPC gained widespread industrial adoption after World War II. Its primary purpose is to monitor process variability through statistical methods, enabling the early detection of process shifts and performance deviations so that corrective actions can be implemented before quality failures occur. Consequently, SPC provides a systematic approach for maintaining process stability and ensuring compliance with established quality standards (Shewhart, 1986; Soares, 2017; De Sousa Júnior, Longhini, Costa, 2018; Valença, Oliveira, 2023; Chang, Ghafariasl, Aryal, 2026).

According to Werkema (2022), Statistical Process Control (SPC) is a methodology based on statistical principles that supports the monitoring of process performance, enabling the identification and control of process variability while contributing to continuous quality improvement. Montgomery (2017) states that SPC is implemented through the use of control charts, which allow the identification and differentiation of common causes and special causes of variation within a process. This distinction provides essential information for decision-making, supports the implementation of corrective actions when necessary, and contributes to maintaining processes under statistical control.

SPC encompasses a set of statistical tools designed to monitor, control, and continuously improve manufacturing processes, thereby enhancing both product quality and operational productivity. Its application enables continuous monitoring of process performance and aims to achieve statistical stability by identifying sources of process variability. By distinguishing common causes from special causes of variation, SPC provides valuable information for implementing corrective and preventive actions that improve overall process performance (Milan, Fernandes, 2002; Carpinetti, 2016; Nascimento, Oliveira, 2020; Tran et al., 2021; Werkema, 2022; Dogan, Hiziroglu, 2024; Knights, Kalevska, Jankuloska, 2025; Chang, Ghafariasl, Aryal, 2026).

2.2 CONTROL CHARTS FOR PROCESS MONITORING

Every manufacturing process, regardless of how well it is controlled, exhibits some degree of variability, making completely stable processes difficult to achieve. In this context, the concept of process variability refers to the differences observed between the actual process performance and the acceptable performance limits. Therefore, variability is considered an inherent characteristic of any manufacturing system and can be classified into two main categories: common causes and special causes (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018; Penedo et al., 2020).

According to these authors, common causes correspond to the natural variability inherent to the process and originate from the production system itself. Such variations arise from routine factors, including minor differences in machinery, operators, raw materials, and operating conditions, and generally remain within a predictable pattern over time. In contrast, special causes refer to abnormal variations or process nonconformities that result in significant deviations from the expected process behavior. These variations may be associated with equipment failures, operator errors, improper machine adjustments, unexpected changes in production conditions, or other external factors that adversely affect process performance.

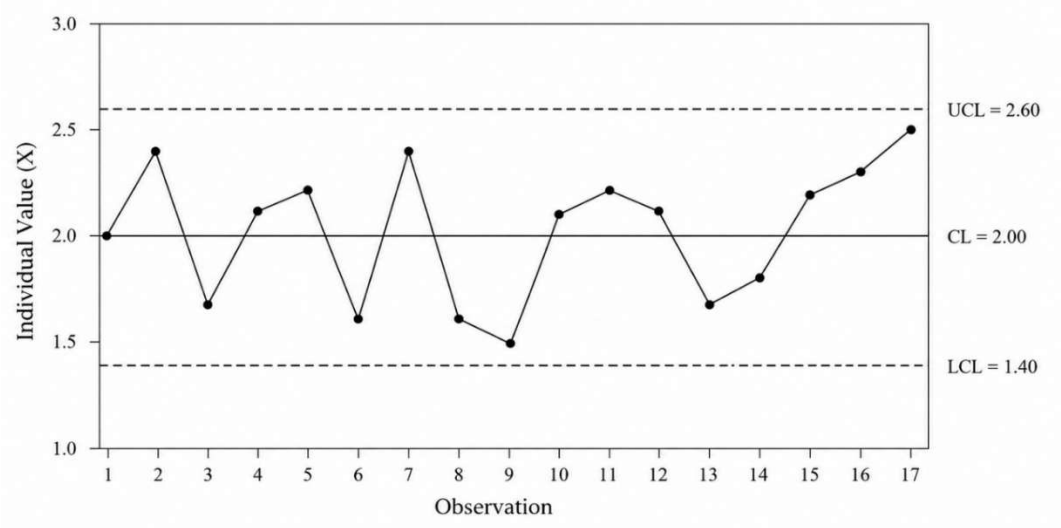
According to Montgomery (2017), distinguishing between common and special causes of variation is fundamental to Statistical Process Control (SPC) because it enables the identification of whether a process is operating under statistical control or requires intervention to eliminate specific sources of variability. To detect and monitor the occurrence of both common and special causes, SPC employs control charts, which are recognized as one of the primary statistical tools for assessing process stability and continuously monitoring process performance (Ali, Pievatolo, Göb, 2016; García et al., 2022).

Control charts constitute one of the primary tools of Statistical Process Control (SPC) and are widely employed to monitor process variability and assess the statistical stability of manufacturing processes. These charts enable the analysis of process behavior over time by verifying whether the observed variations remain within the established control limits and by distinguishing the occurrence of common and special causes of variation. Consequently, they provide essential information for determining whether a process is operating under statistical control (Ali, Pievatolo, Göb, 2016; Montgomery, 2017; Penedo et al., 2020; Piazzetta, 2020; Werkema, 2022).

According to Werkema (2022), control charts provide valuable information to support decision-making by enabling the early detection of changes in process behavior before they adversely affect product quality. Consequently, their application is essential for the continuous monitoring of manufacturing processes, since statistically unstable processes may result in defective products, material waste, production losses, rework, and reduced product quality.

According to Montgomery (2017) and Werkema (2022), a control chart consists of a Center Line (CL), which represents the average value of the quality characteristic being monitored, and two control limits: the Upper Control Limit (UCL) and the Lower Control Limit (LCL). In addition to these elements, the chart displays the observed values of the quality characteristic over time, allowing the behavior of the process to be monitored and its statistical stability to be evaluated, as illustrated in Figure 1.

Figure 1 – Control Chart.



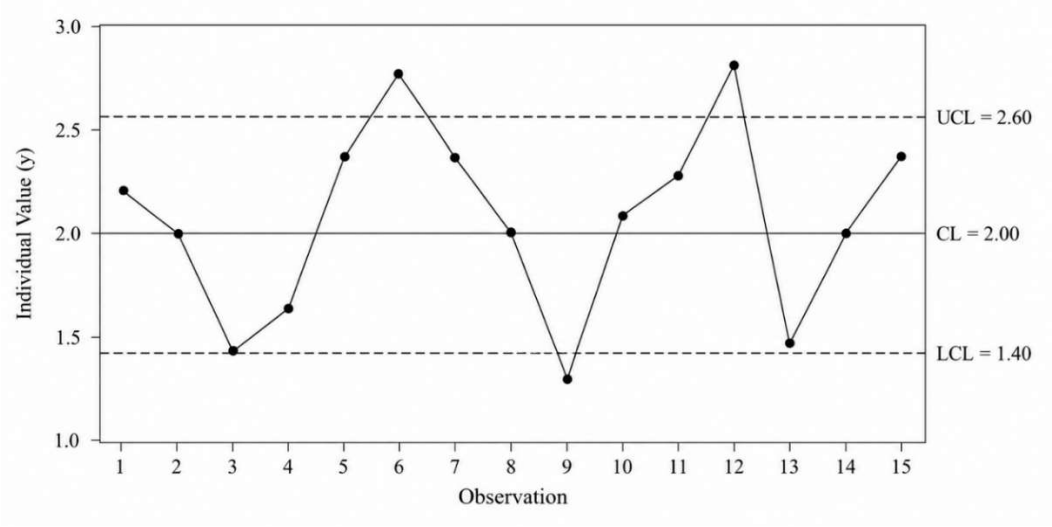
Source: Adapted from Werkema (2022)

As illustrated in Figure 1, the process is operating under statistical control, since all observations remain within the Upper Control Limit (UCL) and Lower Control Limit (LCL). This indicates that the observed process variability is solely attributable to common causes, reflecting a stable and predictable process. However, control charts may also exhibit patterns that indicate the presence of special causes of variation, characterizing a process that is out of statistical control.

Figure 2 illustrates this situation, in which two observations exceed the Upper Control Limit (UCL) and four observations fall below the Lower Control Limit (LCL). These patterns indicate that the process has deviated from its expected behavior, suggesting the

occurrence of special causes of variation. Consequently, the underlying sources of these variations should be investigated before appropriate corrective actions are implemented.

Figure 2 - Out-of-Control Chart



Source: Adapted from Werkema (2022)

In both cases illustrated in Figures 1 and 2, the Center Line (CL) represents the average value of the quality characteristic being monitored. The Upper Control Limit (UCL) and Lower Control Limit (LCL) are statistically determined so that, when the process is operating under statistical control, the vast majority of observations remain within these limits, forming a random distribution of points around the center line (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018; Werkema, 2022).

Accordingly, a process is considered to be under statistical control when the observed variability is attributed exclusively to common causes, reflecting stable and predictable process behavior. Conversely, a process is considered out of statistical control when observations fall outside the control limits or when the data exhibit non-random patterns, indicating the presence of special causes of variation that should be investigated and eliminated to restore process stability (Werkema, 2022).

According to Werkema (2022), control charts can be classified into two main categories: variable control charts and attribute control charts. Variable control charts are used when the quality characteristic is measured on a continuous scale, such as weight, height, thickness, length, or temperature. In contrast, attribute control charts are applied when quality assessment is based on discrete counts, such as the number of defective products or the number of defects identified within an inspection unit.

Within this classification, the most commonly used variable control charts include the $\bar{X}$ chart, the R chart, the S chart, and the Individuals (X) chart. Among attribute control charts, the most widely applied are the p chart, used to monitor the proportion of defective items, and the c chart, which monitors the number of defects within an inspection unit. These charts are extensively employed for quality monitoring in manufacturing processes (Werkema, 2022).

The $\bar{X}$ and R control charts are used to monitor the process mean and process variability (range), respectively, when the quality characteristic is measured on a continuous scale. The $\bar{X}$ chart is designed to monitor changes in the process mean, whereas the R chart

is used to evaluate process variability. These two charts should always be constructed and interpreted together, since the simultaneous assessment of process location and dispersion provides a more comprehensive evaluation of statistical process stability (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018; Werkema, 2022). Consequently, changes in either the process mean or variability can be detected, facilitating the identification of special causes of variation and supporting the implementation of corrective actions whenever necessary.

Process monitoring using control charts is performed through the periodic collection of process samples. At predetermined sampling intervals (h), a sample consisting of n observations is collected, and the selected quality characteristic is measured for each observation. For every sample, the sample mean ($\bar{X}$) and the sample range (R), defined as the difference between the largest and smallest observed values, are calculated. Subsequently, the values of $\bar{X}$ and R obtained from successive samples are plotted on the $\bar{X}$ and R control charts, respectively, allowing continuous monitoring of statistical process stability and process variability over time (Costa, Epprecht, Carpinetti, 2018).

To construct control charts, it is necessary to determine the control limits, namely the Upper Control Limit (UCL) and the Lower Control Limit (LCL). These limits are calculated using statistical expressions that vary according to the type of control chart being employed. For the $\bar{X}$ chart, the control limits are determined using Equations (1) and (2). Similarly, for the R chart, the control limits are calculated according to Equations (3) and (4), as presented below (Montgomery, 2017).

$$UCL = \bar{x} + A_2 \mathrm{R} \qquad Eq.\ 1$$

$$Center\ Line = \bar{\bar{x}} \qquad Eq.\ 2$$

$$LCL = \bar{x} - A_2 R. \qquad Eq.\ 3$$

$$UCL = D_4 R \qquad Eq.\ 4$$

$$Center\ Line = \bar{\bar{x}} \qquad Eq.\ 5$$

$$LCL = D_3 R \qquad Eq.\ 6$$

Where:
UCL: Upper Control Limit
LCL: Lower Control Limit
$\bar{x}$: Mean of Means and Center Line
R: Mean of Ranges.
A_2, D_3 and D_4: Tabulated constants depending on the sample size.

It is important to emphasize that control charts do not directly identify the special causes responsible for the variability observed in a process that is out of statistical control. Rather, their primary function is to provide statistical evidence indicating the presence of these causes, thereby supporting further investigation to determine their origin and enabling the implementation of appropriate corrective actions (Werkema, 2022).

Although control charts are essential for assessing the statistical stability of a process, this analysis alone is not sufficient to ensure that products consistently meet the established specification limits. Therefore, in addition to monitoring process variability, it is

necessary to evaluate whether the process is capable of consistently producing outputs that satisfy the specified requirements through process capability analysis.

2.3 PROCESS CAPABILITY ANALYSIS

To assess whether a process is capable of meeting the established specification limits, process capability indices are commonly employed. This evaluation is based on comparing the natural variability of the quality characteristic with the product specification limits, thereby quantifying the capability of the process to consistently satisfy the required specifications. In general, higher process capability indices indicate a greater ability of the process to produce conforming products while reducing the occurrence of nonconforming items (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018; Rizkiah, Kurniawati, 2025).

According to Montgomery (2017), process capability is directly related to process uniformity, that is, its ability to produce consistent results with low variability over time. Process capability can be estimated through the probability distribution of the quality characteristic, which is defined by its shape, central tendency (mean), and dispersion (standard deviation). Based on this distribution, it is possible to evaluate process performance relative to the established product specification limits. It is important to emphasize that process capability should only be evaluated when the process is under statistical control (Werkema, 2022).

Among the various capability measures available, the process capability index (Cp) and the process capability index (Cpk) are the most widely used for evaluating process performance (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018). The process capability index (Cp) expresses the relationship between the allowable process variability, represented by the difference between the Upper Specification Limit (USL) and the Lower Specification Limit (LSL), and the natural process variability, represented by six standard deviations (6σ). Therefore, higher Cp values indicate a greater potential for the process to satisfy the established specification limits, provided that the process is properly centered (Montgomery, 2017; Werkema, 2022).

The process capability index (Cpk), in turn, considers not only the inherent variability of the process but also the position of the process mean relative to the specification limits. Consequently, Cpk provides a measure of the actual process capability by evaluating the ability of the process to consistently produce conforming products while accounting for potential shifts of the process mean from the target value (Werkema, 2022).

Process capability indices are widely used to evaluate the performance of manufacturing processes by determining whether the observed process variability is compatible with the established specification limits. The Cp index is calculated using Equation (7), whereas the Cpk index is determined according to Equation (8) (Costa, Epprecht, Carpinetti, 2018).

$$\mathrm{Cp} = \frac{US}{6\sigma} \qquad \text{Eq. 7}$$

$$\mathrm{CpK} = \mathrm{Min}\left\{\frac{USL-\mu}{3\sigma}, \frac{\mu - \mathrm{LSL}}{3\sigma}\right\} \qquad \text{Eq. 8}$$

Where:

USL: Upper Specification Limit
LSL: Lower Specification Limit
Cp: Process Capability Index
Cpk: Process Capability Index

According to Werkema (2022), several classification criteria based on the Cp index have been proposed in the literature and are widely adopted in industrial practice to assess process capability, as shown in Figure 3.

Figure 3 – Process Capability Classification

Process Capability Classification	C_p Value
Capable Process	$C_p \geq 1.33$
Marginally Capable Process	$1.00 \leq C_p < 1.33$
Not Capable Process	$C_p < 1.00$

Source: Adapted from Werkema (2022)

According to Werkema (2022), the process capability index (Cp) can be used to classify manufacturing processes according to their ability to meet the established specification limits. As shown in Table X, processes with Cp ≥ 1.33 are considered capable, indicating that the natural process variability is sufficiently small relative to the specification limits. Processes with 1.00 ≤ Cp < 1.33 are classified as marginally capable, suggesting that although the process may satisfy the specifications, its performance should be continuously monitored and improved to reduce the risk of producing nonconforming items. Conversely, processes with Cp < 1.00 are considered not capable, indicating that the natural process variability exceeds the allowable specification range and that corrective actions are required to improve process performance (Montgomery, 2017; Costa, Epprecht, Carpinetti, 2018; Werkema, 2022; Rizkiah, Kurniawati, 2025).

Process capability analysis provides a more comprehensive understanding of manufacturing process performance by relating process variability to the quality requirements established for the product. This evaluation enables the identification of improvement opportunities and supports initiatives aimed at increasing process reliability, thereby reducing nonconformities, material waste, and rework. Consequently, process capability analysis serves as an important decision-support tool, contributing to the development of more robust, consistent, and quality-oriented manufacturing processes.

3. METHODOLOGY

This study was described as an applied, quantitative, descriptive, and case-study-based inquiry carried out in a gypsum packaging process located in the Araripe Gypsum Production Cluster, Pernambuco, Brazil, a hub for gypsum manufacturing. The study aimed to assess the variability in gypsum package weights and to determine whether the packing process complied with the specified limits and operated under statistical control. Package weights were measured using an Electro-brand digital platform scale, which was used to record the mass of the packaged gypsum products and provide the data required for the statistical analysis. The quality characteristic selected for this study was the net mass of gypsum powder packages, with a nominal quantity of 40 kg declared on the product label. This nominal quantity reflects the commercial package size used by the company and served as the target value for evaluating the packaging process. The nominal value was not derived from the statistical analysis; rather, it was established by the product's declared net quantity.

The Lower Specification Limit (LSL) of 39.5 kg and the Upper Specification Limit (USL) of 40.5 kg were based on an internal tolerance adopted by the company for monitoring packaging performance. These limits define a symmetric interval of ±0.5 kg around the nominal quantity of 40 kg. They represent company-defined operational criteria for assessing process variability and capability, rather than limits derived from a specific Brazilian or international standard. No external technical standard or regulatory provision was identified as the source of this particular tolerance interval. Accordingly, the specification limits were used as reference values for the statistical process capability analysis. The Cp and Cpk indices therefore indicate the process's ability to meet the company's internal packaging specifications. Although these limits provide a basis for evaluating process performance, they should not be interpreted as evidence of compliance with applicable metrological regulations or customer-specific requirements. Such compliance would require a separate assessment against the relevant regulatory provisions and any applicable contractual specifications. Direct data collection from the production line was done while the packing process was operating normally. A total of 150 consecutive gypsum packages were weighed using the company's Electro-brand digital platform scale. The net mass of each package was recorded in kilograms, and the observations were maintained in chronological order to support the analysis of process behavior over time.

The sample size of 150 observations corresponded to the number of measurements available for the case study. It was not determined through a formal sample-size calculation or statistical power analysis. The collected data were used to perform descriptive statistical analysis, assess the distribution of package mass, construct Individuals and Moving Range (I-MR) control charts, and calculate process capability indices.

The sampling procedure reflects the packaging process under the operating conditions observed during the selected shift. However, because the measurements were collected consecutively within a single shift, the dataset does not capture potential

differences between shifts or across different production days. Consequently, the findings should be interpreted within the scope of the observed production period and should not be assumed to represent all operating conditions. Future studies should consider collecting measurements across multiple days and shifts at predefined time intervals to investigate temporal and shift-related variations more comprehensively. The dataset was first characterized using descriptive statistical analysis. Sample size, mean, median, standard deviation, minimum value, and maximum value were among the metrics computed. To assess the distribution, dispersion, symmetry, and potential existence of outliers in the package-weight data, a boxplot and a histogram with a fitted normal curve were also created.

In this study, package-weight variability was defined as fluctuations in either the net content or the gross weight of a product package (Kharra, 2025). Package weights were measured using an Electro-brand digital platform scale, which was used to record the mass of the packaged gypsum products and provide the data required for the statistical analysis.

The Shapiro-Wilk test was used to determine whether the data were normal, with a significance level of 5% ($\alpha = 0.05$). The package weights were assumed to have a normal distribution under the null hypothesis. The null hypothesis of normality was rejected when the p-value was less than 0.05. Individuals and Moving Range (I-MR) control charts were utilized to assess the packaging process's statistical stability. Because the weight measurements were gathered separately and chronologically, this kind of control chart was chosen. The Moving Range chart was used to evaluate the variability between successive observations, and the Individuals chart was used to track changes in the process mean. The control limits were calculated using the standard procedures proposed for I-MR charts, with limits established at three standard deviations from the center line.

When no non-random patterns linked to special causes of variation were found and all observations stayed within the control limits, the process was deemed statistically controlled. Points outside the control limits, series of observations on the same side of the center line, trends, cycles, and other patterns suggesting potential process instability were all taken into account when interpreting the control charts. After analyzing process stability, process capability analysis was undertaken using the Cp and Cpk indices. By contrasting the inherent process variability with the specification range, the Cp index was utilized to evaluate the process's potential capability. The actual process capability was assessed using the Cpk index, which takes into account both its variability and the process mean's location in relation to the specification limits. For the purposes of interpretation, processes were deemed capable if their Cp and Cpk values were equal to or greater than 1.33; marginal capability was indicated by values between 1.00 and 1.33; and failure to consistently meet the specified limits was indicated by values below 1.00.

Statistical software was utilized for the analyses in order to compute descriptive statistics, perform the Shapiro-Wilk test, create the boxplot and histogram, create the I-MR control charts, and estimate the Cp and Cpk indices. The specialized literature's

descriptions of process capacity analysis and statistical process control were used to interpret the findings.

4. RESULTS AND DISCUSSION

Initially, descriptive statistical analyses were carried out to provide an overview of the package weight data and to assess the main characteristics of the distribution. The results obtained are summarized in Table 1.

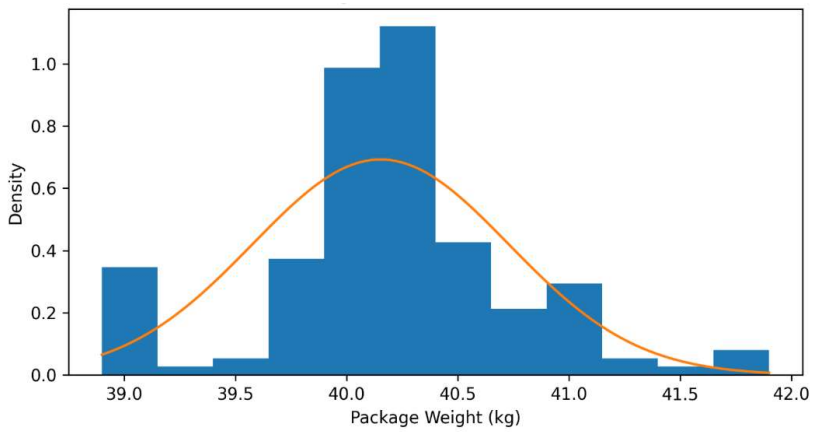
Table 1 - Descriptive statistical

Indicator	Value
Sample Size (n)	150
Mean (kg)	40,153
Median (kg)	40,200
Standard Deviation (kg)	0,576
Minimum (kg)	38,900
Maximum (kg)	41,900

Source: Research data (2026)

Package weights are concentrated around the intended amount of 40 kg, according to the histogram (Figure 3). The majority of observations fall between 39.5 and 40.8 kg, suggesting that the distribution is roughly symmetrical. Although there may be significant variations in the distribution's tails because of inherent process variability, the overlay normal curve shows a respectable approximation to normalcy.

Figure 3 – Histogram with normal curve



Source: Research data (2026)

Although the process is centered close to the nominal target weight of 40 kg, the observed range of 3.0 kg between the minimum and maximum values suggests a substantial degree of variability. This dispersion may indicate the presence of process fluctuations that warrant further investigation to ensure consistency and compliance with established specifications. The Shapiro–Wilk normality test (Table 2) was conducted to evaluate whether the weight measurements followed a normal distribution, thereby verifying one of the key assumptions underlying the statistical analyses performed in this study.

Table 2 - Shapiro–Wilk normality test

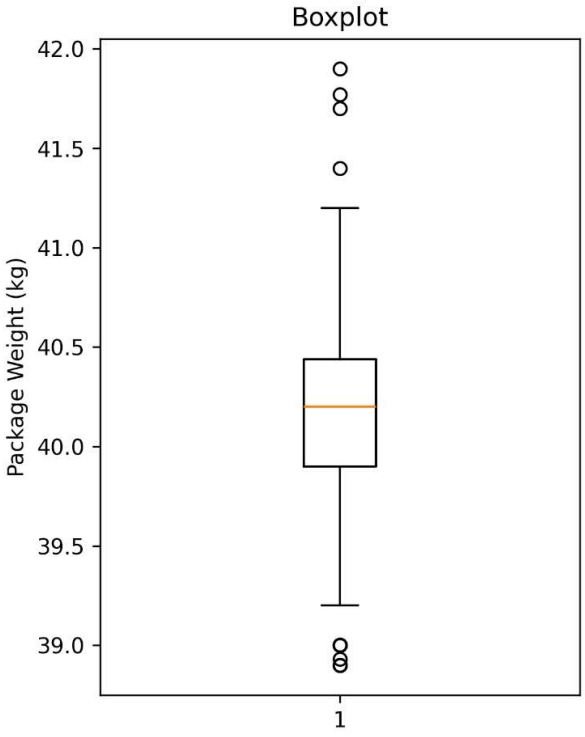
Statistic	Value
W	0,942
p-value	0,000008

Source: Research data (2026)

As the p-value was lower than the significance level of 0.05, the null hypothesis of normality was rejected. Therefore, the weight distribution cannot be considered normally distributed. This deviation from normality may be associated with the presence of outliers, process instability, or special causes of variation influencing the packaging operation.

With the median situated close to the middle of the interquartile range, the boxplot (Figure 4) shows a comparatively symmetric distribution of package weights.

Figure 4 - Boxplot

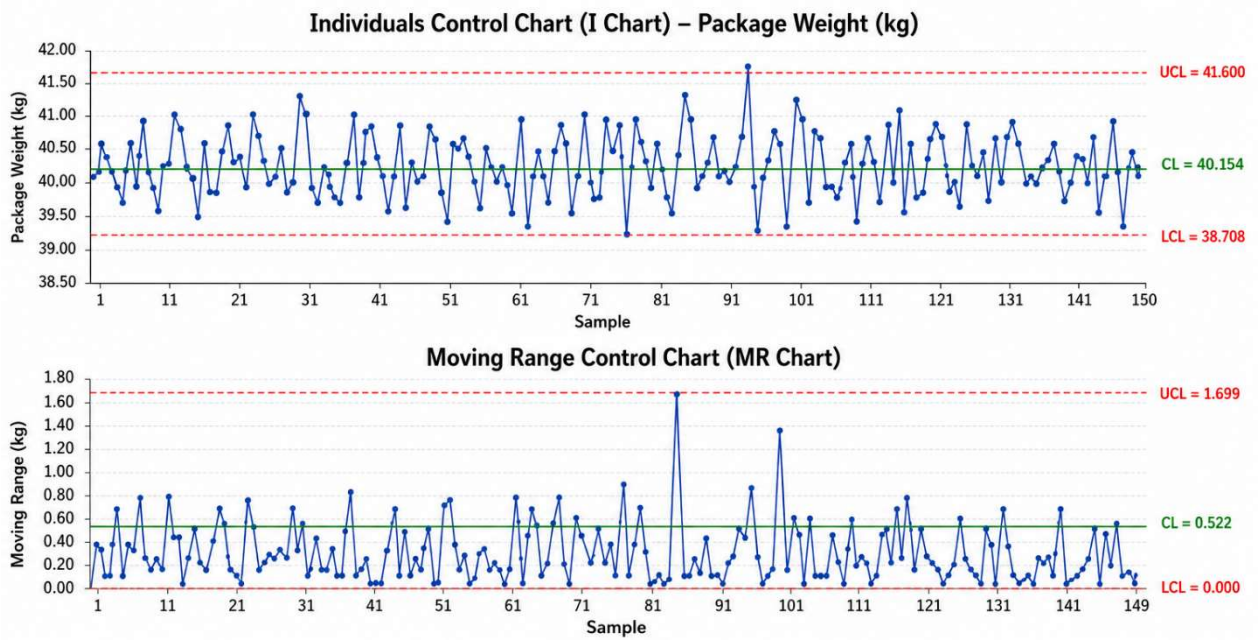


Source: Research data (2026)

The boxplot indicates a relatively symmetric distribution of package weights, with the median located near the center of the interquartile range. Although a small number of potential outliers were identified, their frequency was low and did not compromise the overall stability of the process. These observations may reflect natural process variability rather than systematic process disturbances.

The Individuals and Moving Range (I-MR) control charts used to track package weight fluctuation during the packing process are shown in Figure 5. According to the Individuals chart, no point exceeded the predetermined thresholds, and all observations stayed within the upper and lower control limits (UCL = 41.600 kg; LCL = 38.708 kg). Furthermore, no non-random patterns were seen, including long sequences of dots on one side of the center line, cycles, or trends. These findings show that the process mean held steady over the course of the observation. Additionally, statistical stability was shown by the Moving Range chart. The control limits (UCL = 1.699 kg; LCL = 0.000 kg) contained all moving range values, indicating a consistent and predictable fluctuation between subsequent measurements.

Figure 5 – Individuals Control Chart and Moving Range Control Chart



Source: Research data (2026)

The lack of points outside of the control ranges suggests that there were no unique sources of variation during data collection. All things considered, the I-MR analysis shows that the packing process was statistically controlled, which means that the observed variability is mostly due to common reasons that are part of the process. From a managerial standpoint, this outcome shows process predictability and stability, offering a solid foundation for programs aimed at continuous improvement and upcoming evaluations of process capability.

Even if the process is statistically stable, further analyses, such as Cp and Cpk indices, are advised to ascertain whether the process can reliably satisfy regulatory standards and client specifications.

In terms of adherence to the designated package weight restrictions, the process capacity analysis showed inadequate performance. The computed capability indices, Cp = 0.289 and Cpk = 0.201, were both far below the widely recognized cutoff of 1.00. In general, the data shows that the stability of statistical processes should not be viewed as a sign of process superiority. While the I-MR control charts indicated that the gypsum packaging process was functioning within statistical control, the low Cp and Cpk values demonstrated that the existing inherent variability does not meet the defined specification limits. This discovery emphasizes the complementary relationship between Statistical Process Control (SPC) and process capability analysis, indicating that sustaining statistical stability is merely the initial step toward attaining excellent process performance. From a quality engineering viewpoint, sustainable enhancements should focus on minimizing common-cause variation by means of systematic process optimization, equipment calibration, preventive maintenance, standardized operating procedures, and ongoing operator training.

The variability observed in gypsum package mass may arise from the combined effects of one or more of six categories of potential causes: Human, Machine, Material, Method, Environment, and Measurement. These categories correspond to the six factors commonly used in cause-and-effect analysis, also known as the Ishikawa or fishbone diagram. This framework helps organize potential sources of process variation and guides further investigation; however, the categories should not be interpreted as confirmed causes unless supported by specific evidence (Ishikawa, 1986). In the gypsum packaging process, potential human-related factors include differences in operator practices, training, and adherence to work instructions. Machine-related factors may include filling equipment adjustments, wear, or inconsistent dosing performance. Material-related factors may involve variations in gypsum properties or material flow during filling. Method-related factors may include inconsistent filling procedures, inadequate standardization, or insufficient monitoring frequency. Environmental factors may include operating conditions that affect equipment or material handling. Finally, measurement-related factors may involve scale calibration, resolution, repeatability, or measurement procedures.

These factors were not individually investigated in the present case study and therefore represent potential explanations rather than demonstrated causes of the observed variability. Their systematic investigation would require additional data collection and root-cause analysis. To address the inadequate capability indicated by the results, the company should first verify the weighing system and filling equipment, including scale calibration, equipment condition, and filling adjustments. Standardized operating procedures and operator training should then be reviewed to ensure consistent execution of the packaging process. The company should also examine whether material-flow characteristics and relevant operating conditions contribute to fluctuations in package mass. These actions should be supported by routine monitoring

using control charts and by recording deviations, adjustments, and maintenance activities.

The six categories should be considered together because variability may result from interactions among people, equipment, materials, methods, environmental conditions, and measurement systems. Identifying and controlling the relevant factors can help reduce process dispersion and improve the consistency of package mass. Nevertheless, the effectiveness of each corrective action must be verified through subsequent measurements rather than assumed in advance.

These findings show that the packaging operation cannot reliably create packages within the specified limits of 39.5 kg and 40.5 kg, and that process variability exceeds the standard range. The capability study revealed that the process is unable to satisfy customer needs, even if the I-MR control charts showed statistical stability. This result emphasizes the difference between process capability and stability: a process may be statistically controlled but yet unable to meet specification constraints because of excessive inherent unpredictability.

From an industrial viewpoint, the noted variability could be linked to changes in raw material properties, errors in weighing equipment calibration, variations in filling systems, environmental factors like humidity, and disparities in machine operation settings. Tackling these elements necessitates an organized, ongoing enhancement approach backed by Lean Manufacturing, Six Sigma, preventive maintenance, standardized operating procedures, and operator training. Moreover, incorporating real-time Statistical Process Control alongside digital monitoring systems and predictive analytics would allow for faster detection of process anomalies and support proactive management of quality

Based on the literature on gypsum production (Fernandes et al., 2021; Dantas et al., 2025; Santos et al., 2025; Santos; Ferraz; Clemente, 2025), some important points can be associated with the variability in gypsum production in the production hub of the state of Pernambuco, northeastern Brazil:

- Absence of an Environmental Management System (EMS);
- Inadequate fulfillment of customer requirements and expectations;
- Waste generation throughout the production process;
- Lack of Information Systems (IS) to support operations management;
- Limited value addition to local products and services;
- Insufficient workforce training and development;
- Ineffective marketing policies and strategies;
- Technological lag and low levels of innovation;
- Deficiencies in Production Planning and Control (PPC);
- Waste of by-products and underutilization of resources;
- Operational inefficiencies affecting productivity and performance;
- Lack of Key Performance Indicators (KPIs) related to production management and operational performance (Barros et al., 2010; Cipriano; Rezende, Ferraz, 2019; Coelho, Silva, Santos, 2024; Santos et al., 2025; Santos, Ferraz, Clemente, 2025).

The findings of this study are consistent with those reported by Cronin, Fitzpatrick, and McCarthy (2003), who demonstrated that weight variability directly affects packaging efficiency and may result in overweight packages. According to the authors, reducing process variability is essential for maintaining product weights close to target values and improving operational performance. In this context, Statistical Process Control provides an effective approach for monitoring weight variation, identifying sources of variability, and supporting continuous process improvement.

The study conducted by Leite et al. (2025) analyzed variations in net weight and other quality-related characteristics in a wafer biscuit production line. Data collection and the application of control charts indicated that the process was operating under statistical control according to the standards established by the company. The analyzed product, with a nominal weight of 107 g, was subject to a tolerance limit of 4.5%, allowing a minimum net weight of 102 g. The evaluation of the control charts, performed in accordance with the criteria established by the Brazilian National Institute of Metrology, Quality and Technology (Inmetro), identified some process deviations; however, these remained within acceptable limits. The results demonstrated that Statistical Process Control (SPC) is a valuable tool for monitoring product weight and quality performance. Furthermore, the authors emphasized its potential application to other production lines, contributing to continuous process improvement and supporting quality assurance practices.

Similarly, Abrão and Cardoso (2020) demonstrated how Statistical Process Control (SPC) can be applied to monitor the weight of chemical product packages while integrating quality management tools to identify, analyze, and solve process-related problems. In their study, SPC techniques were combined with quality tools such as the Pareto Chart, Check Sheet, and Ishikawa Diagram to determine the root causes of observed deviations. Following the implementation of corrective actions, the package weight data were reanalyzed, revealing significant improvements in process performance. The results showed that the process became statistically controlled and compliant with the established specification limits, highlighting the effectiveness of SPC as a continuous improvement tool.

The findings reported by Eissa and Abid (2018) further reinforce the importance of Statistical Process Control (SPC) in monitoring product weight and assessing process stability. Although all observations complied with the established specification limits, the control charts revealed instabilities associated with special causes of variation. This evidence demonstrates that compliance with weight specifications alone does not guarantee that a process is statistically controlled. Consequently, SPC tools play a fundamental role in identifying process deviations, reducing variability, and improving the consistency, predictability, and reliability of product weight.

5. CONCLUSIONS

In order to ascertain if the packaging process was statistically stable and able to satisfy the specified constraints, this study assessed the variability of gypsum package weights in a manufacturing company situated within the Araripe Gypsum Production Cluster. A thorough evaluation of process performance was produced by applying descriptive statistics, graphical analysis, the Shapiro-Wilk normality test, Individuals and Moving Range (I-MR) control charts, and process capability indices. The results demonstrated that the packaging process operated under statistical control during the monitoring period. All observations remained within the control limits, and no relevant non-random patterns were identified, indicating that the observed variability was predominantly associated with common causes inherent to the production system. However, the process capability analysis revealed an unsatisfactory performance, with Cp = 0.289 and Cpk = 0.201. These values indicate that, although the process is stable and predictable, its natural variability is substantially greater than the allowable specification range of 39.5 kg to 40.5 kg.

These results demonstrate the essential difference between process capability and process stability. A production process's ability to reliably satisfy technical requirements or client demands cannot be guaranteed by statistical control alone. Therefore, the excessive common-cause variability ingrained in the process has been highlighted as the primary difficulty in the packaging operation rather than the emergence of discrete special causes. Practically speaking, the findings point to the necessity of methodical improvement initiatives meant to lessen process dispersion and enhance process centering. Weighing and filling equipment calibration and preventive maintenance, standardization of working methods, monitoring of raw material properties and ambient conditions, and ongoing operator training are examples of priority actions. Reducing variability, eliminating material losses, and enhancing operational performance may be further enhanced by integrating Statistical Process Control with continuous improvement methodologies like Lean Manufacturing and Six Sigma.

By offering actual proof that a gypsum packaging method may maintain statistical stability while still exhibiting insufficient capacity, the study also adds to the body of knowledge. This emphasizes how crucial it is to use process capability analysis and control charts in conjunction with statistical stability indicators when evaluating manufacturing quality. One drawback of the study was that it was limited to a single production process and a certain time frame for data collecting. Longer monitoring times, the examination of other production factors, the study of the primary causes of common-cause variability, and the use of root-cause analysis and improvement techniques should all be part of future research. Subsequent studies may also evaluate process performance after the implementation of corrective and preventive actions in order to verify whether reductions in variability lead to improved capability indices and greater compliance with established specifications.

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