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BEYOND PROCESS STABILITY: A COMPARATIVE ANALYSIS OF PROCESS CAPABILITY AND TARGET CENTERING IN TWO INDUSTRIAL ENTERPRISES

ALÉM DA ESTABILIDADE DO PROCESSO: UMA ANÁLISE COMPARATIVA DA CAPACIDADE DO PROCESSO E DA CENTRALIZAÇÃO EM RELAÇÃO AO ALVO EM DUAS EMPRESAS INDUSTRIAIS

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ABSTRACT
This study comparatively evaluates the industrial performance of the National Enterprise for Long Products Transformation (NELPT) and Sidi Khaled Dairy (SKD) through an integrated Statistical Process Control (SPC) and process capability assessment framework. The research adopts a quantitative and comparative case-study design based on production data collected from two Algerian industrial enterprises operating in distinct sectors. The analytical procedure combines descriptive statistics, Anderson–Darling normality testing, X̄-R control charts, and process capability indices, including Cp and Cpk, in order to assess process stability, variability, centering, and conformity with established specification limits. Substantial differences were observed in their capability profiles. NELPT exhibited a process mean relatively close to the nominal target, but excessive process variability resulted in low capability levels, indicating an insufficient ability to consistently meet specification requirements. In contrast, SKD demonstrated exceptionally low process variability and very high potential capability. Nevertheless, the considerable difference between Cp and Cpk revealed a systematic displacement of the process mean from the nominal target. The findings demonstrate that statistical stability does not necessarily imply adequate process capability or optimal target centering. The comparative analysis highlights two distinct sources of industrial inefficiency: excessive variability in the NELPT process and systematic target deviation in the SKD process. The study therefore demonstrates the importance of integrating process stability, capability, and centering indicators to provide a more comprehensive basis for industrial

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benchmarking, quality improvement, and evidence-based managerial decision-making.
Keywords: Statistical Process Control; Cp; Cpk; X̄-R Control Charts; Algerian Industrial Enterprises.

RESUMO
Este estudo avalia, de forma comparativa, o desempenho industrial da National Enterprise for Long Products Transformation (NELPT) e da Sidi Khaled Dairy (SKD), por meio de uma estrutura integrada de Controle Estatístico de Processo (CEP) e avaliação da capacidade do processo. A pesquisa adota um delineamento de estudo de caso quantitativo e comparativo, fundamentado em dados de produção coletados de duas empresas industriais argelinas que atuam em setores distintos. O procedimento analítico combina estatística descritiva, teste de normalidade de Anderson–Darling, cartas de controle X̄-R e índices de capacidade do processo — incluindo Cp e Cpk — com o objetivo de avaliar a estabilidade, a variabilidade, a centralização e a conformidade do processo em relação aos limites de especificação estabelecidos. Foram observadas diferenças substanciais nos perfis de capacidade de ambas as empresas. A NELPT apresentou uma média de processo relativamente próxima à meta nominal; contudo, a variabilidade excessiva resultou em baixos níveis de capacidade, indicando uma inabilidade em atender, de forma consistente, aos requisitos de especificação. Em contrapartida, a SKD demonstrou uma variabilidade de processo excepcionalmente baixa e uma capacidade potencial muito elevada. Não obstante, a diferença considerável entre os índices Cp e Cpk revelou um desvio sistemático da média do processo em relação à meta nominal. Os resultados demonstram que a estabilidade estatística não implica, necessariamente, uma capacidade de processo adequada ou uma centralização ideal em relação à meta. A análise comparativa evidencia duas fontes distintas de ineficiência industrial: a variabilidade excessiva no processo da NELPT e o desvio sistemático em relação à meta no processo da SKD. O estudo demonstra, portanto, a importância de integrar indicadores de estabilidade, capacidade e centralização do processo, fornecendo uma base mais abrangente para o *benchmarking* industrial, a melhoria da qualidade e a tomada de decisão gerencial fundamentada em evidências.
Palavras-chave: Controle Estatístico de Processo; Cp; Cpk; Cartas de Controle X̄-R; Empresas Industriais Argelinas.

INTRODUCTION

The significance of this study lies in its application of Statistical Process Control (SPC), control charts, and process capability analysis to the comparative assessment of production performance in two Algerian public enterprises operating in distinct industrial sectors: the National Enterprise for Long Products Transformation (NELPT)

and Sidi Khaled Dairy (SKD). SPC provides a systematic statistical framework for monitoring process behaviour, distinguishing common-cause from special-cause variation, and supporting the early identification of deviations that may compromise product quality and process efficiency (GOMES, FIGUEIREDO, 2025; MITRA, 2021; MONTGOMERY, 2020; OAKLAND, OAKLAND, 2019). Recent developments in statistical quality control further demonstrate the continuing relevance of control-chart methodology for manufacturing environments, including adaptive, nonparametric, and distribution-free approaches (ABID et al., 2024; ALEVIZAKOS et al., 2024; AYESHA et al., 2024; LI et al., 2023; SAŁACIŃSKI et al., 2023).

The study further considers complementary dimensions of process performance through the *Cp*, *Cpk*, and *Cpm* indices. While *Cp* provides information concerning potential capability based on process dispersion, *Cpk* incorporates the position of the process mean relative to the specification limits, thereby providing an indication of actual capability. The incorporation of the Taguchi-oriented *Cpm* perspective extends the analysis by considering the distance between the process mean and the desired target value. This multidimensional approach is consistent with contemporary research emphasizing the joint assessment of process accuracy, precision, and capability (KUO, CHUANG, 2023; LIAO, WU, 2024).

The managerial relevance is strengthened by recent research on advanced control-chart methodologies, which emphasizes the importance of detecting relatively small or gradual changes in process behaviour before they develop into more substantial quality problems (ABBASI, NOOR-UL-AMIN, 2025; ALEVIZAKOS et al., 2024; AYESHA et al., 2024; LI et al., 2023). Thus, the analytical framework used in this study can support a more proactive approach to quality management, moving beyond the identification of defective products toward the identification of underlying process conditions that may generate future non-conformity.

The integration of *Cp*, *Cpk*, and *Cpm* is therefore particularly relevant because it allows process performance to be interpreted from complementary perspectives: dispersion, actual specification capability, and target conformity. Recent research on process capability monitoring similarly emphasizes the importance of evaluating both

process accuracy and precision when assessing process performance (KUO, CHUANG, 2023; LIAO, WU, 2024). Consequently, the present study provides not only a statistical assessment of production processes but also an analytical basis for identifying potential opportunities for process improvement, waste reduction, and more efficient quality-management decision-making.

Overall, the significance of this research derives from the integration of statistical rigour, empirical industrial evidence, methodological application, managerial relevance, and economic efficiency. By applying established SPC and process capability principles to two Algerian public enterprises from different industrial sectors, the study seeks to demonstrate how quantitative quality-control methods can support evidence-based process diagnosis and contribute to the continuous improvement of manufacturing performance.

GENERAL OBJECTIVE AND RESEARCH HYPOTHESES

This study aims to comparatively evaluate the statistical stability, process capability, and target-centering performance of production processes at the National Enterprise for Long Products Transformation (NELPT) and Sidi Khaled Dairy (SKD). Using Statistical Process Control (SPC), $\bar{X}$-R control charts, and the *Cp*, *Cpk*, and *Cpm* capability indices, the study seeks to identify differences in process variability and centering and to propose evidence-based measures for improving production quality and operational efficiency.

The study is based on the following hypotheses: **H1**, both production processes are statistically stable during the period under investigation; **H2**, the two enterprises exhibit different levels of process capability, as reflected in their *Cp* and *Cpk* values; **H3**, the processes differ in their degree of centering relative to their nominal target values; **H4**, differences between *Cp* and *Cpk* reflect the influence of process centering on actual capability; and **H5**, the combined use of *Cp*, *Cpk*, and *Cpm* provides a more comprehensive assessment of process performance than the use of a single capability index.

To achieve these objectives, the study assesses the statistical stability and distributional characteristics of both processes, evaluates their potential and actual capability, examines deviations from target values, and compares process dispersion and centering between the two enterprises. The analysis also identifies the principal quality constraints affecting each process and proposes appropriate measures to reduce variability, improve centering, and strengthen the application of SPC.

RESEARCH METHODOLOGY

The study adopts a quantitative, descriptive-analytical research design, complemented by a comparative case-study approach involving two Algerian industrial enterprises. The empirical analysis is based on quantitative production data obtained from the National Enterprise for Long Products Transformation and Sidi Khaled Dairy. The methodological framework is structured in successive stages to ensure that process stability is assessed before capability is interpreted.

First, descriptive statistical analysis is conducted to characterise the central tendency, dispersion, distribution, and overall behaviour of the observed production measurements. Second, appropriate normality and distributional assessments are performed to determine whether the assumptions underlying the selected statistical-control and capability procedures are reasonably satisfied. Importantly, distributional conformity is treated separately from statistical stability, since a process may exhibit an approximately normal distribution while still being statistically unstable. Third, Statistical Process Control (SPC) techniques are applied using appropriate control charts to determine whether the observed variation is consistent with a statistically stable process. Depending on the structure and characteristics of the data, conventional control charts and, where appropriate, EWMA-based approaches may be considered (MONTGOMERY, 2020; MITRA, 2021; LI et al., 2023; RAMDAN et al., 2025). Fourth, once statistical stability has been established, process capability analysis is performed using appropriate capability and performance indices. These measures are used to evaluate the extent to which the natural variation of each process fits within the established specification limits (SINHA, VATSA, 2022; KUO, CHUANG,

2023; BENKOVÁ et al., 2024). Fifth, process centering is evaluated by examining the relationship between the process mean and the target value. Particular attention is given to the consequences of off-centering, since a process may exhibit relatively low variability while nevertheless producing an unacceptable proportion of outputs when its mean is displaced from the target. Finally, the results obtained from the two enterprises are subjected to a comparative analysis to identify differences in statistical stability, variability, process capability, and centering. The statistical analyses are performed using Minitab, which is employed to facilitate descriptive analysis, distributional assessment, control-chart construction, and process-capability analysis.

This methodological structure allows the study to move beyond a simple assessment of whether products conform to specifications and instead evaluate why and under what statistical conditions production processes are capable of consistently achieving the required quality standards.

THEORETICAL FRAMEWORK

Statistical Process Control (SPC) and process capability analysis constitute fundamental approaches to quality management and continuous process improvement. SPC provides a systematic framework for monitoring process variation over time and distinguishing between common-cause variation, which is inherent to the process, and special-cause variation, which may indicate an identifiable change in the production system (MONTGOMERY, 2020; OAKLAND, OAKLAND, 2019). Process capability analysis complements this approach by evaluating whether a statistically stable process is capable of consistently producing outputs within predetermined specification limits (MITRA, 2021; SINHA, VATSA, 2022).

More recent research has further developed the application of control charts to contemporary manufacturing environments. Chen (2022) proposed a multi-image monitoring framework for SPC aimed at improving manufacturing systems, demonstrating the continuing relevance of statistical monitoring in complex production environments. Sinha and Vatsa (2022) examined control charts and process capability

analysis as complementary components of SPC, reinforcing the importance of evaluating process stability before interpreting capability indices.

Particular attention has also been given to the development of more sensitive control-chart methodologies. Li et al. (2023) proposed a robust adaptive exponentially weighted moving average (EWMA) control chart with a distribution-free design strategy, illustrating the increasing use of adaptive and robust statistical procedures for detecting process changes. Sałaciński et al. (2023) investigated control charts with variable parameters, further demonstrating the development of SPC methodologies designed to improve the responsiveness of process monitoring.

Process capability analysis has likewise received considerable attention in recent research. Kuo and Chuang (2023) examined process capability control charts for monitoring process accuracy and precision, highlighting the importance of simultaneously considering process location and variability. Benková et al. (2024) further examined capability indices as an integral component of SPC, reinforcing the complementary relationship between statistical process monitoring and capability assessment.

Recent contributions have also expanded the use of EWMA-based approaches. Alevizakos et al. (2024) investigated the exponentiated EWMA control chart, while Ayesha et al. (2024) developed an adaptive EWMA coefficient-of-variation control chart and demonstrated its application to an industrial sintering process. Ramdan et al. (2025) further examined the application of EWMA control charts to industrial product control. Collectively, these studies demonstrate the continuing evolution of SPC towards more adaptive and sensitive approaches to process monitoring.

The literature also demonstrates growing interest in integrating process capability with broader quality-management objectives. Gomes and Figueiredo (2025) provide a recent overview of statistical quality control, while Abbasi and Noor-ul-Amin (2025) examined adaptive sample-size strategies for monitoring process dispersion using EWMA control charts. These recent contributions indicate that contemporary SPC research increasingly seeks to improve the sensitivity, adaptability, and practical usefulness of statistical monitoring techniques.

Overall, the literature indicates that effective quality control should not be restricted to the detection of defective products. Rather, it should encompass the systematic monitoring of process variation, assessment of statistical stability, measurement of process capability, and identification of deviations from target values. The integration of these dimensions provides a more comprehensive basis for evaluating manufacturing performance and supporting continuous improvement.

RESEARCH GAP

Although the literature on Statistical Process Control and process capability is extensive, several gaps remain that provide a rationale for the present study. First, there is a limited body of comparative research involving different industrial sectors within the same national context. Much of the empirical literature examines individual production processes, specific industrial applications, or particular statistical techniques. Comparatively fewer studies apply a common analytical framework to enterprises operating in substantially different sectors. The present study addresses this issue by comparing a long-products manufacturing enterprise with a dairy-processing enterprise within the Algerian industrial context.

Second, the integration of process stability, capability, and centering remains insufficiently explored in applied industrial studies. Control charts determine whether a process exhibits statistically stable behaviour, whereas capability indices evaluate its ability to satisfy specification requirements. These are complementary but conceptually distinct dimensions of process performance (Montgomery, 2020; Mitra, 2021; Sinha & Vatsa, 2022). A process should therefore be demonstrated to be statistically stable before its capability indices are interpreted.

Third, the role of process centering deserves greater attention. Traditional capability assessment frequently focuses on indices such as Cp and Cpk, which provide information about process variation and the relationship between the process mean and specification limits. However, the consideration of target deviation provides an additional perspective on process performance. This is particularly relevant when

the economic consequences of producing values that deviate systematically from the target are considered.

Fourth, there remains a need to connect statistical evidence with managerial implications. Capability indices are valuable not only as statistical measures but also as indicators that can support decisions concerning process adjustment, quality improvement, resource utilisation, and waste reduction. The practical interpretation of statistical results is therefore essential if SPC is to contribute effectively to organisational decision-making.

Fifth, the application of contemporary SPC techniques in Algerian industrial environments remains an area requiring further empirical investigation. Recent international research has increasingly examined adaptive, robust, and EWMA-based control-chart procedures (LI et al., 2023; ALEVIZAKOS et al., 2024; AYESHA et al., 2024; RAMDAN et al., 2025), while empirical evidence from Algerian industrial enterprises remains comparatively less developed.

The present study addresses these gaps by adopting an integrated framework combining statistical distribution analysis, control-chart analysis, process capability indices, and process-centering assessment. The comparative application of this framework to two Algerian enterprises operating in different industrial sectors provides an opportunity to evaluate not only whether their production processes are statistically controlled, but also whether they possess sufficient capability to consistently satisfy established technical specifications.

QUALITY CONTROL CHARTS (STATISTICAL CONTROL CHARTS)

Control charts constitute one of the fundamental instruments of Statistical Process Control. Their primary purpose is to monitor process behaviour over time and determine whether observed variation is consistent with the natural variation of a stable process or indicates the presence of assignable causes requiring investigation (MONTGOMERY, 2020; OAKLAND, OAKLAND, 2019).

A control chart provides a graphical representation of a selected quality characteristic or sample statistic across successive observations or subgroups. By

plotting the observations in chronological order against statistically determined control limits, the researcher or quality manager can identify unusual patterns, shifts, trends, or individual observations that may indicate changes in the underlying production process.

An important distinction must be made between control limits and specification limits. Control limits are statistically derived from the behaviour of the process and are used to assess statistical stability. Specification limits, in contrast, are established externally on the basis of technical requirements, customer expectations, regulatory standards, or product design. Consequently, a process may be statistically stable while still being incapable of meeting the required specifications, or it may produce observations within specifications while exhibiting evidence of statistical instability.

A conventional control chart generally consists of three principal reference lines:

- Upper Control Limit (UCL): the upper statistical boundary used to identify unusually high process variation;
- Center Line (CL): represents the estimated central tendency of the monitored process;
- Lower Control Limit (LCL): the lower statistical boundary used to identify unusually low process variation.

For many conventional control-chart applications, the control limits are established at approximately three standard deviations from the process centre line. The three-sigma principle provides a widely used statistical basis for identifying observations that are unlikely to arise from the expected common-cause variation of a stable process (MONTGOMERY, 2020).

The horizontal axis normally represents the chronological order of observations or rational subgroups, whereas the vertical axis represents the measured quality characteristic or an appropriate sample statistic, such as a sample mean or range. The interpretation of a control chart should not, however, be restricted to observations falling outside the control limits. Non-random patterns within the control limits may also provide evidence of process changes. Consequently, the analysis should consider not only individual points but also systematic patterns, runs, trends, shifts, and changes in variability.

For a generic quality characteristic (w), a control chart can be represented through a centre line and corresponding upper and lower control limits: CL = process centre; UCL = CL + 3σ; LCL = CL − 3σ. Where (σ) represents the relevant estimate of process standard deviation.

The precise formulation of the control limits depends on the type of control chart, the statistical properties of the data, the subgroup structure, and the estimation procedure adopted. For example, $\bar{X}$-R charts are commonly used for monitoring the mean and within-subgroup variability of continuous measurements, whereas individual and moving-range charts are appropriate when observations are collected individually rather than in rational subgroups.

In addition to conventional Shewhart charts, contemporary SPC research has developed more sensitive approaches for detecting relatively small or persistent changes in process behaviour. EWMA charts, for example, assign greater importance to recent observations while retaining information from previous observations, making them particularly useful for detecting gradual or small shifts in a process (Li et al., 2023; Alevizakos et al., 2024; Ayesha et al., 2024; Ramdan et al., 2025).

Therefore, control charts should be understood not simply as graphical tools for detecting defective production, but as statistical instruments for understanding process behaviour, identifying sources of variation, and supporting preventive quality management.

PROCESS CAPABILITY ANALYSIS

Process capability analysis is a fundamental component of Statistical Process Control (SPC) because it provides a quantitative assessment of the extent to which a stable production process can consistently satisfy predefined technical and customer specifications. Unlike statistical control, which evaluates whether process variation is predictable over time, capability analysis evaluates whether the magnitude and centering of that variation are compatible with the specification limits. Consequently, process stability and process capability should be regarded as complementary but

conceptually distinct dimensions of process performance (MONTGOMERY, 2020; OAKLAND, OAKLAND, 2019).

Process capability is influenced by several factors that contribute to process variation and the achievement of specified quality characteristics. These include the quality and consistency of raw materials, the technological characteristics and maintenance of production equipment, operator competence, working conditions, and the adequacy and precision of measurement systems. Measurement reliability is particularly important because inaccurate or excessively variable measurement systems may distort the estimated level of process capability and consequently lead to inappropriate managerial decisions.

For capability analysis to provide meaningful results, the process should first be demonstrated to be statistically stable. Capability indices calculated from an unstable process may combine common-cause and special-cause variation and therefore fail to represent the long-term capability of the underlying process. Accordingly, control-chart analysis should normally precede capability analysis. In addition, the distributional characteristics of the quality variable should be examined to determine whether the assumptions underlying the selected capability indices are appropriate. Although normality is a common assumption in conventional capability analysis, non-normal processes can also be evaluated using alternative statistical approaches when justified by the characteristics of the data (MONTGOMERY, 2020; MITRA, 2021; BENKOVÁ et al., 2024).

CAPABILITY INDEX CP

The potential capability index, Cp, evaluates the relationship between the width of the specification interval and the natural spread of the process. Assuming that the quality characteristic (X) follows an approximately normal distribution with process standard deviation (\sigma), and that the lower and upper specification limits are LSL and USL, respectively, Cp is defined as: $Cp = (USL - LSL) / 6\sigma$

Cp measures the potential capability of the process under the assumption that the process mean is centered between the specification limits. It therefore evaluates

the process dispersion relative to the available specification tolerance but does not take process centering into account (MONTGOMERY, 2020).

The interpretation of Cp should be made in conjunction with the characteristics and requirements of the specific production process. A value below 1.00 indicates that the natural process spread exceeds the specification interval, suggesting inadequate potential capability. Values around or above 1.00 indicate progressively greater potential capability, while Cp = 1.33 is frequently adopted as a practical benchmark for a capable process in many industrial applications. However, this threshold should not be interpreted as a universal criterion, since acceptable capability levels may be more demanding in processes involving critical safety, regulatory, or customer requirements (MONTGOMERY, 2020).

ONE-SIDED CAPABILITY AND THE CPK INDEX

When specification limits are asymmetric relative to the process mean, Cp alone may provide an overly optimistic assessment because it does not consider process centering. The actual capability index, Cpk, addresses this limitation by incorporating the distance between the process mean and each specification limit.

The two one-sided capability components are expressed as: $Cpu = (USL - \mu) / 3\sigma$ and $Cpl = (\mu - LSL) / 3\sigma$. Consequently: $Cpk = \min(Cpu, Cpl)$, where μ represents the process mean and σ the process standard deviation.

Cpk therefore reflects both process dispersion and process centering. A substantial difference between Cp and Cpk indicates that although the overall process variation may be relatively small compared with the specification interval, the process mean is displaced from the center of that interval. This distinction is particularly important because a process may have a satisfactory Cp while simultaneously exhibiting a considerably lower Cpk as a consequence of poor centering. In such circumstances, corrective action may need to focus not only on reducing variability but also on adjusting the process mean toward the desired target or specification center (Montgomery, 2020; Kuo & Chuang, 2023).

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For processes with both upper and lower specification limits, Cpk is generally interpreted using the same broad benchmarks as Cp, although the specific acceptance criterion should be defined according to the technical and managerial requirements of the process.

For a process with only an upper specification limit, capability is assessed using:
Cpu = (USL − μ) / 3σ
Conversely, for a process with only a lower specification limit, the appropriate index is:
Cpl = (μ − LSL) / 3σ
These one-sided indices are particularly relevant when quality characteristics have only one critical boundary, such as a maximum allowable concentration, dimension, defect level, or minimum required strength.

TAGUCHI CAPABILITY INDEX CPM

The Taguchi capability index, Cpm, extends conventional capability analysis by explicitly incorporating the deviation of the process mean from a predefined target value. While Cp focuses exclusively on process dispersion and Cpk considers both dispersion and centering relative to specification limits, Cpm additionally penalizes deviations from the target value. Cpm is expressed as: Cpm = (USL − LSL) / [6√(σ² + (μ − T)²)], where T represents the target value.

The inclusion of the term ((μ − T)^2) makes Cpm particularly useful when achieving the target value is important, even when the process remains within the specification limits. Thus, two processes may have similar Cp values but different Cpm values if their means are located at different distances from the target. Cpm consequently provides a more target-oriented perspective on process performance and is consistent with the broader quality philosophy associated with Taguchi, in which deviation from the target is regarded as an important component of quality loss (Montgomery, 2020).

The comparison between Cp, Cpk, and Cpm therefore provides a more comprehensive assessment of process capability. Cp primarily evaluates potential capability based on process dispersion; Cpk evaluates actual capability by considering

both dispersion and process centering relative to the specification limits; and Cpm incorporates the deviation of the process mean from the desired target. The simultaneous use of these indices can therefore help distinguish whether inadequate performance is primarily associated with excessive variability, process displacement, or deviation from the target.

EMPIRICAL STUDY

This empirical study aims to comparatively assess the production performance of the National Enterprise for Long Products Transformation (NELPT) and Sidi Khaled Dairy (SKD) through statistical process control and process capability analysis. The analysis focuses on three complementary dimensions of process performance: statistical stability, process variability, and compliance with established technical specifications. Accordingly, the study combines descriptive statistics, distributional assessment, $\bar{X}$-R control charts, and process capability indices, including Cp, Cpk, and the Taguchi capability index Cpm.

The analytical framework is designed to distinguish between process stability and process capability. Statistical stability is examined first through control-chart analysis, while capability is assessed subsequently by comparing the observed process variation and centering with the applicable specification limits and target values. This sequential approach is important because capability indices calculated from an unstable process may provide a misleading representation of its sustained production performance (MONTGOMERY, 2020; MITRA, 2021).

The first case concerns the National Enterprise for Long Products Transformation (NELPT), Tiaret Unit. The quality characteristic selected for analysis is the weight of steel wire coils. The product consists of double wire subjected to high-temperature treatment in specialized furnaces designed to prevent re-oxidation. The product is primarily intended for use in construction and public works.

According to the applicable production requirements, the weight of the wire coils should fall within the specified interval of 15 to 25 kg, while the wire diameter must also comply with the corresponding technical requirements. For the present analysis, the

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weight characteristic was selected as the principal variable because it provides a directly measurable quality characteristic for evaluating process dispersion, centering, statistical stability, and capability.

A total of five observations were collected for each of 20 production days, resulting in 100 individual measurements. For each subgroup, the arithmetic mean, maximum value, minimum value, range, and standard deviation were calculated.

Table 1. Weight Measurements of Steel Wire Coils at NELPT (A) and Milk Bags at Sidi Khaled Dairy (B)

Source: Authors' calculations based on production data provided by the National Enterprise for Long Products Transformation (A) data provided by Sidi Khaled Dairy (B).

A

Days	X1	X2	X3	X4	X5	Mean	Max	Min	Range	S.D
1	17,3	18,9	21,4	16,5	22,1	19,24	22,1	16,5	5,6	2,14
2	18,5	19,2	24,4	23,1	19,7	21,18	24,4	18,5	5,9	2,91
3	20,2	23,1	15,6	18,2	19,3	19,28	23,1	15,6	7,5	2,77
4	20,1	17,4	15,2	24,5	20,2	19,48	24,5	15,2	9,3	4,06
5	20,3	20,2	19,8	19,2	23,0	20,46	23,0	19,2	3,8	1,51
6	18,2	24,9	21,7	19,9	24,8	21,92	24,9	18,2	6,7	3,12
7	19,7	22,4	22,0	21,0	17,5	20,52	22,4	17,5	4,9	1,98
8	21,4	21,7	22,1	19,0	19,2	20,68	22,1	19,0	3,1	1,47
9	21,4	23,0	18,0	24,5	20,3	21,44	24,5	18,0	6,5	2,50
10	19,0	23,1	17,4	20,2	24,9	20,92	24,9	17,4	7,5	3,05
11	15,6	15,2	19,8	21,0	22,0	18,72	22,0	15,2	6,8	3,13
12	20,2	24,9	22,4	21,7	23,0	22,44	24,9	20,2	4,7	1,73
13	17,5	19,2	20,3	24,9	22,0	20,78	24,9	17,5	7,4	2,83
14	22,4	21,7	23,0	23,1	15,2	21,08	23,1	15,2	7,9	3,33
15	18,0	19,0	23,1	17,4	20,2	19,54	23,1	17,4	5,7	2,26
16	19,2	20,3	24,9	22,0	23,0	21,88	24,9	19,2	5,7	2,24
17	18,0	19,7	21,4	21,4	19,0	19,9	21,4	18,0	3,4	1,50
18	18,0	17,4	19,8	22,4	20,3	19,58	22,4	17,4	5,0	1,99
19	16,0	16,0	20,0	24,0	23,0	19,8	24,0	16,0	8,0	3,77
20	19,2	20,3	24,9	22,0	23,0	21,88	24,9	19,2	5,7	2,24
Mean						20,37			6,17	2,53

B

Days	X1	X2	X3	X4	X5	Mean	Max	Min	Range	S.D
1	1035	1028	1030	1028	1026	1029,4	1035	1026	9	3,44
2	1038	1040	1034	1030	1038	1036	1040	1030	10	4,00
3	1038	1025	1032	1028	1025	1029,6	1038	1025	13	5,50
4	1032	1035	1033	1030	1028	1031,6	1035	1028	7	2,70
5	1037	1034	1035	1034	1037	1035,4	1037	1034	3	1,52
6	1030	1032	1034	1033	1032	1032,2	1034	1030	4	1,48
7	1034	1034	1033	1032	1030	1032,6	1034	1030	4	1,67
8	1037	1032	1036	1035	1038	1035,6	1038	1032	6	2,30
9	1032	1032	1031	1028	1026	1029,8	1032	1026	6	2,68
10	1028	1037	1033	1030	1034	1032,4	1037	1028	9	3,51
11	1036	1028	1032	1035	1034	1033	1036	1028	8	3,16
12	1040	1035	1038	1038	1039	1038	1040	1035	5	1,87
13	1033	1036	1035	1035	1036	1035	1036	1033	3	1,22
14	1041	1034	1037	1037	1040	1037,8	1041	1034	7	2,77
15	1032	1035	1031	1030	1028	1031,2	1035	1028	7	2,59
16	1032	1033	1030	1028	1026	1029,8	1033	1026	7	2,86
17	1030	1029	1029	1030	1026	1028,8	1030	1026	4	1,64
18	1035	1040	1036	1040	1031	1036,4	1040	1031	9	3,78
19	1030	1033	1033	1038	1030	1032,8	1038	1030	8	3,27
20	1041	1035	1035	1034	1035	1036	1041	1034	7	2,83
Mean						1033,17			6,8	2,74

The descriptive statistics indicate variation in the weight of the coils across the observed production days. The subgroup means fluctuate around the nominal target, while the ranges and standard deviations provide an initial indication of within-subgroup variability. These descriptive measures are subsequently complemented by control-chart analysis to determine whether the observed variation is consistent with a statistically stable production process.

The second case concerns Sidi Khaled Dairy (SKD), located in Tiaret Province. The selected quality characteristic is the weight of packaged milk bags. Weight measurements were collected over the same 20-day observation period, with five measurements recorded for each day, resulting in 100 individual observations.

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The nominal target weight of the milk bags is 1,000 g. The daily subgroup means, maximum and minimum observations, ranges, and standard deviations were calculated to characterize the observed production process.

The descriptive results indicate relatively limited within-subgroup dispersion, although the subgroup means appear systematically higher than the nominal target of 1,000 g. This preliminary observation is particularly relevant for the subsequent analysis of process centering. A process may exhibit low variability while nevertheless operating away from its intended target; therefore, consistency and accuracy should be evaluated separately.

DISTRIBUTIONAL ASSESSMENT AND VERIFICATION OF PROCESS STABILITY

The second stage of the empirical analysis evaluates the statistical assumptions underlying the subsequent capability analysis. Two complementary aspects are considered: the distributional characteristics of the observations and the temporal stability of the production processes.

The Anderson–Darling test was applied to assess whether the observed weight measurements were consistent with an approximately normal distribution. The null hypothesis of the Anderson–Darling normality test assumes that the observations originate from the specified normal distribution. At the 5% significance level, a p-value greater than 0.05 indicates that there is insufficient statistical evidence to reject the null hypothesis of normality.

Table 2. Anderson–Darling Normality Test Results
Source: Authors' calculations based on Minitab outputs.

Enterprise	Variable	A-D Statistic	p-value	Conclusion
NELPT	X1	0.209	0.841	Normal
	X2	0.201	0.863	Normal
	X3	0.359	0.415	Normal
	X4	0.308	0.530	Normal
	X5	0.505	0.179	Normal
SKD	X1	0.324	0.503	Normal
	X2	0.454	0.242	Normal
	X3	0.199	0.866	Normal
	X4	0.590	0.109	Normal
	X5	0.527	0.157	Normal

Note: A-D = Anderson–Darling.

The results presented in Table 2 show that all p-values exceed the 0.05 significance level for both enterprises. Accordingly, the null hypothesis of normality is not rejected for any of the five measurement series in either NELPT or SKD.

For NELPT, the Anderson–Darling statistics range from 0.201 to 0.505, with corresponding p-values ranging from 0.179 to 0.863. For SKD, the statistics range from 0.199 to 0.590, while the corresponding p-values range from 0.109 to 0.866. These results provide no statistically significant evidence against the normality assumption at the conventional 5% level.

However, normality should not be interpreted as evidence of statistical process control. The two properties address different questions: normality concerns the distributional form of the observations, whereas statistical control concerns the temporal behaviour and stability of the process. Therefore, the normality results establish the suitability of conventional capability procedures under their distributional assumptions but do not, by themselves, establish process stability.

$\bar{X}$-R control charts were subsequently employed to assess the statistical stability of the two production processes. The $\bar{X}$ chart monitors variation in subgroup means, whereas the R chart monitors within-subgroup variation. Together, these charts enable the identification of unusual patterns that may indicate special causes of variation (MONTGOMERY, 2020; MITRA, 2021).

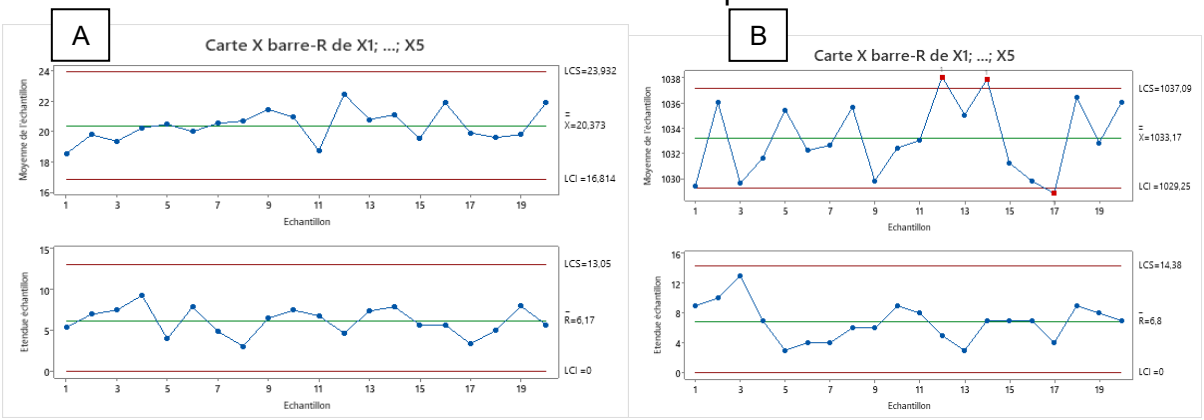
The control limits should be distinguished from the technical specification limits. Control limits are statistically estimated from the observed process and represent the expected range of common-cause variation under statistical control. Specification limits, by contrast, are externally established technical requirements defining acceptable product performance. Consequently, a process may remain statistically controlled while producing output that is systematically off-target.

The $\bar{X}$-R control charts for NELPT indicate that the observed subgroup means and ranges remain within the corresponding control limits. No evident out-of-control signal is reported in the charts, suggesting that the process was statistically stable during the observation period.

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Figure 1. X̄-R Control Charts for NELPT (A) and for Sidi Khaled Dairy (B)

Source: Authors' calculations based on Minitab outputs.



The X̄ chart for NELPT indicates that the subgroup means fluctuate around the process average without an evident persistent shift or systematic trend. The R chart likewise indicates that within-subgroup variation remains statistically controlled. Therefore, the observed variability appears to be predominantly attributable to common-cause variation during the period examined.

The process average is reported as approximately 20.37 kg, which is relatively close to the nominal target of 20 kg. Nevertheless, proximity to the target should not be equated with capability. The subsequent capability analysis is required to determine whether the magnitude of process variation is sufficiently small relative to the specification interval.

The X̄-R control charts for Sidi Khaled Dairy indicate that the process remained statistically controlled during the observation period. All subgroup means and ranges appear to remain within their respective control limits, with no clear evidence of special-cause variation based on the control-chart criteria applied.

The results nevertheless reveal an important distinction between statistical control and target centering. Although the process appears statistically stable, the subgroup means are consistently located above the nominal target of 1,000 g. The reported overall mean of approximately 1,033.17 g indicates a positive deviation from

the target of approximately 33.17 g, corresponding to an over-target deviation of approximately 3.32%.

This finding suggests that the process is characterized by relatively consistent but systematically elevated output. Such a pattern can be described as stable but poorly centered. Importantly, the control charts alone do not establish the underlying cause of this deviation. Although equipment calibration or filling-machine settings may constitute possible explanations, identifying calibration error would require additional technical evidence, such as verification of equipment settings, calibration records, or measurement-system analysis.

The R chart indicates relatively narrow within-subgroup variation compared with the displacement of the process mean from the target. This distinction is particularly relevant from a quality-management perspective: a process can demonstrate high repeatability while simultaneously exhibiting inadequate accuracy with respect to its intended target. Consequently, reducing variability is not necessarily the primary corrective action when the principal problem is process centering.

PROCESS CAPABILITY INDEX COMPUTATION

This section presents the core quantitative analysis of the study, focusing on the assessment of production-process capability through the calculation and interpretation of the potential capability index (Cp), the actual capability index (Cpk), and the Taguchi capability index (Cpm). These indices provide complementary information concerning process dispersion, process centering, and the ability of production processes to operate consistently within established specification limits.

The capability analysis was conducted after the assessment of statistical stability presented in the preceding section. This sequence is methodologically important because capability indices are intended to characterize the performance of a predictable process. When special causes of variation are present, capability estimates may combine different sources of variation and therefore provide an unreliable representation of the underlying process capability (MONTGOMERY, 2020; MITRA, 2021).

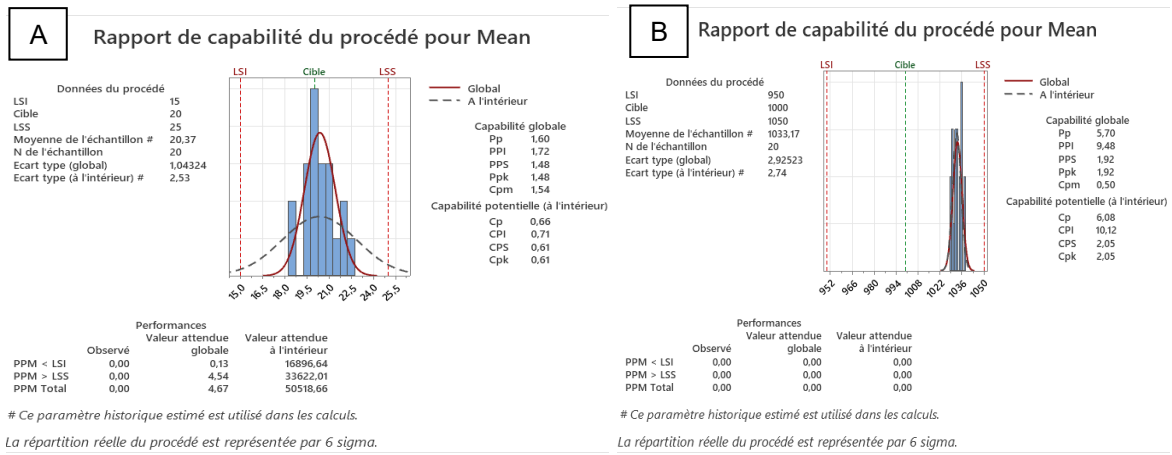
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For the National Enterprise for Long Products Transformation (NELPT), the specification limits for steel wire reel weight were defined as 15 kg (LSL) and 25 kg (USL), with a nominal target of 20 kg. The capability assessment therefore evaluates whether the observed process variation is sufficiently small relative to the 10-kg specification interval and whether the process remains adequately centered around the nominal target.

The NELPT process can be characterized as statistically stable but insufficiently capable, based on the control-chart and capability results considered together. Although the process mean is relatively close to the 20-kg target, the high level of dispersion results in low Cp and Cpk values.

Figure 2. Process Capability Analysis of Steel Wire Reel Weights – NELPT (A) and Milk Bag Weights – Sidi Khaled Dairy (B)

Source: Authors' calculations based on Minitab outputs.



The process capability analysis provides the indicators mentioned on table 3.

Table 3. Key Process Capability Indicators – NELPT – Tiaret Unit (A) and Sidi Khaled Dairy (B)

Source: Authors' calculations based on Minitab outputs.

A	B

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Indicator	Value	Interpretation
Cp (Potential Capability)	0.66	Low potential capability
Cpk (Actual Capability)	0.61	Low actual capability
Cpm (Taguchi Index)	To be verified	Requires confirmation from Minitab output
Mean	20.37 kg	Close to the 20-kg target
Standard deviation	2.53 kg	Relatively high dispersion
LSL	15 kg	Lower specification limit
USL	25 kg	Upper specification limit
Target	20 kg	Nominal target

Indicator	Value	Interpretation
Cp (Potential Capability)	6.08	Very high potential capability
Cpk (Actual Capability)	2.05	High actual capability
Cpm (Taguchi Index)	To be verified	Target-centering requires verification
Mean	1033.17 g	33.17 g above target
Standard deviation	2.74 g	Low process dispersion
LSL	950 g	Lower specification limit
USL	1050 g	Upper specification limit
Target	1000 g	Nominal target

Overall, the NELPT case demonstrates an important distinction between statistical stability and process capability. A process may remain statistically controlled, with no evidence of special-cause variation, while nevertheless being incapable of consistently satisfying its technical specifications. In the present case, the evidence points to a stable but excessively variable process, making dispersion reduction the principal avenue for capability improvement.

The process capability analysis for milk bag weights at Sidi Khaled Dairy provides a substantially different statistical profile from that observed for the steel wire reel process.

The Sidi Khaled Dairy process presents a combination of low dispersion and substantial displacement from the nominal target. The Cp and Cpk results indicate that the process has considerable capability with respect to the stated specification limits, whereas the mean of 1033.17 g demonstrates that production is systematically positioned above the 1000-g target.

From a process-improvement perspective, the results suggest that future intervention should focus primarily on process centering and filling-machine calibration, provided that operational and regulatory requirements permit adjustment toward the nominal target.

Reducing the systematic deviation from the target could improve target-oriented performance while maintaining the process's existing low level of dispersion. However, the financial implications of the additional product weight should be quantified using actual production volumes, product costs, and the frequency of production before a monetary-loss conclusion is made.

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COMPARATIVE ANALYSIS AND DISCUSSION OF RESULTS

The comparative analysis examines the statistical characteristics of the two production processes using the same conceptual framework: process dispersion, centering, and conformity with specification limits. The comparison is intended to identify the specific quality characteristics that constrain process performance in each enterprise rather than to reduce process quality to a single capability indicator.

Table 4. Comparative Process Capability Indicators

Source*:* Authors' calculations based on Minitab outputs.

Statistical Indicator	NELPT – Tiaret Unit	Sidi Khaled Dairy
Lower Specification Limit (LSL)	15 kg	950 g
Upper Specification Limit (USL)	25 kg	1050 g
Target	20 kg	1000 g
Overall Mean	20.37 kg	1033.17 g
Standard Deviation	2.53 kg	2.74 g
Cp	0.66	6.08
Cpk	0.61	2.05
Cpm	To be verified	To be verified

The comparative results demonstrate that the two production processes are characterized by different capability constraints. For NELPT, the principal issue is process dispersion. The Cp value of 0.66 indicates that the natural process spread is large relative to the specification interval. The Cpk value of 0.61 is only slightly lower than Cp, suggesting that the relatively low actual capability is predominantly associated with excessive variability rather than with a major centering displacement. Although the process mean of 20.37 kg is relatively close to the 20-kg target, the magnitude of the standard deviation limits the process's ability to maintain a sufficient statistical margin within the specification limits.

In contrast, Sidi Khaled Dairy exhibits substantially lower relative dispersion, as reflected by its Cp value of 6.08. Its Cpk value of 2.05 is lower than Cp because the process mean is displaced toward the upper specification limit. The difference between the two indices therefore highlights a centering issue rather than a fundamental problem of process spread.

The comparison consequently indicates two distinct improvement priorities. For NELPT, improvement efforts should primarily address variation reduction, including investigation of equipment, operating conditions, raw materials, measurement systems, and other sources of process variability. For Sidi Khaled Dairy, the statistical evidence points primarily toward mean adjustment and target centering, while preserving the existing low level of process dispersion.

An important implication of this comparison is that specification capability and target performance should not be treated as synonymous. The dairy process illustrates how a process may exhibit strong specification capability while operating substantially away from its nominal target. Conversely, the NELPT process demonstrates that a process can be relatively well centered while remaining incapable because of excessive dispersion.

The use of Cp, Cpk, and Cpm together therefore provides a more comprehensive diagnostic framework than reliance on a single capability index. Cp identifies the relationship between process spread and specification width; Cpk additionally considers process location within the specification interval; and Cpm incorporates deviation from the target. This multidimensional perspective is consistent with the broader statistical process-control literature, which emphasizes the importance of distinguishing process stability, variability, centering, and specification conformity (MONTGOMERY, 2020).

From a managerial perspective, the findings suggest that corrective actions should be process-specific rather than uniform across enterprises. NELPT would require measures directed toward reducing process variability, whereas Sidi Khaled Dairy would benefit from investigation of the causes of systematic target displacement. Such differentiation can help organizations allocate quality-improvement resources according to the statistical characteristics of their respective production processes.

Finally, the observed absence of nonconforming observations in the analysed samples should be interpreted cautiously. Zero observed defects does not establish long-term zero-defect performance. Rather, it should be considered alongside control-chart evidence, capability indices, sample size, measurement-system adequacy, and

continued monitoring. Sustained statistical control and periodic reassessment of capability are therefore necessary to determine whether the observed performance remains stable over time.

CONCLUSION

This study comparatively evaluated the production processes of the National Enterprise for Long Products Transformation (NELPT) and Sidi Khaled Dairy (SKD) through Statistical Process Control (SPC) and process capability analysis. By combining $\bar{X}$-R control charts with the capability indices *Cp*, *Cpk*, and *Cpm*, the study examined statistical stability, process variability, specification capability, and target centering.

The findings demonstrate that the two enterprises face fundamentally different process-performance challenges. NELPT exhibited a process mean relatively close to its nominal target; however, its high process variability resulted in low *Cp* (0.66) and *Cpk* values, indicating insufficient capability to consistently operate within the established specification limits. In contrast, SKD demonstrated very low process variability and high potential capability. Nevertheless, the substantial difference between *Cp* and *Cpk* revealed a significant deviation of the process mean from the nominal target, with an average weight of approximately 1,033.17 g compared with the target of 1,000 g.

These findings confirm that statistical stability and specification conformity alone are not sufficient indicators of overall process performance. A process may be stable but incapable because of excessive variability, as observed at NELPT, or highly capable with respect to specification limits while remaining insufficiently centered on its target, as observed at SKD. Therefore, the combined application of *Cp*, *Cpk*, and *Cpm* provides a more comprehensive framework for evaluating industrial performance by simultaneously considering process dispersion, specification conformity, and target deviation. However, the reported *Cpm* values should be verified before any definitive conclusions based specifically on this index are retained.

From a managerial perspective, the results indicate that improvement strategies should be adapted to the specific characteristics of each process. NELPT should primarily focus on reducing process variability through improved equipment maintenance, process standardization, and continuous monitoring. SKD, meanwhile, should focus on improving process centering and equipment calibration while maintaining its existing low level of variability. Overall, this study demonstrates that the effective application of SPC and process capability analysis can support evidence-based decision-making and contribute to improved product quality, material efficiency, and operational performance.

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