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Reducing Energy Consumption Using DOE and SPC on Cork Agglomeration Line

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Abstract: The industrial landscape has revealed two trends: increased competitiveness and a greater demand for sustainable solutions. Materials with cork in their composition are an appealing solution, since they guarantee the desired mechanical characteristics while contributing to the prevention of environmental degradation. Given the change in external factors, there has been a substantial rise in energy costs. Thus, it is essential to optimize processes, with the aim of reducing the consumption of resources, such as electricity. This project was developed at a company that manufactures cork blocks, sheets, and rolls. Regarding blocks, a critical operation of this line is the high-frequency heating, being the bottleneck of this work center. With the critical variables previously identified, planned experiments were conducted based on DOE's full factorial methodology. Two out of four products revealed inputs with statistical significance. With these results, a reduction in parameters was implemented in the factors and interactions that showed no statistical significance. Finally, average and amplitude control charts, based on the SPC methodology, were applied to solidify and guarantee the quality of the agglomerated blocks, with the parameter changes already introduced. The company benefited from this study by having a significant reduction in its energy consumption.

Keywords: DOE; cork; full factorial; SPC; sustainability; parameter optimization

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1. Introduction

New solutions must be found to handle the ever-changing climate degradation, and cork, with its renewable nature, is arguably one of the best solutions.

The last few years have proved to be distinctive, considering the social and political context that surrounds all kinds of sectors and industries. Following the emergence of a pandemic and the outbreak of a war, the world economy has changed considerably, and the price of various products and services has reflected the impact of this change. Essential goods, electricity and water, for example, have become more expensive.

In this context, resource management and process optimization have become even more important in every industry globally. The lean philosophy promotes waste reduction and has become increasingly more relevant [1]. In addition to avoiding the overuse of materials and resources, companies in general are trying to significantly reduce the energy consumption of their processes.

One aspect that has gained substantial popularity is sustainability, which can be intertwined with the lean philosophy, on a worldwide scope. Both concepts are the primary focus of this study. Given the current situation that affects the planet's environment, sustainable solutions are increasingly sought after, and indicators such as the carbon footprint are increasingly valued. As such, novel solutions emerge, such as cork. Cork is not only a natural resource, but it is also renewable [2]. It grows in the Mediterranean area, utilizing a warm climate for its growth [3]. It has advantages in various aspects, such as mechanical performance, thermal resistance, moisture [4], and a more appealing visual and natural appearance [2] than most of its competitors.

Considering both cork and lean techniques, an intriguing challenge is to reduce the energy consumption associated with the manufacturing process of cork products. Achieving this goal would mean spending less energy and generating greener productions, as well as bringing more profit to companies. In an ever-growing and ambitious market with a tendency of becoming increasingly competitive, the correct parameterization of the manufacturing process promises to bring strategic advantages to companies that decide to implement it.

At a deeper stage of the context presented, the present study is carried out at a Portuguese cork manufacturer of various types of cork-based products. It uses widely used tools, such as continuous improvement methods like the DMAIC methodology or PDCA cycle, in mechanical engineering and industrial management to achieve improvements in the process and its outputs.

The work described in this paper seeks to deepen and refine techniques such as DOE (planned experiments) and SPC (quality control method)—both regular methodologies of the lean philosophy that seek to improve the performance of a process and its parameters—and the application of these in an industrial scenario. The goal is to improve the production unit performance as well as present a solution for similar studies. The study's contribution lies in applying theoretical concepts to real-world production, revealing the positive impact of these techniques. It also serves to present cork as a real solution to the problems that currently exist in multiple industries, with all its advantages and variations, with a special focus on its eco-friendly attribute.

Regarding the paper's structure, Section 1 contextualizes the details of which the paper consists and prepares the reader for the application of two methodologies: DOE and SPC. Section 2 seeks to deepen the knowledge on every concept through literature research, starting with a review of cork, followed by the DMAIC and DOE methods and ending with SPC. Section 3 explains the steps taken to properly apply the information gathered in the research phase. Once this step is complete, Section 4 explores its results, ending with Section 5, which presents the conclusions that can be drawn from this work.

2. Literature Review

With the goal of obtaining the expected results and improving the temporal and energetic performance of the cork agglomeration process, it is necessary to fully assimilate all the necessary knowledge. As such, the next sections explore cork as a material, followed by the analysis of all the tools that seek to improve the production process. Finally, different variations of the control charts are presented, which are used to ensure the statistical control of the process.

2.1. Cork

Cork is a natural material extracted from one of the most biodiverse ecosystems of the Mediterranean, growing in the oak tree [5]. It has been used since ancient times, mainly as a float and sealant. These applications have contributed to the industrial growth of this material [6].

In Portugal, the cork industry has been an important economic sector since the 19th century, being one of the most exported products, employing a large number of specialized operators [2], contributing positively to lowering the unemployment rate. However, despite the historical predominance of the sector, it has achieved even more significant growth in recent years, being recognized as a vital sector at a strategic level in the Portuguese economy [7].

Cork is defined as the subereous parenchyma of the cork oak, forming the trunk and branches of the tree [8]. In microscopic analysis, it is known to have cells with a honeycomb appearance, the cell membranes having a high level of impermeability, being surrounded by a gas with properties equivalent to air, occupying around 90% of the cell volume [6].

Its division consists of 45% suberin, this being a synthetic wax processed by the tree, and 27% lignin, an amorphous macromolecule found in various plants. The remaining 28% is composed of cellulose, other waxes and polysaccharides, tannins, and ceroids. The suberin guarantees the material's waterproof and protective properties, while the lignin confers rigidity and resistance to several types of attacks, including microbiological and mechanical. Its closed cell structure is shown in Figure 1 [6].

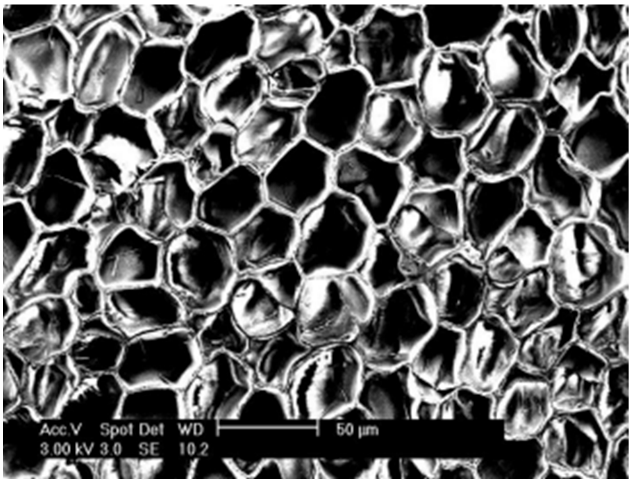

Figure 1. Cork cellular structure.

Regarding harvesting, it should only be initiated once the cork oak tree is at least 25 years old and the quality of the raw material in the first harvest is lower, called virgin cork, as shown in Figure 2. The second harvest can be performed 9 years after the first harvest, and the cork is of sufficient quality to be treated industrially. Subsequent extractions follow the same time interval of 9 years [8]. A detail worth noting is that there is an ideal moisture content at the time of both extraction and processing, which is typically around 6–10% [9].

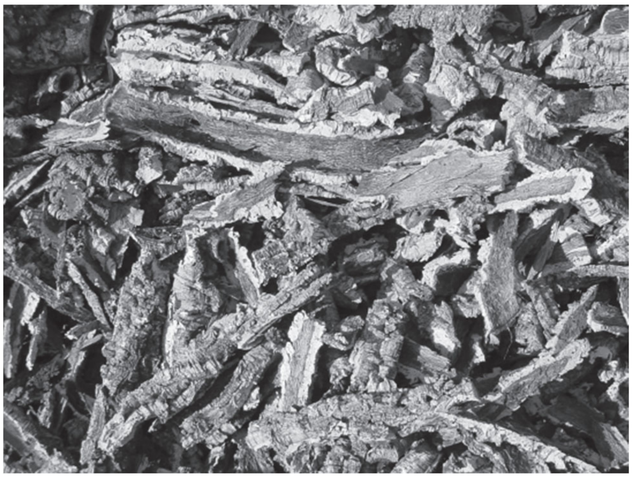

Figure 2. Virgin cork.

In addition to these attributes, this material is hypoallergenic, resilient, and resistant to compression efforts [6]. It is also an excellent acoustic and thermal insulator, highly resistant to fire and high temperatures. It also has electrical insulation capacity [8]. Finally, one of its main advantages is its sustainable nature, as it can be totally reused and recycled, thus complementing the green nature of its extraction [10].

Considering all the characteristics described above, it is sensible to state that cork is a versatile material with good mechanical properties for various applications. Since the 1960s, cork has been regularly used in aerospace and football pitches, among other applications [6].

Sustainability is a concept that is becoming more popular and relevant each year, and companies such as the cork company where this work was developed have experienced a strong growth in demand, with numerous new projects for the development of more financially advantageous market plans.

The main product that cork is used to produce has always been stoppers. As with any production, cork stopper manufacturing generates a lot of waste, which promotes the development of new solutions. In this context, the agglomeration of cork composites emerged [5]. This product uses the waste not used in the main business, the stoppers, and produces new solutions that are distributed across various sectors [6].

Cork granules are classified according to the time when the bark was extracted, as well as its grain size. These are the basis of agglomerates. Mixing very different grain sizes in a block or roll results in a defective product, commonly called contaminated [6]. Granulates vary between 0.25 mm and 8 mm. The specific waste of these should vary between 55 kg/m^3 and 75 kg/m^3 [11]. According to [11], cork granulates are typically divided into two types in the Catalonian industry: white granulates, commonly used for stoppers, and black granulates, usually processed to serve other industries, such as flooring or panels. In this study, only black-type granulates are used.

The composites can be made up of only natural cork and glue, as well as other types of material, such as rubber [5]. This material may appear as waste from other industries, as is the case of the rubber from the shoe industry, or car parts in the automotive industry.

It is interesting to use the waste from other industries, such as stopper producers, to add value and provide other markets, while contributing positively to water retention, preventing soil degradation [9]. For all the reasons presented in this section, it can be affirmed that cork is a sustainable and attractive alternative to other materials.

2.2. DMAIC

DMAIC (Define, Measure, Analyze, Improve, Control) is an acronym for the five phases of the cycle. This is a methodology largely applied in the lean philosophy and has the potential to be properly applied to the study in this paper. It allows the understanding of a process in a detailed and precise way, enabling the problem in question to be clearly clarified and the relationships between parameters to be found [12]. It also allows the process to be improved with a subsequent control system to prevent the same problem from occurring. As such, the parameters related to cork block production can be optimized following this methodology. The result of its application is highlighted, as a rule, in the improvement of the process. This methodology is represented in Figure 3.

Figure 3. DMAIC phases.

We start with the Define phase, which starts the cycle. Define is responsible for clarifying the problem, the objective, and identifying all actors. All the key factors influencing the process are then selected, subject to later evaluation and correction with the intention of improving the process. In this phase, tools like the ones that will be explored throughout this article are regularly used, including SIPOC (Suppliers, Inputs, Process, Outputs, Customers) and high-level process mapping, among others [12].

After the first phase is concluded, one should proceed to data collection to obtain a more detailed view of the process inputs, outputs, and the relationship between them. In this phase, sufficient data should be collected in order to identify the critical factors, that is, the most influential aspects for the problem stated in the Define phase [13]. The Measure phase measures both inputs and outputs with Pareto charts or even control charts.

Early hypotheses and conclusions should be made, so that answers are found in the next phase [14]. In this phase, the R&R (Repeatability and Reproducibility) calibrator is often used. This is a type of ANOVA (Analysis of Variance), a topic discussed in detail in subsequent sections [15].

Next, the Analyze phase should be performed. This phase seeks to find the true root of the problem and identify which inputs most affect the system. It is in this phase where one finds which variables should be tested in the next phase. In the same context, it allows quantifying the distance between the baseline at the beginning of the project and the project objectives in the Define phase [16].

When the project team considers the data collected and analyzed, steps should be taken towards searching for new solutions and parameters. This phase is the Improve phase. In this phase, tools like DOE and VSM (Value Stream Mapping) [17] are used. The tests performed in this phase are based on the parameters identified as CTQ (Critical to Quality) in previous phases [18]. It is also in this phase that changes leading to process improvement are made. Some examples include Kanban and Mizusumashi audits, among others [1].

The final phase of the DMAIC method addresses the control of the process with the implemented improvements and is therefore called the Control phase. It is at this point that statistical control is applied, often using control charts. Control plans are developed, such as PDCA (Plan–Do–Check–Act) [18] and documentation, thus ensuring the solidification of the improvements developed throughout the method [17].

2.3. DOE

DOE (Design of Experiments) resorts to planning, execution, data collection, and subsequent data treatment and analysis, dealing with both independent and dependent variables [19]. This methodology is based on statistical tools such as ANOVA and *t*-tests, among others [20]. For the correct operation of this type of statistical tool, a previous analysis is recommended in order to distinguish the factors that make a difference from the irrelevant ones. This fits perfectly with the DMAIC methodology, explained in the previous subpoint, where, prior to the implementation of DOE in the Improve phase, a statistical analysis is performed on the data collected in the Analyze phase.

Historically, this methodology is nothing more than a process of planning and handling experiences. It is, therefore, based on the concept of experiment, which can itself be defined as the alteration of parameters to promote the discovery of new information. Its foundations were built by Ronald Fisher during the 1920s and 1930s and underwent significant development after the end of the Second World War [21].

Later, several authors contributed to the development of DOE, with a brief description for each in Table 1.

Table 1. Some authors of DOE and their contributions to the field.

Author	Contribution to the Scientific Community
Ronald Fisher	Introduction of statistical principles in experiments in the areas of agriculture and animal testing science; factorial designs [22]
George Box	Introduction of RSM (Response Surface Methodology) and the concept of matrix robots; evolution of sequential experiments [23]
R.L. Plackett and J.P. Burman	Use of orthogonal matrices as a screening tool, enabling unbiased predictions with a reduced number of trials [24]
Genichi Taguchi	Introduction of a new design of orthogonal matrices, aiming to reduce the number of tests; calculation of the S/N index (signal-to-noise ratio); evolution of the concept of robust designs [23]

DOE is a methodology that can be applied in several areas. Despite usually consuming some time and effort, it has proven to be a very effective methodology [25].

The complexity of a DOE is determined by its type, as well as the number of factors (variables to be studied) and the number of levels in each of these factors. The levels mean the extreme points of the planned amplitude, usually ordered in increasing order, for the study in question. The larger this range, the easier it is to identify the effect of one of the factors or interaction of factors [20].

The application of any iteration of DOE should be followed by some statistical approval tool, in order to confirm conclusions drawn in the experimental phase. One of the most used is ANOVA. To be applied, this tool must verify the normality of the data, but there are cases where this is not verified. To overcome this obstacle, transformations such as logarithmic transformations are used [20].

The steps of the development and application of a DOE, which may have small variations depending on the author, are shown in Figure 4.

Figure 4. DOE regular application steps.

In DOE, there are two key concepts, randomization and replication. The former is the opposite of the act of performing tests with some logical order, that is, they are performed in a random order to avoid bias. Replication can be explained as the repetition of the same conditions in two different tests, giving consistency to the information collected in the equivalent attempts [26]. Associated to these two concepts, there is another complementary one, called blocking. It deals with the impermeability of the experiment to external factors that may affect the process. A golden rule is to block everything possible and randomize everything else [20].

A distinction can be made between two types of experiments: comparative and screening. The first is the simplest iteration, comparing alternatives using statistical tools to find the best alternative. The second seeks to understand which factors influence the process, i.e., those of more or less importance [20]. Examples of comparative experiments arise in randomized designs that use blocking, and these seek to study especially one factor, always considering others that may affect the process. On the other hand, full or fractional factorial experiments are examples of screening experiments.

Inputs will be the data that the process receives, these being controllable or not. They can be considered normal factors, that is, variables with direct effects and interesting for the study, or they can be noise factors, variables that affect the process but are not under the control of the user [20]. The latter type of factor is undesirable, but should also be considered, and the robustness of the experiment reveals the sensitivity of the process to these types of factors [27], something that is addressed in later sub-points.

Outputs are the result of the process, the inputs, and the effects between all the variables addressed. Both outputs and inputs must be measurable, the former being just that and nothing more.

The classical DOE model uses Equation (1) as an assumption, with the assumption that all measured responses have an associated error value. y_m is the measured response, y_t is the theoretical response, and ε is the term referring to the assumed value [28].

$$y_m(x) = y_t(x) + \varepsilon \tag{1}$$

2.4. Full Factorial

Full factorial experiments use the totality of factors and their respective levels. As such, all effects and interactions between factors are studied. Interactions tend to be the catalyst for optimizing process improvements [29]. The expression used to calculate the number of tests, N, in complete factorial experiments is shown in Equation (2) [19]:

$$N = L^k \tag{2}$$

where L is the number of test levels, and k is the number of factors.

As is possible to analyze in Equation (2), the number of tests grows rapidly with the growth of the number of levels and the number of factors, so this type of DOE is usually preferable for tests with two or three levels [19].

In tests with two levels, coding with positive and negative signs is recommended. In the following example, Table 2, considering the outputs X_1 and X_2 and the factors A, B, and C with two levels, a typical table for a two-level coded DOE is presented, with merely representative values.

Table 2. Two-level full factorial.

Index	Run	A	B	C	Y_1	Y_2
1	8	–	–	–	74	3.1
2	1	+	–	–	75	3.7
3	2	–	+	–	61	1.3
4	4	+	+	–	80	1.2
5	3	–	–	+	82	0.7
6	5	+	–	+	77	0.2
7	7	–	+	+	42	0.5
8	6	+	+	+	32	0.3

2.5. SPC

Statistical Process Control through control charts was developed by Walter Shewhart [30]; in association with the continuous improvement supported by statistical tools, this methodology has become increasingly relevant in industrial and academic contexts [31]. This methodology fits in with the last DMAIC phase, presenting itself as a proper technique to be applied to cork block production optimization.

The quality of a process is directly dependent on customer satisfaction and meeting customer expectations [32].

As such, there are two types of causes that can make the quality of a product vary: common causes, being intrinsic to the process and context where it is executed, and special causes, which can be the result of a multitude of consequences [33]. The first type of cause is expected, while the second is unexpected and spontaneous [32], and should be properly studied.

In general, despite providing the user with more statistical knowledge, control charts for continuous variables tend to be more expensive and complex to implement [31].

2.6. X-R Charts

In this context, two types of charts arise: charts for large samples (n equal to or greater than 25) and small samples (n less than 25). For the first type, X and S charts, referring to mean and standard deviation, should be used. For the second type, X and R charts, referring to mean and range, are recommended [33]. In all control charts based on the mean, the central limit theorem can be applied, allowing us to assume that the variable studied has a normal distribution [33]. For sample sizes with less than 10 units, the most appropriate types are the X and R charts, and so it is necessary to first proceed to calculate the average amplitude, $\overline{R}$ [33]:

$$\overline{R} = \frac{R_1 + R_2 + \ldots + R_k}{k} \quad (3)$$

This results in the following control limits, represented in Equations (4)–(9), where d_2 is a constant that depends on the sample size in question [34].

$$UCL = \overline{x} + 3\frac{\overline{R}}{d_2\sqrt{n}} \quad (4)$$

$$CL = \overline{x} \quad (5)$$

$$LCL = \overline{x} - 3\frac{\overline{R}}{d_2\sqrt{n}} \quad (6)$$

$$UCL = \overline{R} + 3\frac{d_3\,\overline{R}}{d_2} \quad (7)$$

$$CL = \overline{R} \quad (8)$$

$$LCL = \overline{R} - 3\frac{d_3\,\overline{R}}{d_2} \quad (9)$$

Graphically, this type of chart, where the red lines represent the UCL, LCL, and CTR lines, while the blue dots are plotted with the gathered data, is visualized as the example present in Figures 5 and 6 [34]:

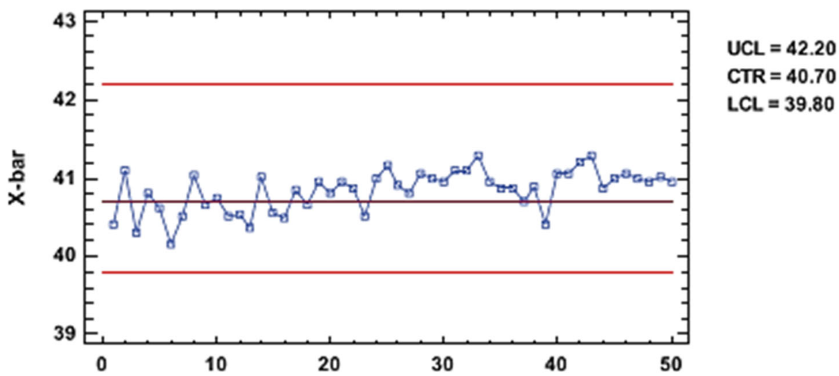

Figure 5. X-bar chart example.

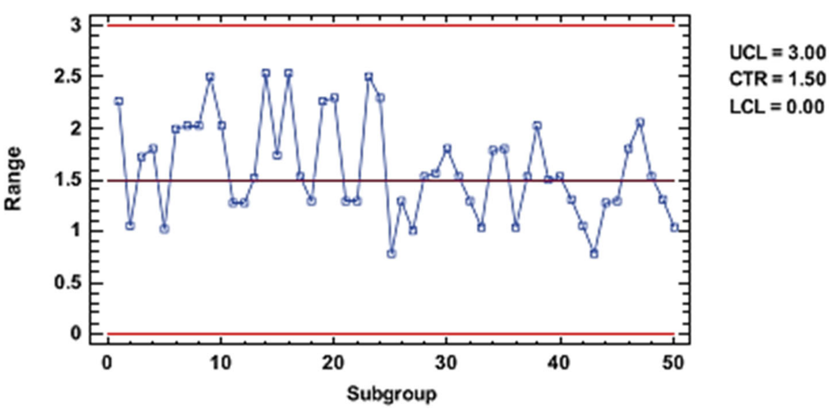

Figure 6. Range chart example.

3. Materials and Methods

Cork blocks follow the order of operations; first, the granulates are mixed with the glue and water in a blender, then the mix suffers compression molding, followed by high-frequency heating, and ending on the stabilization inside and outside the respective mold.

With the goal of properly conducting the study, three main methodologies were selected: DMAIC, DOE, and SPC. The first functioned as structural and directional guidance for the entirety of the study, including both phases present in the article, mainly the Improve and Control phases, as the ones applied prior to this description, being the Define, Measure, and Analyze phases. DMAIC was applied due to the clear direction and effectiveness shown, highly cemented by the scientific community.

Similarly, DOE presents itself as a diverse methodology, with all its different variations, allowing for its application in a variety of studies. With this, one specific strategy was selected, the full factorial, which will be deepened in the present chapter. The application of this specific DOE variation is based on the accessibility of application, as well as the security of results this provides. Phenoms such as noise factors are not well comprehended in this methodology, but considering the project and factory where the study was conducted, it is a clear way to properly conduct the study.

Regarding SPC, its scope ranges from continuous or discrete data, as explained in the literature review chapter, which allows for it to be applied in different scenarios. Given the ease of application of the X and R charts, and the historical presence of these within the day-to-day monitoring of production of the unity, these charts were effective and easy to apply.

Prior to the application of tools such as DOE, it is essential to filter which variables are worth including in the factor group, which is subsequently tested through different combinations. As such, qualitative and quantitative tools, such as the Fishbone Diagram and *t*-tests, were used before the current project to identify these inputs, based on a previous gathering phase that collected data for the four products present in this study. These processes were conducted according to the Define and Measure phases of the DMAIC methodology.

Once the critical variables, which are independent, have been identified, improvements are implemented in the process. For that, planned experiments were applied. Three inputs are considered: the current intensity of the high-frequency oven, baking time, and the stabilization time. These function as the independent variables. The output for the trials were properties: Compressibility, Recovery, Yield Strength, and Density. These variables are dependent on the process and independent variables. As such, the factors are displayed as follows, in Table 3.

Table 3. DOE factors with the respective letters, levels, and units.

Factor	Letter	Superior Level (+)	Inferior Level (−)	Units
Current Intensity	A	90	80	Amperes (A)
Heating time	B	150	115	Seconds (s)
Stabilization Time	C	4	1	Days (d)

Table 3 details the scope of the factors, as well as its units. It is essential to highlight that the superior and inferior level represent the values to be executed in the planned experiments. The amplitude of the scope was intended to be as large as possible, considering the process possibilities, having each factor amplitude adjusted individually.

To make this phase more effective and robust, replications were executed. For each run, two blocks are clustered, resulting in a total of four sheets per trial. Each sheet has the following dimensions: $950 \times 650 \times 4$ mm.

Once the three critical factors have been identified and their levels defined, and considering the productive capacity and availability of the unit, a full factorial methodology was implemented. The number of experiments, based on Equation (2), for each reference, results in eight:

$$2^3 = 8 \quad (10)$$

Having the number of runs defined, it is necessary that these be carried out randomly, so that no uncontrollable effects are created in the planning of the experiments, an undesirable phenomenon explained in the literature review chapter. The results of the combination of runs in a random order are shown in Table 4. It is also worth noting that the run with all the factors on its highest level serves as the control sample, given that there are historical data with this parameter setup amongst the company's records.

Table 4. Planned experiment runs and disposition.

RUN	A	B	C	AB	BC	AC	ABC
1	+	−	−	−	+	−	+
2	+	−	+	−	−	+	−
3	−	−	+	+	−	−	+
4	+	+	−	+	−	−	−
5	−	+	−	−	−	+	+
6	−	+	+	−	+	−	−
7	−	−	−	+	+	+	−
8	+	+	+	+	+	+	+

Table 4 shows all the trials, as well as the interaction effects between the factors.

It is important to mention that, according to [20], it is unlikely that the relationship between the three factors will have a significant effect. For this order, a factor count of two was selected, which excludes the interaction between three factors and only focuses the interaction between two factors.

This configuration is applied to the four items filtered by the number of units produced per reference during the year 2022.

The structure of the analysis follows the order presented:

1. Pareto diagram of effects of factors A, B, and C, also associating the interactions AB, BC, and AC.
2. ANOVA of the factors A, B, and C, also associating the interactions AB, BC, and AC.
3. Summary of the model with the factors A, B, and C, and the interactions AB, BC, and AC.

Once the runs are executed, the selected sheets, with the previously described dimensions, go to the factory's lab, which presents the values of the four outputs (dependent variables). Details from the tests are not allowed to be publicly available by the company where the study was produced.

Regarding step two of the analysis, it is worth noting that the ANOVA test, which uses the null and alternative hypothesis to compare the statistical significance of a proposition [35], largely depends on the p-value obtained from the software. If this is bigger than α, the confidence level of the test, then the significance of the effect in the analysis is considered irrelevant. Else, if the p-value is smaller than α, it can be concluded that the factor or interaction being analyzed has statistical significance on the output [36].

It is important to clarify that Products A and C use granulate size X, while B and D use granulate size Y. This will prove to be a significant detail, as explained in further chapters. The only difference between Products A, B, C, and D is the formulation, which is confidential, due to the company's policy.

Considering the process limitations, described in the subsequent sections of this document, it is concluded that the sample size will be less than 10 units, and since all the variables under analysis are continuous, mean and range control charts X and R were applied. For this purpose, four test blocks are clustered, with their respective parameter changes defined after due analysis of the results of the planned experiments. From each block, two plates are removed, one from the upper face and another from the lower face, thus trying to ensure homogeneity in block quality. Control charts will only be applied to the products that reveal statistical significance of factors or interactions. It is also worth noting the necessity of grouping the results from the sheets of the same block into a subgroup, due to Minitab's restriction of having a group with a size of at least two in order to apply the selected control charts. As such, DOE works as a funnel to select the products in which changes will be applied. The data will be analyzed in the software Minitab (version 22.1).

4. Results

Having applied the previously described methodology, we obtained some notable results.

In this section, the results from the full factorial technique, a variation of planned experiments, with three factors and two levels each, along with the respective results of the application of the X and R charts, are shown and explained.

It is worth noting that products A, B, C, and D were selected in a previous phase of the DMAIC methodology, the result of the most produced references in the factory portfolio. Then, through quantitative and qualitative techniques, the three variables were chosen: A being the current intensity, B being the heating time ("tempo de cozedura" in Portuguese), and C being the stabilization time.

Then, having the products, outputs, and variables (inputs) selected, as well as its respective levels, the runs were conducted according to the full factorial technique, with three factors and two levels per factor. The entirety of the methodology applied in this studied is discussed in detail in the previous section.

Only the results with statistical significance were analyzed in this chapter. The rest of the results are not worth including. In those cases, conclusions are drawn to understand why no effect or interaction is relevant to the output, explored in subsequent sections.

4.1. DOE Results of Product B

Based on the following data, it can be concluded that for the Compressibility of Product B, the BC factor interaction has a significant impact, as it exceeds the *p*-value set for the confidence interval, as shown in Figure 7, confirmed by the ANOVA value presented in Table 5, due to the *p*-value of the interaction BC being lower than α, which determines the confidence level of the test [37]. Since both the S and R^2 are desirable, it can be concluded that the model is appropriate to the data gathered, as shown by Table 6.

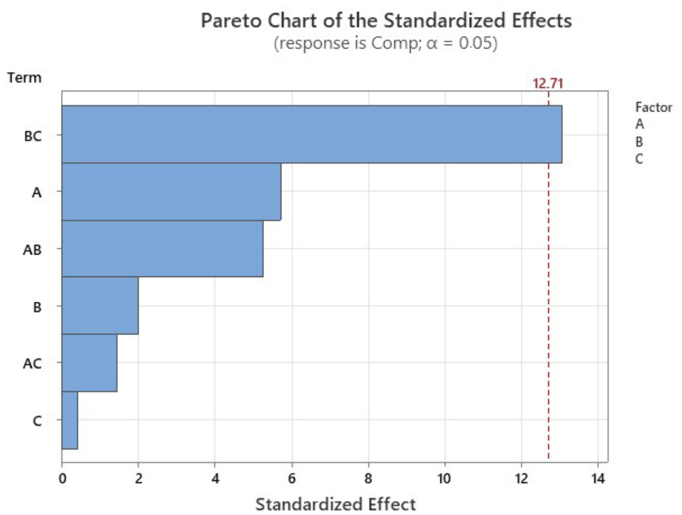

Figure 7. Pareto diagram of the Compressibility of Product B.

Table 5. ANOVA of the Compressibility of Product B.

Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	***p*-Value**
Model	6	6.72312	1.12052	39.44	0.121
Linear	3	1.04816	0.34939	12.30	0.206
I. Corrente	1	0.92701	0.92701	32.63	0.110
T. Cozedura	1	0.11598	0.11598	4.08	0.293
T. Estab	1	0.00516	0.00516	0.18	0.743
2-Way Interactions	3	5.67496	1.89165	66.58	0.090
I. Corrente*T. Cozedura	1	0.78328	0.78328	27.57	0.120
I. Corrente*T. Estab	1	0.06068	0.06068	2.14	0.382
T. Cozedura*T. Estab	1	4.83100	4.83100	170.04	0.049
Error	1	0.02841	0.02841		
Total	7	6.75153			

Table 6. Model summary of the Compressibility of Product B.

Model Summary			
S	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
0.168557	99.58%	97.05%	73.07%

Note that "*" in the following figures and tables means the interaction between two factors.

The other output that presents significant results within Product B is the Tensile Strength, which is supported by the same explanations given for the Compressibility.

As can be seen in the Pareto diagram of effects in Figure 8, this presents statistical significance through the interaction between factors B and C. The values of the ANOVA analysis, as shown in Table 7, prove the significance of the interaction.

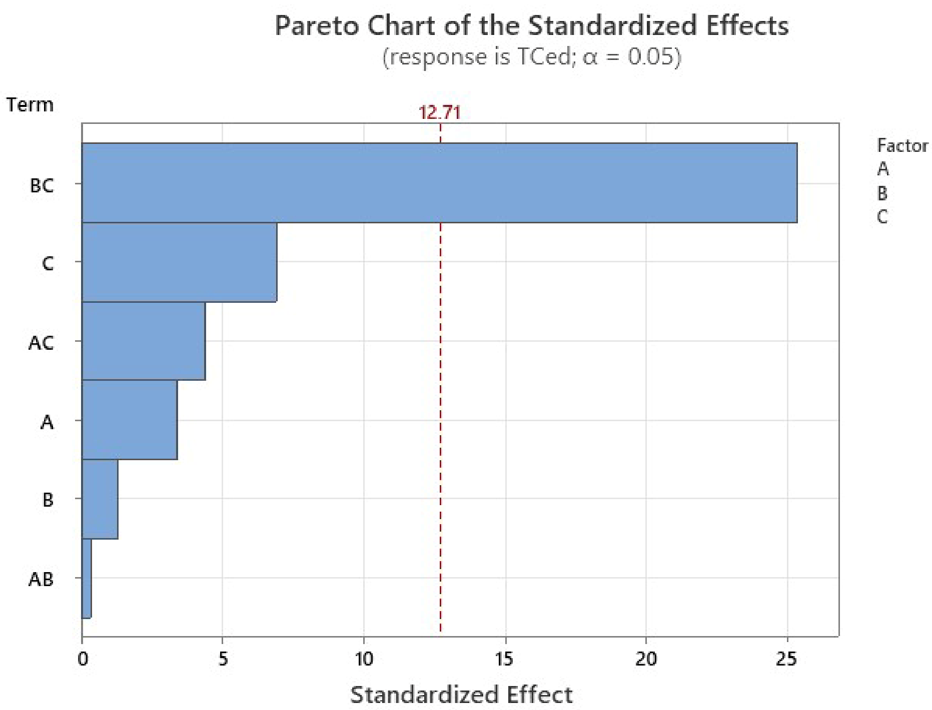

Figure 8. Pareto diagram of the Tensile Strength of Product B.

Table 7. ANOVA of the Tensile Strength of Product B.

Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	***p*-Value**
Model	6	13624.5	2270.7	120.20	0.070
Linear	3	1145.9	382.0	20.22	0.162
I. Corrente	1	215.6	215.6	11.41	0.183
T. Cozedura	1	32.5	32.5	1.72	0.415
T. Estab	1	897.7	897.7	47.52	0.092
2-Way Interactions	3	12478.5	4159.5	220.17	0.049
I. Corrente*T. Cozedura	1	2.1	2.1	0.11	0.794
I. Corrente*T. Estab	1	361.9	361.9	19.16	0.143
T. Cozedura*T. Estab	1	12114.5	12114.5	641.25	0.025
Error	1	18.9	18.9		
Total	7	13643.4			

The model summary verifies the adequacy of the model for the data introduced, due to the R^2 value being appropriate to the data analyzed, as shown in Table 8.

Table 8. Model summary of the Tensile Strength of Product B.

Model Summary			
S	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
4.34650	99.86%	99.03%	91.14%

Considering the results of Compressibility and Tensile Strength, it can be concluded that the interaction between factors B and C is the intervenient with the most effect on the two mechanical characteristics, so it is recommended to maintain the standard values used so far, so as not to harm the quality of the product in these two outputs. The current intensity (factor A) should be decreased for the subsequent control phase, so that it is possible to obtain a reduction in energy consumption.

4.2. DOE Results of Product D

The Pareto diagram for Compressibility of Product D, as shown in Figure 9, shows that factor C directly affects the output, with a *p*-value that graphically reaches beyond the statistical significance line, highlighted in red, and is below the confidence limit previously established in the respective ANOVA, as shown in Table 9.

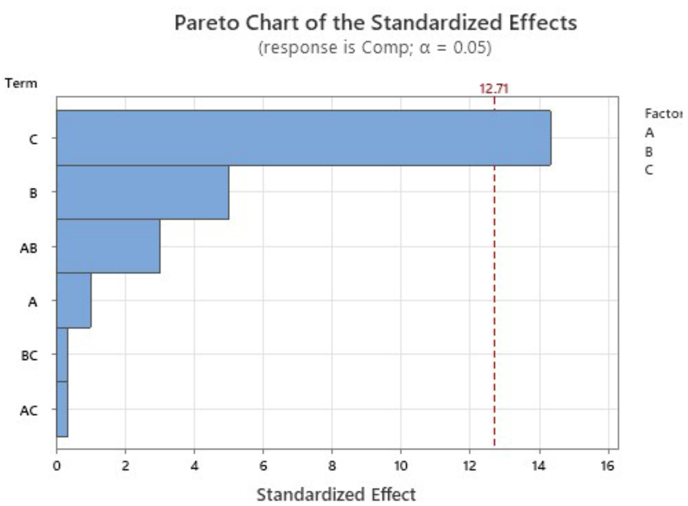

Figure 9. Pareto diagram of the Compressibility of products.

Table 9. ANOVA of the Compressibility of Product D.

Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	***p*-Value**
Model	6	10.8300	1.80500	40.11	0.120
Linear	3	10.4150	3.47167	77.15	0.083
I. Corrente	1	0.0450	0.04500	1.00	0.500
T. Cozedura	1	1.1250	1.12500	25.00	0.126
T. Estab	1	9.2450	9.24500	205.44	0.044
2-Way Interactions	3	0.4150	0.13833	3.07	0.392
I. Corrente*T. Cozedura	1	0.4050	0.40500	9.00	0.205
I. Corrente*T. Estab	1	0.0050	0.00500	0.11	0.795
T. Cozedura*T. Estab	1	0.0050	0.00500	0.11	0.795
Error	1	0.0450	0.04500		
Total	7	10.8750			

The model summary, as shown in Table 10, proves that the study is valid, with the model fitting the data, due to its low S value and R^2 value close to 100%.

Table 10. Model summary of the Compressibility of Product D.

Model Summary			
S	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
0.212132	99.59%	97.10%	73.52%

Similarly to Product B, Product D shows statistical significance in the Tensile Strength. However, this is not revealed through the BC interaction, but by factor C. The Pareto diagram, as shown in Figure 10, displays the effect of this factor, given that it is graphically crossing the red line, which represents statistical significance. The *p*-value, inferior to α, of the respective ANOVA, as shown in Table 11, proves this statement.

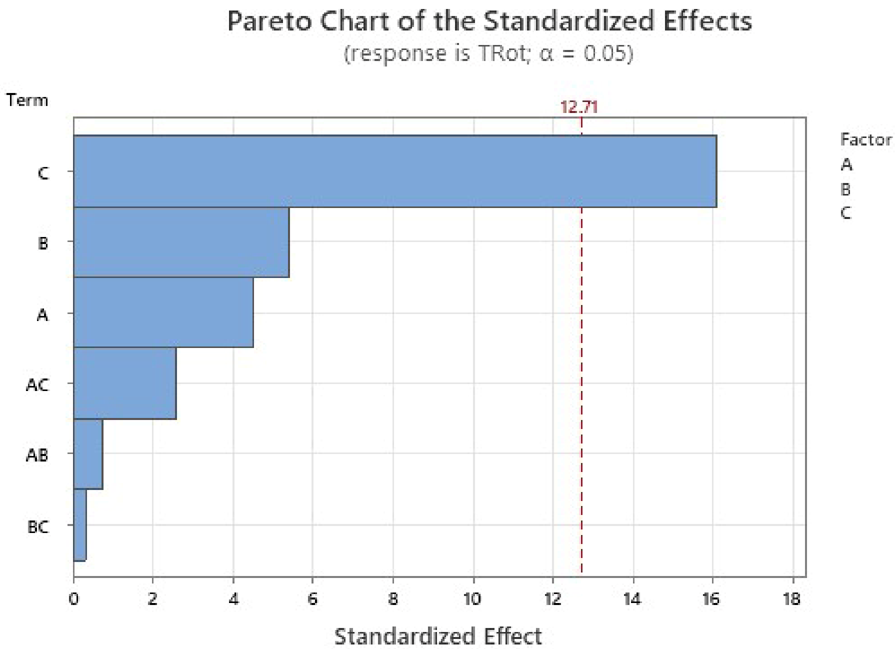

Figure 10. Pareto diagram of the Tensile Strength of Product D.

Table 11. ANOVA of the Tensile Strength of Product D.

Analysis of Variance					
Source	**DF**	**Adj SS**	**Adj MS**	**F-Value**	***p*-Value**
Model	6	48433.3	8072.2	52.75	0.105
Linear	3	47330.1	15776.7	103.09	0.072
I. Corrente	1	3120.9	3120.9	20.39	0.139
T. Cozedura	1	4457.1	4457.1	29.12	0.117
T. Estab	1	39752.1	39752.1	259.75	0.039
2-Way Interactions	3	1103.2	367.7	2.40	0.435
I. Corrente*T. Cozedura	1	79.4	79.4	0.52	0.603
I. Corrente*T. Estab	1	1007.8	1007.8	6.59	0.237
T. Cozedura*T. Estab	1	16.0	16.0	0.10	0.801
Error	1	153.0	153.0		
Total	7	48586.4			

Despite having a relatively high value of S, the model summary, as shown in Table 12, consolidates the statistical significance values obtained, supported by the value of R^2, which is close to 100%.

Table 12. Model summary of the Tensile Strength of Product D.

Model Summary			
S	**R-sq**	**R-sq(adj)**	**R-sq(pred)**
12.3708	99.69%	97.80%	79.84%

Interpreting the values presented for the Compressibility and the Tensile Strength of Product D, it is possible to conclude that factor C is the one that most interferes with the quality of the product. In this sense, the "term" quality is presented as the performance of the mechanical characteristics. As explained previously, factor C represents the stabilization time, measured in number of days, and being that it affects two of the four mechanical characteristics, it should not be altered, since it can compromise the quality of the final product. As such, since no other factors or interactions are statistically significant in any output, these can be decreased in order to allow an increase in the process cadence, in the case of the baking time (factor B), which is presented as the process bottleneck, and energy saving by reducing the current intensity (factor A).

Only factor A (current intensity) was changed in Product B since the interaction of BC factors proved to be statistically significant in the characteristics Compressibility and Tensile Strength.

4.3. SPC Results of Product B

Once the experimental runs are finished and the changes in parameters are applied, statistical control was applied to the production of cork blocks, in order to make sure that the alterations implemented do not affect the mechanical performance of these products.

Product B's only change occurs on factor A, current intensity, from 90 A to 80 A. Its Compressibility can be observed to be perfectly within control, presenting low amplitude between the results obtained, as shown in Figure 11, since it does not reveal any point out of control.

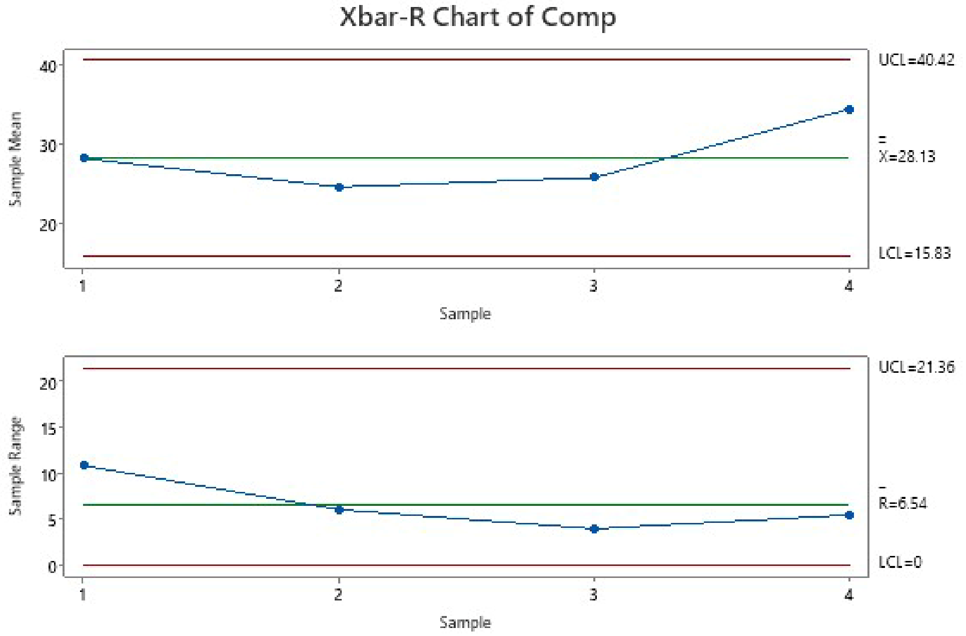

Figure 11. X and R charts for the Compressibility of Product B.

In the Recovery of this product, it is possible to observe that one agglomerated block, from which the two sheets result, presents a point above the upper control limit, as shown in Figure 12.

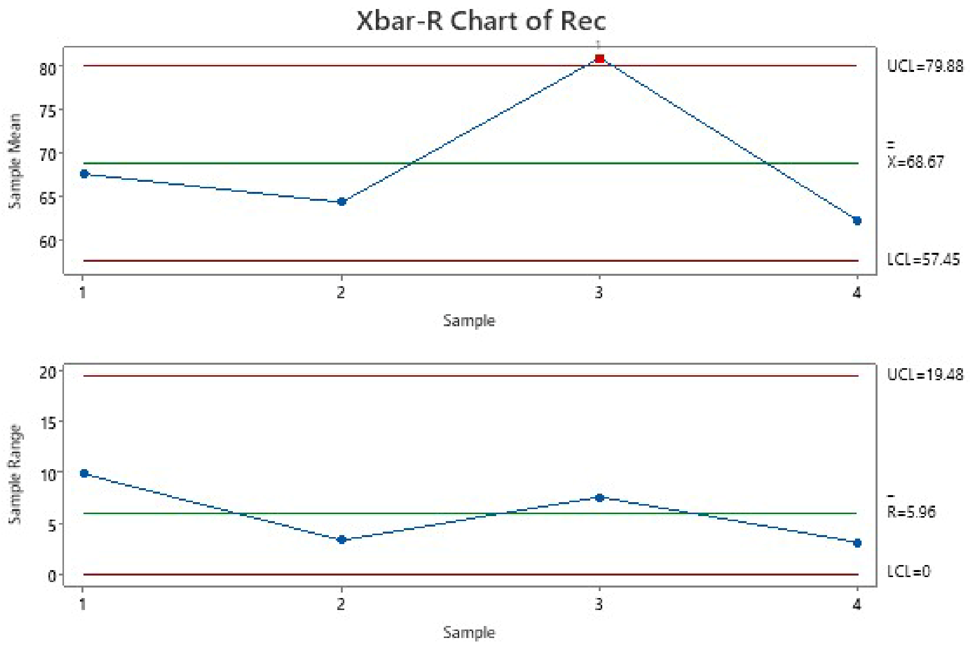

Figure 12. X and R charts for the Recovery of Product B.

No person involved in the production of this block, such as the operator or supervisor, can identify the origin of the variation, which may be due to the quality of the raw material itself, or even to circumstances in the process, such as excessive time spent in some operation prior to heating, causing the mixture to overheat in those same operations of the agglomeration line, such as in the press or in the mixer itself. This is something that can happen due to a variety of circumstances that could not be controlled by the operator.

Therefore, this point is removed, as it was a one-time event. With this, the control chart is now perfectly within the set limits, as shown in Figure 13.

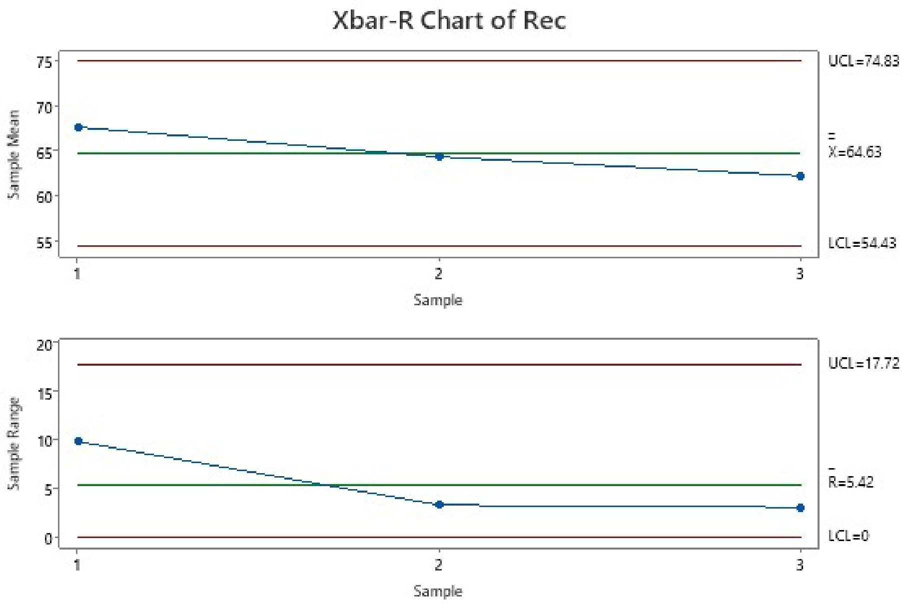

Figure 13. X and R charts for the Recovery of Product B with the out-of-control point removed.

The Density of Product B is within the expected values, as shown in Figure 14, given that there are no points above or below the control limits. It is important to note that this characteristic is the one where the least variation is expected, since it depends on the formula (quantity and quality of the granulate, amount of glue, etc.), so the change mentioned for Product B should not introduce much variation in the results of this characteristic. Therefore, all the variation present is the natural variation inherent to the characteristic itself.

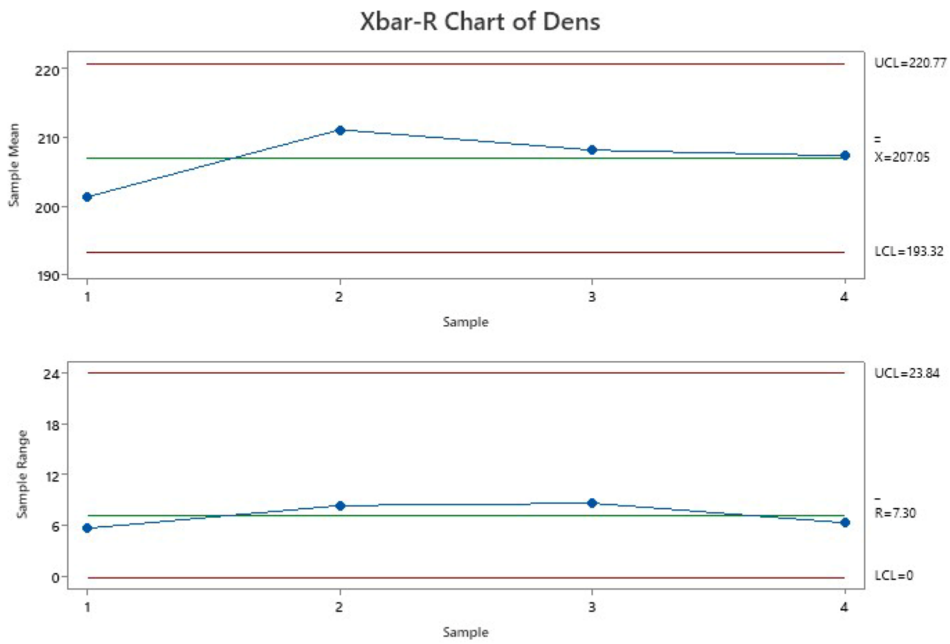

Figure 14. X and R charts for the Density of Product B.

The last characteristic is the Tensile Strength, and this again shows the points within the control limits of the mean and amplitude control chart, as shown in Figure 15.

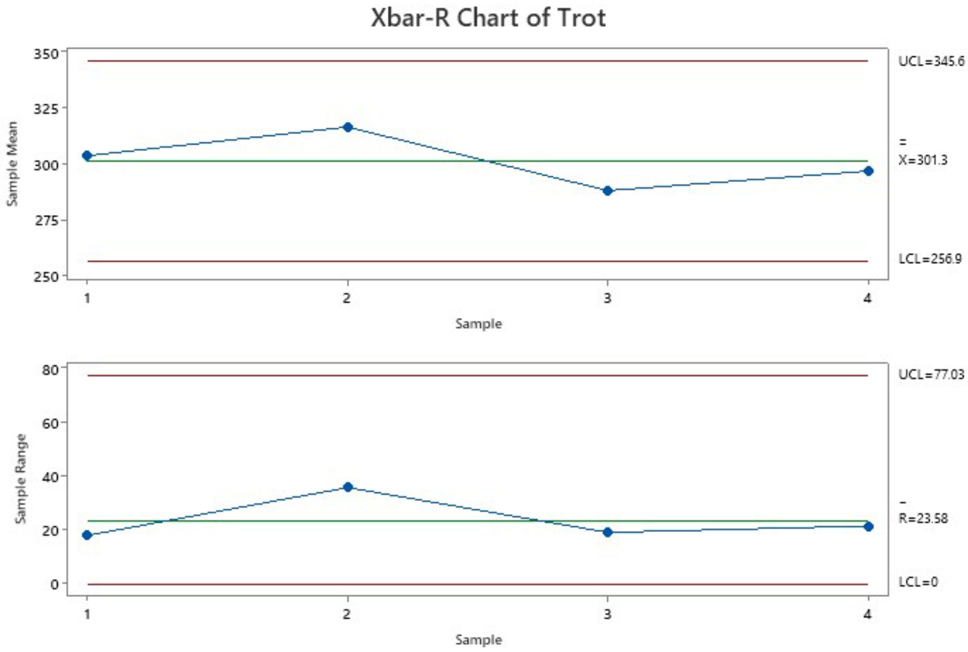

Figure 15. X and R charts for the Tensile Strength of Product B.

4.4. SPC Results of Product D

Regarding Product D, considering the results obtained in the planned experiment phase, changes are induced in factors A (from 90 A to 80 A) and B (from 150 s to 115 s), current intensity and heating time, respectively. The only parameter that remains the same is factor C, stabilization time, measured in number of days.

The Compressibility of Product D was again shown to be under control, as shown in Figure 16, despite point three showing a relatively large amplitude.

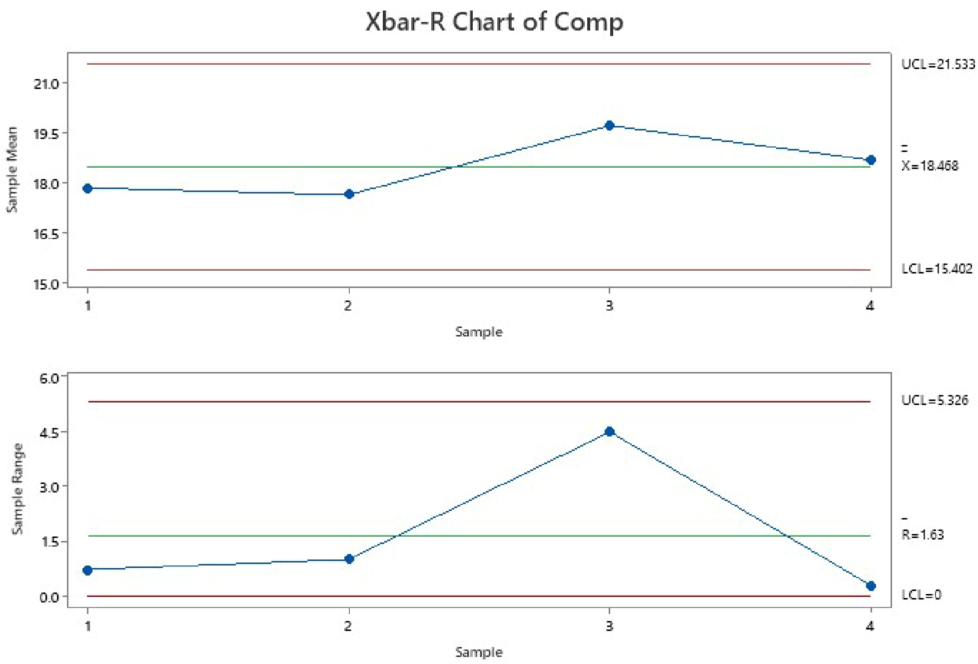

Figure 16. X and R charts for the Compressibility of Product D.

The only out-of-control point present on the Product D charts also appears in the Recovery, as shown in Figure 17, similar to the same out-of-control point of Product B.

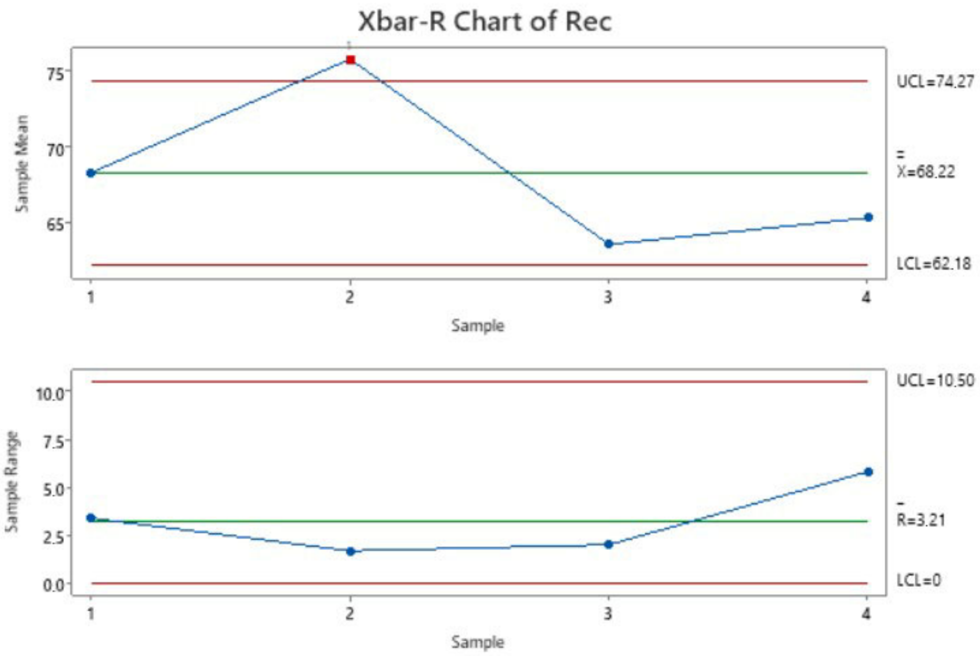

Figure 17. X and R charts for the Recovery of Product D.

Identically to Product B's out-of-control point, it was not possible to identify the cause of the variation, so this point must be removed, and a new analysis must be carried out. In this analysis, it is verified that after removing the out-of-control point, the other values are now in accordance with the limits stipulated by the mean and range chart, as shown in Figure 18.

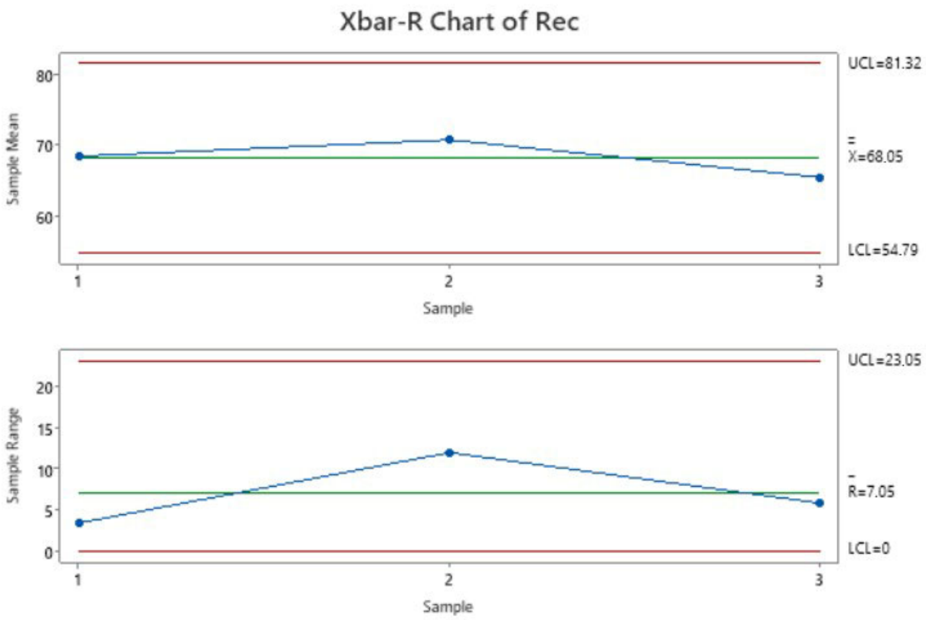

Figure 18. X and R charts for the Recovery of Product D with the out-of-control point removed.

The Density appears perfectly within control, since it theoretically depends more on variables related to the mixture formula, as shown in Figure 19.

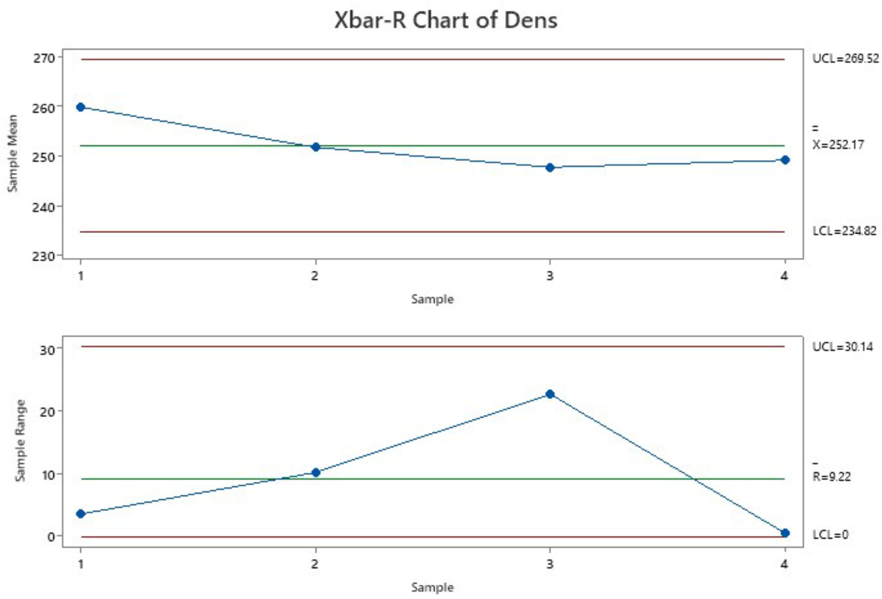

Figure 19. X and R charts for the Density of Product D.

To conclude, the Tensile Strength of Product D is also within the limits of the control charts X and R, as shown in Figure 20.

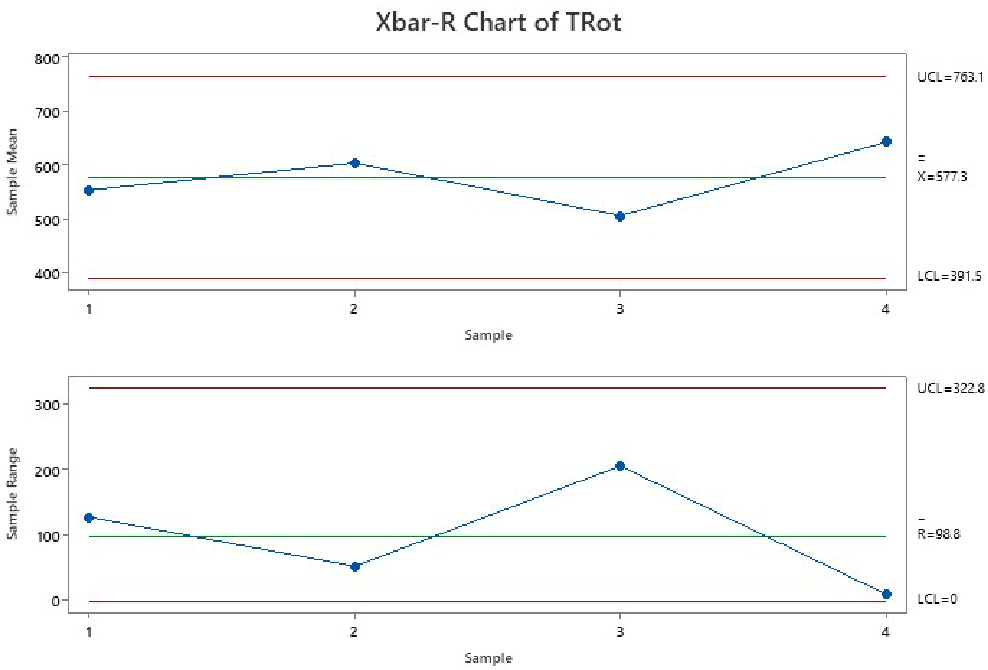

Figure 20. X and R charts for the Tensile Strength of Product D.

5. Conclusions and Discussion

Implementing process improvement in a production line, such as the one presented in this article, requires knowledge of various degrees of complexity. It is preferable to analyze and implement any sort of changes in a planned way, using proper resources that are historically proven, such as DOE and SPC.

The growth of DOE in the scientific community and in industrial contexts is evident. It is also a reality for other methods, such as Taguchi's, which can be applied to metaheuristics [38,39].

Regarding the content presented about the control charts, it is possible to conclude that they are versatile and can be applied to various sample sizes. Focusing on the charts used in this article, X and R charts appear to be effective for validating the proposed parameter changes.

This paper effectively establishes historical techniques, shortening the gap between academic concepts and real-world implementation. Considering the positive results and conclusions presented in this chapter, it validates the importance that concepts such as DOE have. Along with the application in revolutionary solutions, such as the ones that derive from cork agglomerates, this combination presents the paper as one that considers the history of the methodologies and cork and shows how they can be applied to make the environment a better place, allowing for more resource savings.

After presenting the entirety of results, it is possible to draw conclusions about the parameters selected as factors. Furthermore, it is possible to understand the influence that non-controllable variables, such as the quality of the cork granulate, may have on the results of the tests performed.

As for products A and C, which have the same raw material as a base, i.e., cork quality, the results converge to only one conclusion; the variation in a base component, such as the raw material, can make the study applied in the planning of experiments unfeasible. The molds in which the project was carried out did not allow the quality of the raw material to be controlled and, as such, products using the variety with the least availability in the market, and with the respective quotation in constant variation, end up being difficult to study. For these products, it is not recommended that changes be applied, as statistical significance is not supported by models appropriate to the data and may lead to the conclusion that no factors or interactions influence the outputs, when they actually might.

Interesting conclusions could be drawn for products B and D. To begin with, it was in the same mechanical characteristics, Compressibility and Tensile Strength, where these results appeared, which suggests that these outputs are the ones that present the greatest sensitivity to variations in parameters related to high-frequency baking. In Product B, it was the interaction between factors B and C that stood out, while in Product D, it was factor C. As such, the conclusion can be drawn that the stabilization time (factor C) should not be altered for either, while in Product B, the heating time (factor B) should also be maintained. Product D can change the current intensity (factor A) and heating time (factor B). For Product B, on the other hand, only changes in current intensity (factor A) are recommended.

Having presented all the results of the control charts applied to the products that have undergone factor changes, it is possible to conclude that the success rate of the whole process is relatively high, since the only out-of-control points appear in one mechanical characteristic for each of the products.

The only characteristic with out-of-control points was the Recovery in both cases, which leads one to think that it may be more sensitive to variations in the process parameters. Since only one out-of-control point appears for each product, it can be concluded that it is not necessarily something to worry about from the perspective of the selected critical parameters. It is not desirable to have a characteristic outside the specification limit, but the control of a characteristic that is so sensitive to parameters other than those chosen should be carried out by responsible supervision. The out-of-control point can hardly be explained by the variation in one or two applied factors, not least because there are no data to validate the theory that this variation did not happen before the project in question. As such, it can be concluded that the application of the SPC methodology revealed that the process was still in control after the implementation of the parameter changes.

Based on the results presented in the previous chapter, it can be deduced that the changes applied after carrying out the planned experiment study benefited the factory unit, as they allow energy savings and gains in cadence. This happened because, depending on the product in question, factors A and B, current intensity, and cooking time, respectively, are decreased, separately or complementarily. Even if the high-frequency oven, which has both of the parameters mentioned, is not the bottleneck, the fact that it is not in activity, i.e., conducting electric flow while waiting for other operations, means that less electricity is spent. If this operation is the bottleneck of the process, it allows a gain in cadence which, in turn, and relating it to the cooking time, also leads to lower energy expenses.

The application of DOE with SPC highlighted the importance that the raw material, an uncontrollable variable, can have on the results, going beyond the normal control limits. This conclusion was transparently portrayed in Products A and C, where no factor or interaction between factors has statistical significance. Taking the above statement as a fact could cause serious problems in the manufacturing unit, as it is highly unlikely that none of the factors cause an effect on the mechanical characteristics of the block, because otherwise, it would not make sense for the heating operation to exist. As such, it makes no sense to apply changes to the parameters of these two products, which consequently leads to the use of control charts in this context being obsolete. Although Products B and D present an out-of-control point, both in the output Recovery, and taking into consideration the explanation given in the previous sub-chapter, it is considered that the control charts solidify the change in the size of the parameters. Therefore, it is important to conclude that the raw material must present some homogeneity, as well as the operator must be present in the control of the several variables of this process, this being the biggest difficulty of the implementation of improvements in certain products.

The realization of the project had limitations. One of these, which conditioned the results, was the variation in raw materials, specifically cork granulates. As explained, these are the basis of every cork agglomerate formulation, and strongly depend on the suppliers of cork. Limitations were also found, inherent to the process and information flow within the company where the project was performed.

One aspect to consider is that executing the study depended on the availability of the production, since the study was applied in an industrial context. As explained in previous chapters, during the Define and Measure phases, the products on which the study was conducted were selected, with the support of the appropriated tools, such as the Pareto diagram. This tool was applied on the number of units produced per reference, in the year 2022. This analysis was important due to the multitude of different references produced in the factory. Therefore, since there was only a range of products to be studied, there were several moments that these items were not being produced, thus causing unwanted difficulty in collecting data. For this, the authors suggest a different filtering strategy: select the references to be studied by type of granulate.

The last limitation to be highlighted is the lack of availability of the production unit to increase the sample size in the Control phase, where the SPC methodology is applied, which would strongly cement the statistical validation of the study.

In conclusion, studies like the one conducted in this paper are important to the industrial context, given the demand for sustainable solutions. As such, the dichotomy of the use of cork with the power saving achievement in this project results in an example that can be projected to other market and industrial sectors. Given the importance of preserving resources and the hope to make our planet a better place for the future, the production of goods must be greener with each evolution made.

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