DOI: https://doi.org/10.62985/j.huit_ojs.vol26.no3E.542

IMPROVING PROCESS CAPABILITY IN PLASTIC FILM THICKNESS CONTROL

Nguyen Thi Duc Nguyen[1,2,*], Ngo Qui Tuong[1,2]

[1]*School of Industrial Management, Ho Chi Minh City University of Technology (HCMUT), 268 Ly Thuong Kiet Street, Dien Hong Ward, Ho Chi Minh City, Vietnam*

[2]*Vietnam National University Ho Chi Minh City, Linh Xuan Ward, Ho Chi Minh City, Vietnam*

*Email: *ntdnguyen@hcmut.edu.vn*

Received: 1 April 2026; Revised: 26 April 2026; Accepted: 16 May 2026

ABSTRACT

This study aims to deploy the Six Sigma DMAIC framework to improve process capability in plastic film-thickness control, which is applied to a 31 μm LLDPE blown-film extrusion process. The crossed Gauge Repeatability and Reproducibility method is ultilized to confirm measurement system adequacy in this study. The baseline analysis of 260 observations reveals Cp = 1.07, Cpk = 0.78, and a 5.8% out-of-tolerance rate; which is shown that the process is not properly centered within the specified engineering boundaries. Notably, performance improves to Cp = 1.32, Cpk = 1.13, while significantly reducing the defect rate to 0.9%, thanks to the targeted enhancements, which include parameter stabilization, consistent resin feeding, and improved calibration. Accordingly, this study emphasizes the significance of statistical-driven process control and dependable measurement methods in addition to mechanical optimization. Therefore, for extrusion operations suffering from continuous thickness instability, the combined application of measurement systems analysis, SPC, root-cause verification, and standardized control techniques offers a workable foundation for achieving more stable and economically viable output.

Keywords: Gauge Repeatability and Reproducibility (GR&R), measurement system analysis, DMAIC (Define, Measure, Analyze, Improve, Control), process capability, blown-film extrusion.

1. INTRODUCTION

Currently, manufacturing companies must go beyond simple specification compliance to achieve operational excellence through resource optimization and waste minimization in the face of escalating global competitiveness, economic challenges, and the shift toward sustainability. In the plastics industry, where manufacturers must deal with unstable raw material prices, strict environmental regulations, and elevated quality standards, these challenges are especially severe. The high-volume, material-intensive nature of continuous manufacturing guarantees that even little variations in product characteristics—caused by process drift or operational inefficiency—quickly add up to substantial financial losses for producers of flexible packaging and film converters [1].

In fact, film thickness is a crucial quality attribute in blown-film manufacturing that has a significant impact on material usage, selling effectiveness, downstream converting stability, and overall operational efficiency. Despite maintaining specification conformance, a process that routinely surpasses the nominal objective has significant financial consequences due to needless resin consumption and increased manufacturing costs. Operating below the necessary thickness threshold, on the other hand, increases the possibility of non-conforming output, reduced mechanical performance, and downstream processing instabilities, all of which might jeopardize customer satisfaction. As a result, thickness control needs to be seen as a strategic operational necessity that directly affects process capability, cost effectiveness, and manufacturing competitiveness rather than just as a technical quality characteristic [2, 3].

Research to date confirms that the Six Sigma and Define–Measure–Analyze–Improve–Control (DMAIC) frameworks remain highly effective for mitigating process variation, enhancing capability, and strengthening operational discipline within manufacturing environments [e.g., 3–6]. Systematic application of DMAIC has been demonstrated to minimize waste, maximize machine efficiency, and eliminate defects in the context of plastics processing, hence increasing overall profitability [4, 5, 7]. Additionally, current research indicates that Industry 4.0 integration, predictive analytics, and digital monitoring are increasingly enhancing quality improvement. This change reflects a basic progression in process control, shifting from reactive inspection to a data-driven, preventative management paradigm [8–11].

Remarkably, the research currently emphasizes that process capability analysis is only statistically significant when it is supported by a measurement system that is sufficiently reliable [12–20]. Calculated control limits and capacity indices may be significantly distorted by high measurement variation, reflecting gauge error rather than true process behavior. This restriction is especially important in thickness-control applications since even small metrological inaccuracies can cause Cp and Cpk values to be misrepresented, which could lead management to take counterproductive or inefficient corrective action. To guarantee that statistical decision-making is founded on reliable, high-fidelity data, companies in the plastics sector must emphasize the validation of their measurement systems rather than merely optimizing machine settings and operator discipline.

In light of this, this study looks into how to improve film-thickness control in a blown-film extrusion process that produces a 31 μm linear low-density polyethylene product in a flexible-packaging facility that has been anonymized. The Six Sigma DMAIC framework is used in the investigation, with a focus on measurement-system validation prior to process-capability interpretation. Through the use of Gauge Repeatability and Reproducibility (GR&R), statistical process control, capability analysis, and root-cause diagnosis, the study seeks to ascertain the present condition of process capability, identify the primary reasons for low capability, carry out improvement measures, and assess the efficacy of those measures.

2. LITERATURE REVIEW

2.1. Process capability

Process capability is still a key quantitative metric for assessing industrial advancements. There is a crucial difference between potential and actual performance, as Montgomery [21] highlights that Cp represents the potential capability under ideal centering, whereas Cpk represents the combined effect of process spread and centering. This distinction is important from an operational perspective in extrusion contexts. If the mean is continuously adjusted above the target, a process may display an acceptable spread (Cp) but still incur needless costs. Therefore, rather than depending on a single index, a robust capability interpretation must combine Cp and Cpk with the process mean, variation patterns, and the economic consequences of deviations. Montgomery [21] offered theoretical clarity, but much applied research just shows Cpk improvements without sufficiently addressing process centering. This oversight reveals a significant gap between theoretical capability and practical implementation. Specifically, a favorable Cpk may still mask an underlying process bias that compromises resource efficiency and cost-effectiveness. This is particularly critical in material-intensive manufacturing, where process centering directly influences both regulatory conformance and economic performance. Furthermore, recent Industry 4.0 research suggests that the integration of real-time monitoring, automated data acquisition, and predictive analytics enhances capability evaluations by facilitating the early detection of process drift [8–11].

2.2. DMAIC framework

Contemporary literature positions DMAIC as a strong framework for mitigating process variation and enhancing manufacturing economics. Chiarini [3] shows how Six Sigma can be combined with Lean principles to maximize equipment effectiveness where waste and variability are connected. De Mast and Lokkerbol [6] credit its effectiveness to a disciplined structure that moves from symptom recognition to data validation and controlled implementation. This strategy is especially important in the material-intensive plastics industry. While Siddiqui and Tabassum [5] claim that DMAIC in extrusion systems decreased rejection rates from 12% to 4.06% and almost doubled machine efficiency, Desai and Prajapati [4] demonstrate that structured variation reduction in injection molding delivers significant annual savings.

Particularly, in the material-intensive plastics sector, the DMAIC framework is a vital tool for managing continuous processes sensitive to parameter drift. Desai and Prajapati [4] leveraged structured variation reduction in injection molding to achieve strategic cost savings, while Siddiqui and Tabassum [5] utilized it in extrusion to nearly double machine efficiency and halve rejection rates. More recently, Abd Elnaby et al. [7] integrated machine learning to elevate sigma levels from 3.14 to 4.30, signaling a paradigm shift from traditional statistical control toward predictive, data-driven optimization. This evolution suggests that the modern effectiveness of DMAIC is increasingly contingent upon the depth of technological integration. Furthermore, the literature underscores that process capability analysis is only statistically valid when underpinned by a reliable measurement system [15]. Following the AIAG [12] standards, practitioners must validate repeatability, reproducibility, and discriminatory power (ndc) before interpreting process data. This metrological foundation ensures that subsequent statistical process control (SPC) and capability decisions reflect actual process behavior rather than measurement error, providing the necessary confidence for operational decision-making.

2.3. Measurement system analysis

Recent studies consistently emphasize that measurement system analysis (MSA), particularly Gage Repeatability and Reproducibility (GR&R), is a critical prerequisite for reliable process evaluation. Prior research shows that inadequate GR&R performance can distort SPC and mask true process variation, while improved discrimination capability (ndc) enhances the detection of meaningful process shifts [19–20]. Accordingly, capability analysis should only be conducted after confirming measurement system adequacy, as highlighted by Runje et al. [15] and standardized in the AIAG guidelines [12].

Recent literature further demonstrates that GRR is evolving beyond a routine validation tool into a more advanced analytical framework. ANOVA-based approaches are widely preferred for their ability to decompose variance components and capture interaction effects, while newer studies increasingly combine methods to improve diagnostic capability [13], [22]. However, GRR does not represent total measurement uncertainty; rather, it quantifies the proportion of variation introduced by the measurement system itself [14]. Therefore, low GRR and high ndc provide practical assurance of data reliability, though they do not replace formal uncertainty analysis.

In addition, several studies highlight the critical role of measurement-system validation in capability analysis. Measurement errors, outliers, and unstable data can significantly bias Cp and Cpk values, leading to incorrect conclusions about process performance [16–18]. Consequently, data screening procedures—including outlier detection, stability verification, and normality assessment—are essential to ensure that capability indices accurately reflect true process behavior rather than measurement noise or unstable data structures.

Current quality-engineering literature increasingly emphasizes that process capability analysis must transcend isolated statistical evaluation, necessitating a foundation of validated measurement systems and robust data architectures [12, 15]. Furthermore, the interpretation of capability indices requires a critical assessment of process centering effects, moving beyond a reductive reliance on Cp and Cpk indices [21]. Aligning with this paradigm, this study integrates GRR-based validation with multifaceted capability interpretation and DMAIC-led interventions within a continuous extrusion manufacturing setting.

3. METHODOLOGY

The DMAIC methodology is extensively utilized within manufacturing for process optimization, defect reduction, and parameter stabilization, with particular efficacy noted in plastics and extrusion-based operations [4, 5, 7]. Within such frameworks, process capability indices—specifically Cp and Cpk—serve as the primary metrics for evaluating operational performance and the efficacy of improvement interventions [21]. However, existing literature frequently prioritizes numerical gains in capability without adequately addressing measurement system integrity or the critical influence of process centering on performance interpretation.

To address these methodological gaps, this study implements a measurement-driven DMAIC framework. A pivotal GR&R validation is executed prior to capability analysis, ensuring that subsequent SPC evaluations and capability indices represent authentic process behavior rather than measurement artifacts. Furthermore, this study extends conventional DMAIC applications by integrating centering considerations into the capability assessment of a continuous extrusion process.

The study is conducted at an anonymized manufacturing facility utilizing a blown-film line for 31 µm linear low-density polyethylene (LLDPE) production. Adopting the DMAIC framework, the research sought to minimize material overconsumption, stabilize process variance, and enhance overall capability, predicated on the establishment of a validated measurement system. The baseline analysis utilized 260 observations, structured into 26 rational subgroups of size 10, evaluated against engineering specifications of 29.45µm to 32.55 µm and a nominal target of 31.0 µm.

To validate the thickness gauge, a crossed Gauge Repeatability and Reproducibility (GRR) study is conducted involving three appraisers and ten parts with three replicates. Upon confirming measurement system adequacy, baseline process performance is evaluated using histograms, $\bar{X}$-R charts, and capability indices. Root cause identification integrated direct process observation with structured brainstorming and a cause-and-effect framework. Following the implementation of improvement actions, the process is re-evaluated using identical statistical indicators to quantify the shift from baseline to post-intervention conditions.

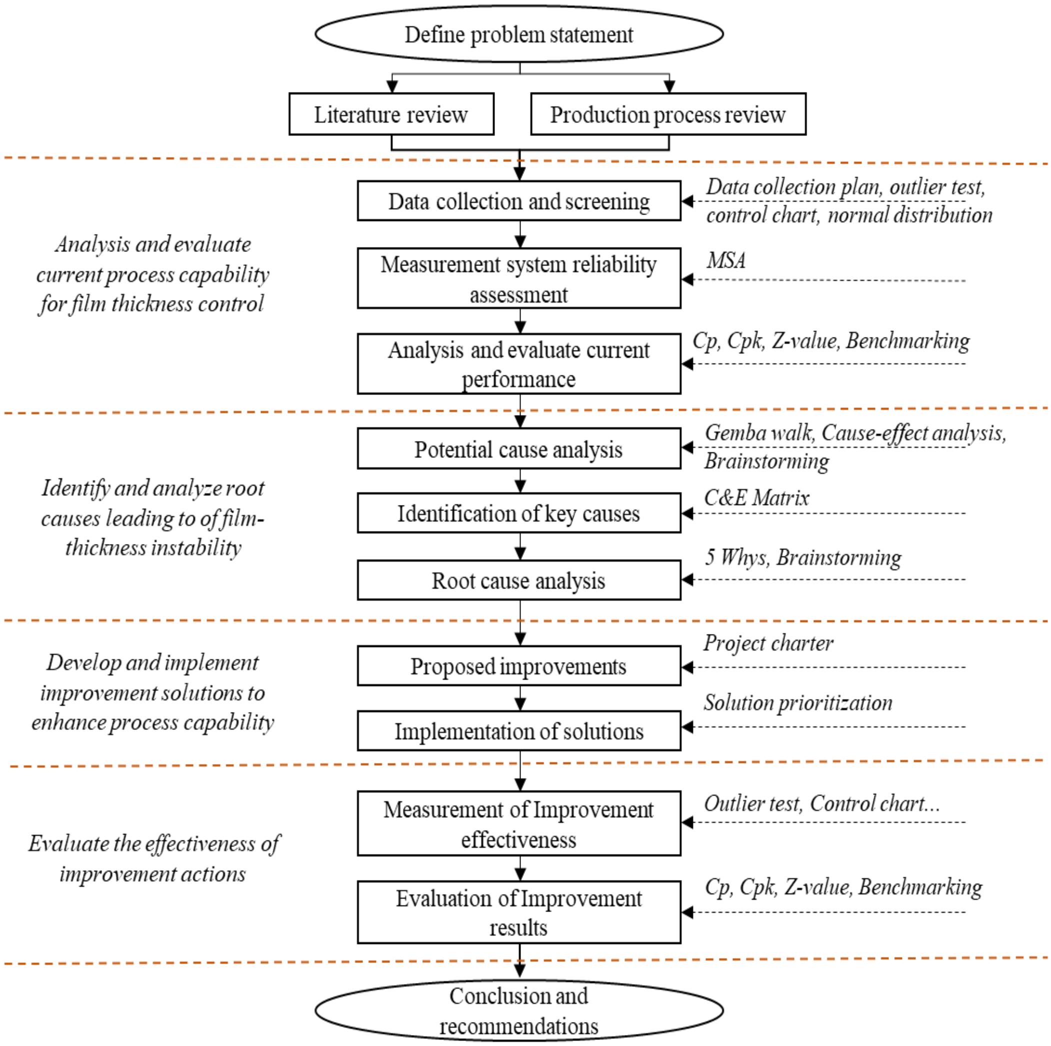

Figure 1. Research objectives of the study.

Source: By authors.

Structured around the DMAIC framework, the study comprises four integrated objectives, such as capability assessment, root-cause identification, solution implementation, and effectiveness evaluation. This methodological sequence frames (Figure 1) the project as a continuous improvement cycle rather than a static descriptive report, emphasizing a systematic transition from diagnostic analysis to verified operational enhancement.

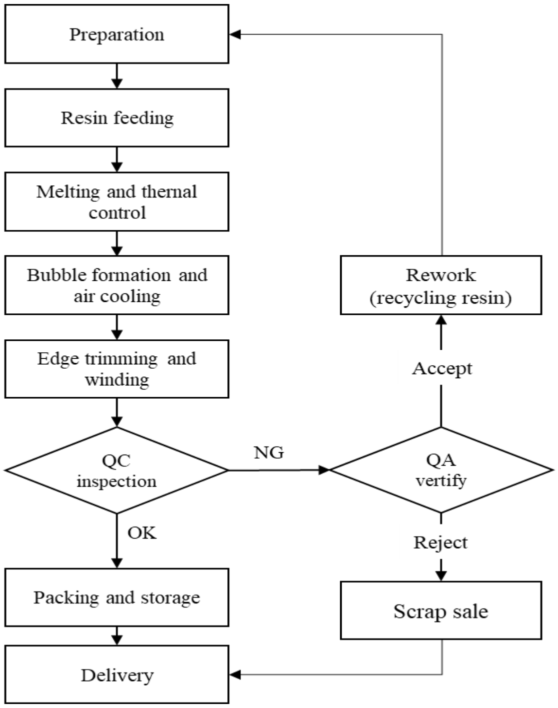

Figure 2. Simplified blown-film production flow.

Source: By authors.

The production flow (Figure 2) suggests that thickness variation is a multi-stage phenomenon rather than the result of a single mechanical adjustment, necessitating a dual approach of process mapping and statistical diagnosis. By integrating these methods, the investigation can effectively differentiate between systematic environmental factors and localized equipment variances that contribute to film instability.

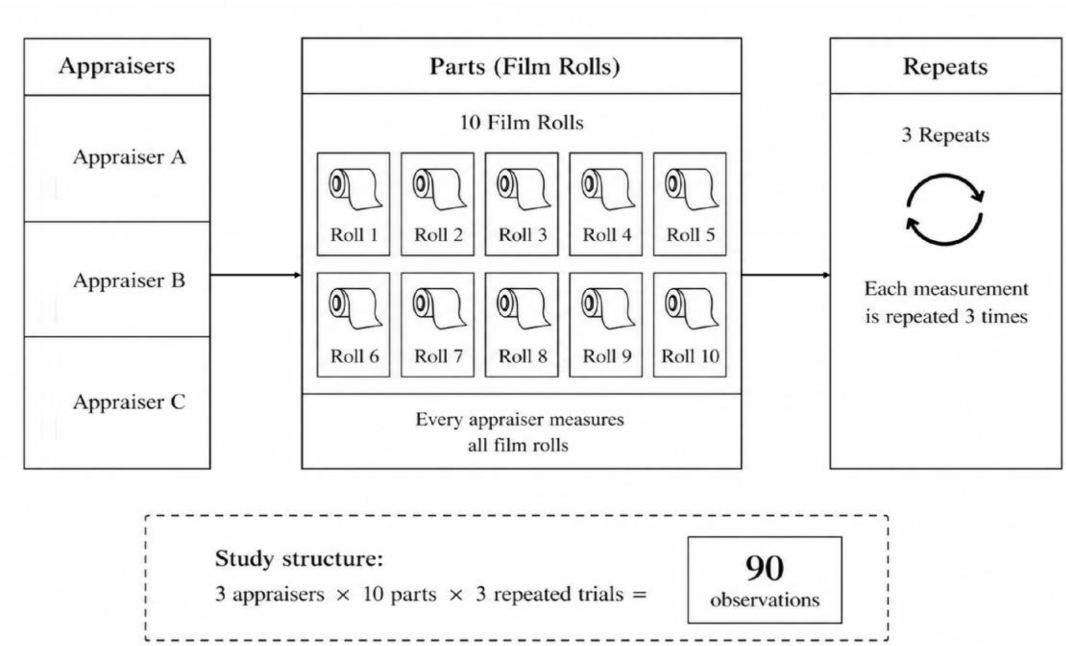

Figure 3. Crossed study design used for GRR.

Source: by authors.

The utilized crossed experimental design (Figure 3.), featuring three measurements per part by each appraiser, facilitates the systematic decomposition of total measurement variance into repeatability and reproducibility components. This rigorous structure is essential for verifying measurement system discrimination and ensuring the gauge possesses the requisite precision to support valid downstream capability analysis and statistical process control.

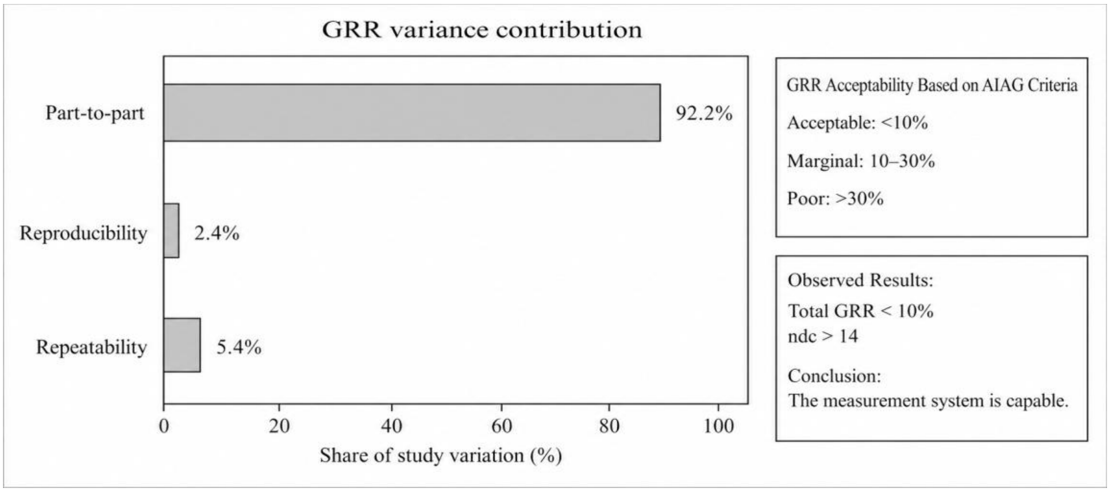

Figure 4. GRR contribution, acceptability, and discriminatory power.

Source: by authors.

Figure 4 demonstrates the study's primary measurement finding: most of the observed variation is attributable to part-to-part differences rather than gauge error. Total GRR remained below the standard acceptability threshold, while the number of distinct categories (ndc) confirms a robust practical capacity to distinguish meaningful process variations from noise measurement.

4. RESULTS AND DISCUSSION

4.1. Measurement-system reliability

The GRR study validated the measurement system's suitability for process evaluation, with total GRR remaining below 10%. Specifically, repeatability and reproducibility contributed 5.4% and 2.4% to study variation, respectively, while part-to-part variation accounted for 92.2%, indicating that most of the observed variability reflected actual process fluctuations rather than instrument or appraiser error. Furthermore, a number of distinct categories (ndc) exceeding 14 confirm the gauge's robust discriminatory power, ensuring the system can detect meaningful thickness deviations for downstream capability analysis.

Table 1. Summary of measurement-system analysis results.

Metric	*Result*	*Interpretation*
Study design	3 appraisers × 10 parts × 3 repeats	Crossed GRR design
Total %GRR	< 10%	Acceptable for process analysis
Repeatability	5.4%	Primary gauge-related component
Reproducibility	2.4%	Low appraiser effect
Part-to-part variation	92.2%	Real process differences dominate
ndc	> 14	High discriminatory power

Source: by authors.

These findings are methodologically significant as they validate the subsequent application of control charts and capability indices. By ensuring that gauge-related variation is minimal, the study confirms that fluctuations in Cp, Cpk, or defect rates represent authentic process shifts rather than metrological noise. Consequently, the acceptable GRR results establish a credible foundation for interpreting the observed performance improvements as genuine operational gains.

4.2. Baseline process performance

Baseline performance analysis reveals a process mean of 31.411 µm, exceeding the 31.0 µm nominal target and indicating systematic over-thickness (Figure 5). With a within-process standard deviation of 0.513 µm, the resulting Cp of 1.07 and Cpk of 0.78 highlight a significant disparity between potential and actual capability, primarily driven by poor process centering and insufficient short-term stability. This misalignment results in a 5.8% out-of-tolerance rate, representing substantial material waste and operational instability.

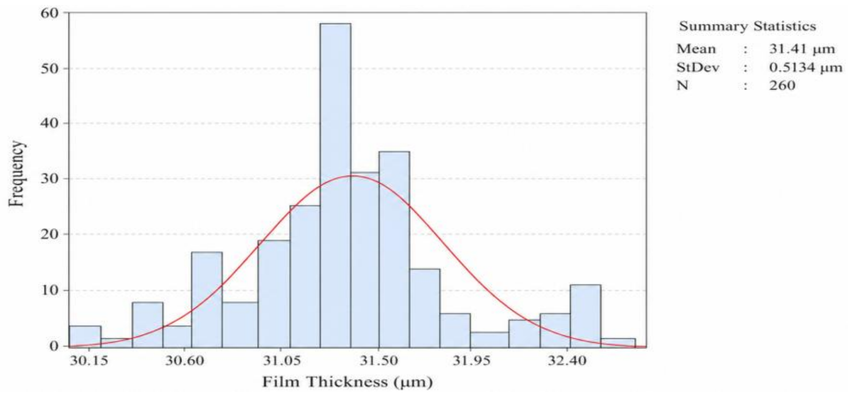

Figure 5. Histogram of film thickness during the baseline period.

Source: by authors.

The baseline distribution (Figure 5) exhibited a significant positive shift relative to the nominal target, indicating that the process is both excessively variable and economically inefficient. This misalignment resulted in a mean thickness consistently exceeding the target specification, leading to systemic resin overconsumption. Consequently, the lack of process centering exacerbated material "give-away" where engineering compliance is achieved only through costly overproduction rather than precision control.

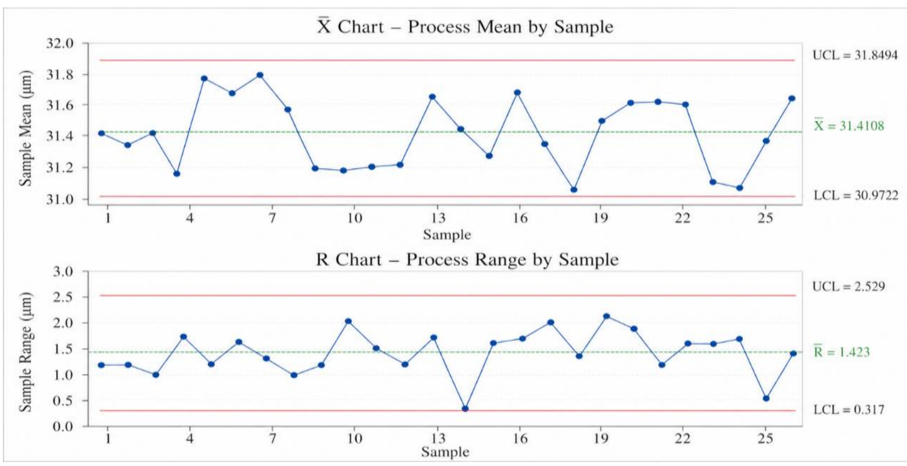

Figure 6. X̄ -R chart of baseline thickness data.

Source: by authors

The baseline control charts (Figure 6) exhibit significant subgroup fluctuation and an expanded range pattern, indicating that the process is not operating in a state of statistical control. This behavior suggests that observed thickness deviations are not merely the result of inherent common-cause variation but were driven by assignable factors or poorly regulated operational variables. Consequently, the instability highlighted by these patterns necessitates a systematic root-cause investigation to identify the specific environmental or mechanical stressors influencing thickness performance.

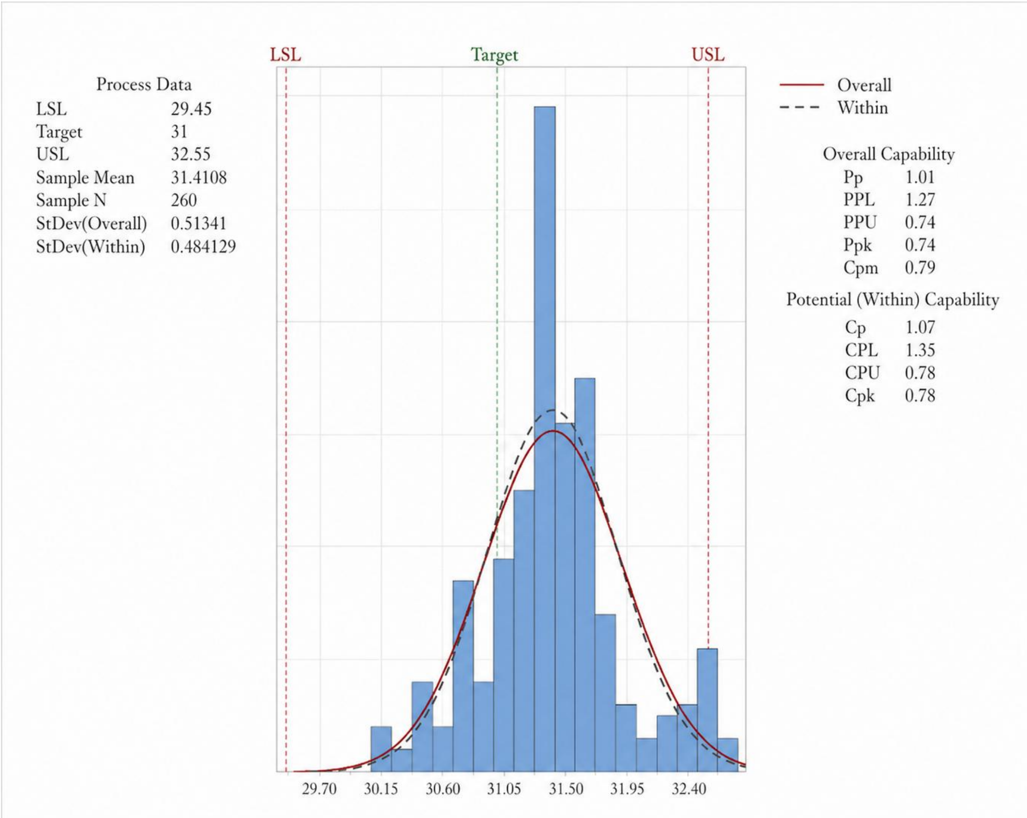

Figure 7. Capability plot for the baseline period.

Source: by authors.

Figure 7 shows that the process is not properly centered within the specified engineering boundaries, as confirmed by the baseline capability study. The substantial difference between the Cpk and Cp indices suggests that operational underperformance is mostly caused by process location rather than intrinsic spread alone. This misalignment indicates that, despite the process's potential for increased precision, a centering technique is required to reduce resin overconsumption and maintain output quality due to the systemic positive bias of the mean compared to the nominal objective.

4.3. Root-cause analysis

A root-cause analysis revealed that a complex interplay of elements involving methodologies, environment, measurement discipline, materials, staff, and equipment is responsible for the process underperformance. The inquiry brought to light a number of important influencers. inconsistent extrusion profile configurations and non-uniform operator reactions to drift in thickness. variations in the flow of recyclable materials and resin feeding. Prior to the investigation, there is a lack of calibration discipline that compromised measurement reliability. The intervention changed the process from reactive troubleshooting to a disciplined, data-driven control environment by tackling these multifaceted core causes.

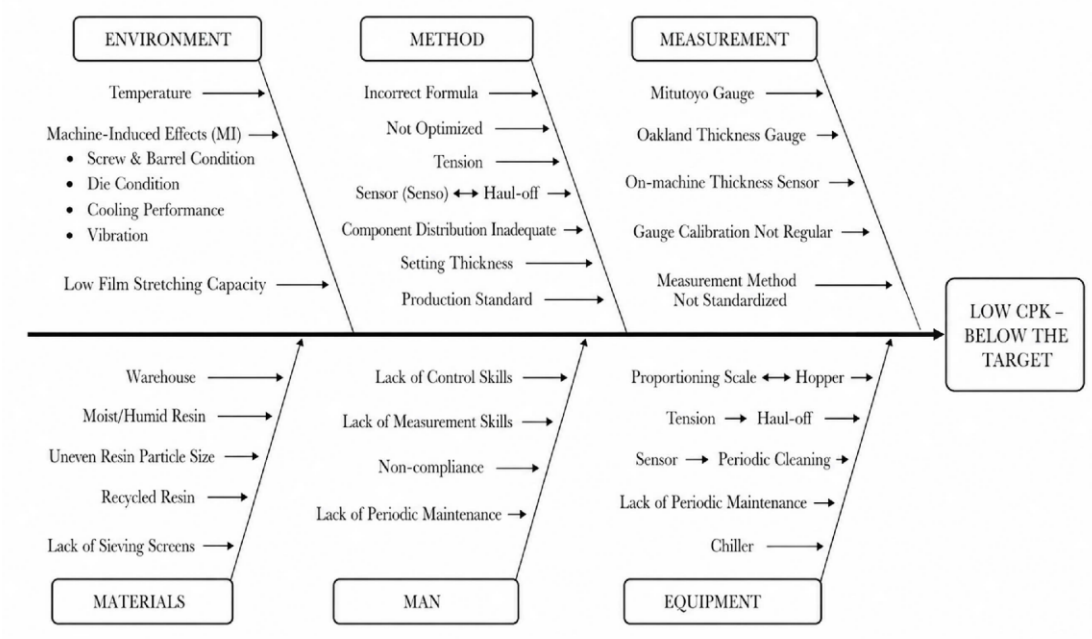

Figure 8. Cause-and-effect analysis of low thickness-control capability.

Source: by authors.

As shown in Figure 8, the cause-and-effect map demonstrates that low capability is not a single-point issue but rather a system-level issue. This backs up the choice to put in place a comprehensive improvement package that addresses settings, materials, measurement discipline, and operator reaction procedures all at once.

The study additionally employs the 5 Whys approach to go beyond surface symptoms and pinpoint the underlying causes of insufficient thickness-control capabilities in order to deepen the root-cause investigation. Several fundamental concerns are the focus of the questioning sequence: (1) Why does film thickness drift from the target? (2) Why are operator adjustments unable to stabilize the process consistently? (3) Why do resin-feeding conditions vary during production? (4) Why isn't the deviation identified or fixed sooner? and (5) Why do these conditions endure over time? This iterative analysis reveals that a number of root causes, such as unstable extrusion-profile settings, inconsistent recycled-resin circulation, inaccurate or inadequately controlled proportioning and hopper-scale conditions, incorrect resin-feed positioning, and a lack of calibration and maintenance discipline, are responsible for the issue rather than a single isolated fault. These results explained why thickness variation persisted and supported the use of a more comprehensive improvement package as opposed to a single corrective action.

4.4. Improvement actions

The improvement package prioritized the standardization of thickness-related operating conditions to minimize the necessity for ad hoc manual corrections. The core interventions involved the continuous adjustment and stabilization of extrusion profile parameters, more rigorous control of cooling conditions, and optimized resin-feed positioning. Complementing these mechanical adjustments, the study implemented stricter calibration practices and a formalized out-of-tolerance reporting routine. These actions specifically targeted the dual objectives of centering and variability reduction, directly addressing the baseline gap between

Cp and Cpk. By shifting from reactive operator adjustments to a disciplined, parameter-driven framework, the process achieved a more predictable statistical state where both the mean and the dispersion were brought into alignment with engineering targets.

4.5. Post-improvement performance

Following implementation, the process mean approaches the target and drops to 31.217 µm (Table 2). From 0.513 µm to 0.402 µm, the within-process standard deviation decreased by about 21.7%. From Cp=1.07 to Cp=1.32 and from Cpk=0.78 to Cpk=1.13, capability increased. There is a significant improvement in both statistical performance and operational efficiency as the out-of-tolerance rate decreased from roughly 5.8% to 0.9%.

Table 2. Comparison of before–after process performance.

Indicator	Before	After	Change
Mean thickness (µm)	31.411	31.217	Closer to target
Within-process SD (µm)	0.513	0.402	-21.7%
Cp	1.07	1.32	+23.4%
Cpk	0.78	1.13	+44.9%
Out-of-tolerance rate	5.8%	0.9%	-84.5%

Source: by authors.

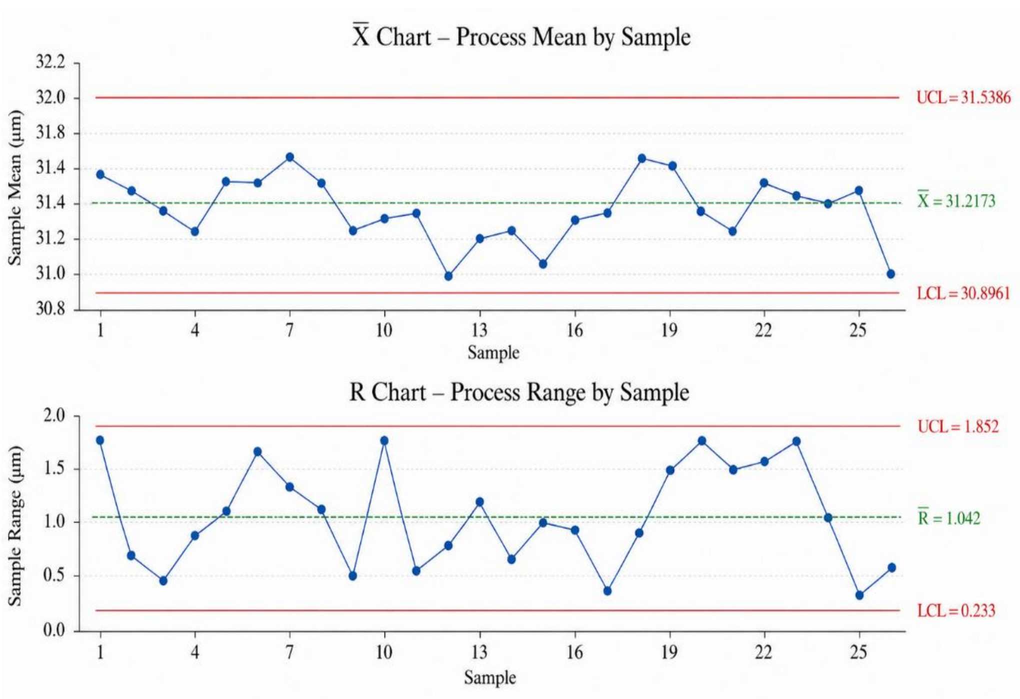

Figure 9. $\bar{X}$ -R chart after implementation of improvement action.

Source: by authors.

The post-improvement figure indicates a more disciplined subgroup pattern and a smaller spread when compared to the baseline condition. The conclusion that the improvement package improved short-term process control is supported by this.

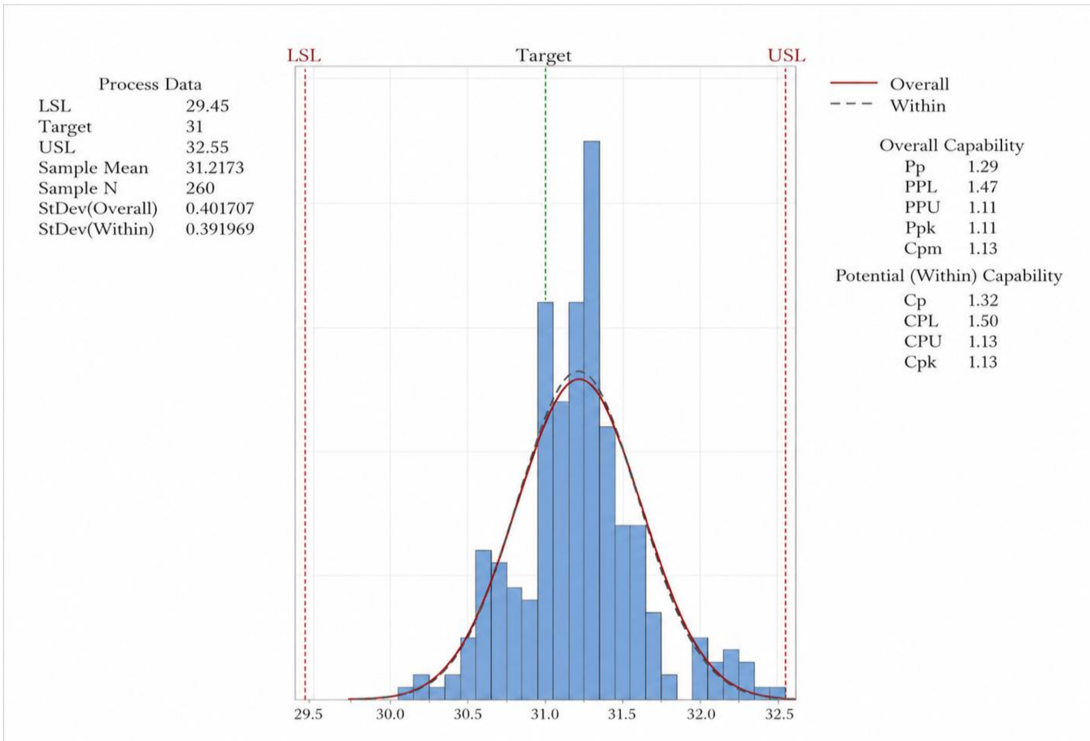

Figure 10. Capability plot after implementation of improvement action. Source: by authors.

The post-improvement capability graphic shows that spread and location have simultaneously improved. The improvements cannot be exclusively attributed to a decrease in dispersion because both Cp and Cpk rose; improved centering also made a significant contribution.

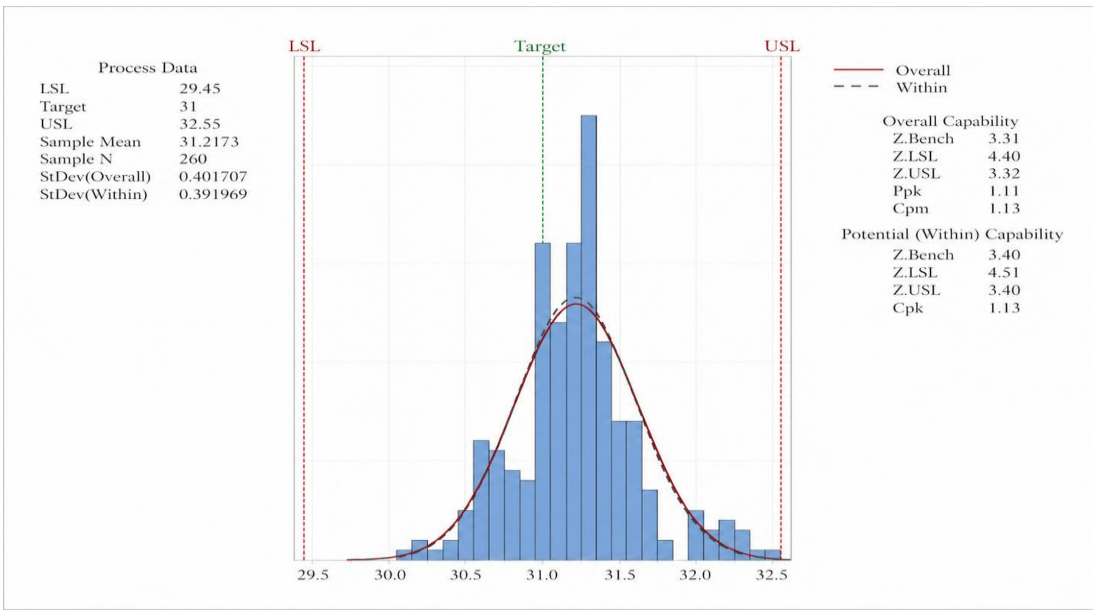

Figure 11. Z-value trend after implementation of improvement action. Source: by authors

The capability indices are supported by the rising Z-value trend, which shows that the post-intervention procedure produced a stronger statistical position (Figure 11). The likelihood of non-conforming output is decreased by this shift, which shows a considerable increase in the safety margin between the process mean and specification limits. The inference that the production line achieved greater operational reliability and less susceptibility to thickness-related problems is thus supported by the higher Z-score.

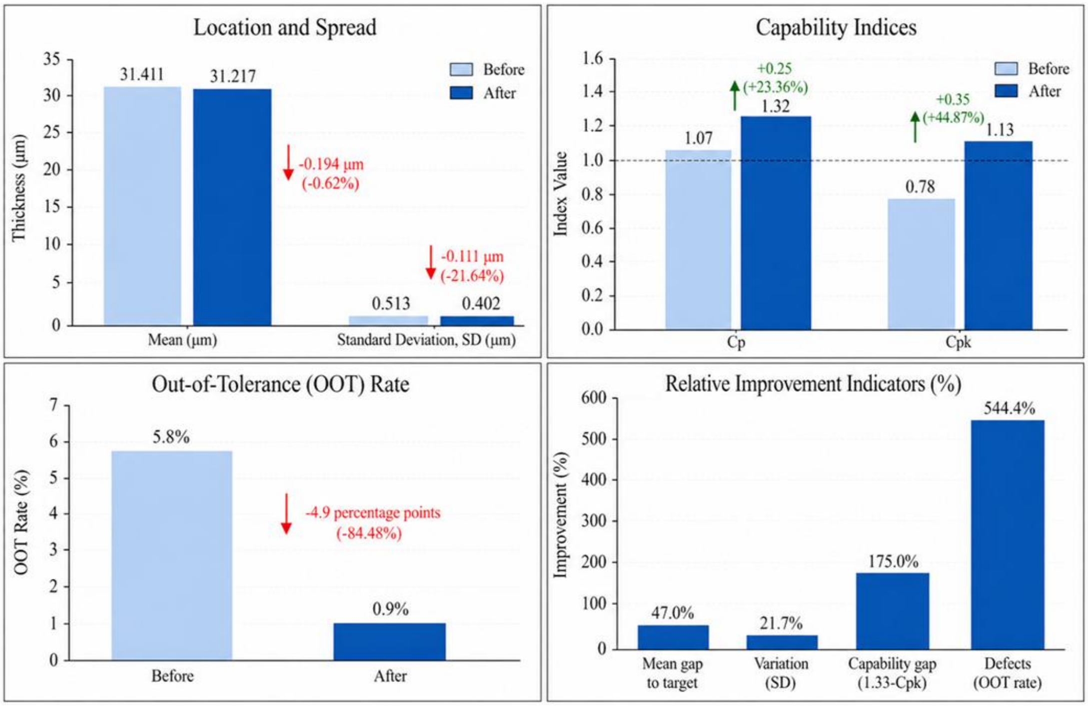

Figure 12. Before–after process improvement dashboard for key process indicators.

Source: by authors.

The dashboard shows a thorough change in operational performance by summarizing the extensive improvements made in process location, spread, capability, and defect rates (Figure 12). By combining various measurements, the summary shows that rather than only optimizing a single index, the intervention improved the process's overall statistical and economic behavior. This multifaceted enhancement demonstrates that the project is successful in balancing cost effectiveness and engineering accuracy, creating a more capable and stable manufacturing environment.

4.6. Discussion

The findings highlight a key idea in metrological literature: statements about process improvement are only credible if the measuring method is proven to be adequate. The acceptable Gauge R&R (GRR) results in this study provided the reliability basis required to interpret the ensuing decrease in out-of-tolerance output, the expansion of process capability, and the reduction in standard deviation. This methodological sequencing is in line with the guidelines established by AIAG [12] and the conclusions of Runje et al. [15], Soares et al. [13], and Razumić et al. [14], all of which stress that process data should not be taken for granted until the measurement system's contribution to overall variance has been thoroughly evaluated.

Additionally, the improvement pattern is consistent with previous research on plastics manufacturing. Like Desai and Prajapati [4], Siddiqui and Tabassum [5], and Abd Elnaby et al. [7], an integrated method that combined process mapping, cause analysis, parameter control, and follow-up discipline yielded the most significant results. Practically speaking, the change from Cpk=0.78 to 1.13 is significant since it signifies a transition from an obviously subpar state to a more stable working window. The observed gain is already significant enough to suggest significant material and quality benefits, even if more improvement would still be ideal to get closer to best-in-class performance.

Beyond immediate process gains, these results align with the broader paradigm shift toward Industry 4.0. Recent literature suggests that real-time monitoring and predictive analytics enhance process control by facilitating the preemptive detection of process drift [8–11]. In this context, the measurement-driven DMAIC framework applied here serves as a foundational precursor to advanced, data-integrated control systems. Notably, the contribution of this study is threefold. First, it establishes measurement system validation as a mandatory "decision gate" prior to capability assessment, ensuring that Cp, Cpk, and SPC signals reflect authentic process dynamics rather than gauge-related noise [12, 15]. Second, it extends conventional DMAIC methodologies by explicitly linking capability improvements to process centering, arguing against a purely index-centric interpretation of performance [21]. Third, it provides an integrated improvement logic for blown-film extrusion, where MSA, SPC, and standardized control routines are synthesized into a scalable framework for mitigating thickness instability.

While traditional DMAIC applications in the plastics sector often prioritize isolated parameter adjustments [4, 5, 7], this research emphasizes system-level intervention. The novelty of this approach lies in treating GR&R as a prerequisite for analysis and viewing improvement as holistic structural refinement. Ultimately, the adopted sequence—measurement validation, capability diagnosis, and standardized control—provides a robust template for continuous manufacturing environments where measurement uncertainty might otherwise obfuscate process interpretation.

From a broader perspective, the methodological sequence adopted—measurement validation, capability diagnosis, root-cause verification, and standardized control—aligns with recommendations in quality engineering and metrology literature, which emphasize that reliable data and validated measurement systems are essential for meaningful process improvement [12, 15]. Although this study focuses on blown-film extrusion, the approach is applicable to other continuous manufacturing processes where variability is influenced by multiple interacting factors and where measurement uncertainty can distort process interpretation. In addition, while these case-specific metrics should be interpreted with appropriate caution, the measurement-driven DMAIC framework itself remains highly transferable to other continuous manufacturing sectors characterized by analogous variability dynamics. Therefore, the contribution of this work extends beyond the specific case by demonstrating how integrating measurement system analysis with capability evaluation and structured improvement logic can support more robust and transferable process improvement strategies across different industrial contexts.

A significant contribution of this study is the critical distinction between specification conformance and economic centering. A process may maintain high levels of in-tolerance production yet remain economically inefficient if the mean persistently exceeds the nominal target. By simultaneously shifting the mean toward 31 μm and reducing overall variation, the project enhanced both functional conformity and resin efficiency. This finding is particularly salient for blown-film operations, where marginal thickness excesses— often considered negligible in practice often dismissed as negligible—accumulate rapidly into substantial avoidable material costs over high-volume production cycles.

5. CONCLUSION

This study demonstrates that the effective optimization of film-thickness control in blown-film extrusion necessitates a holistic integration of trustworthy measurement, statistically guided diagnosis, and disciplined operational control. The initial Gauge R&R

study served as a critical reliability gate, confirming the measurement system's adequacy before the interpretation of process capability and control-chart data. Quantitatively, the intervention yielded significant performance gains: the process mean shifted closer to the nominal target, and the within-process standard deviation declined. These improvements are reflected in the capability indices, with Cp increasing from 1.07 to 1.32 and Cpk rising from 0.78 to 1.13. Consequently, the out-of-tolerance rate is reduced from approximately 5.8% to 0.9%. Collectively, these metrics indicate that the production process achieved a superior statistical state, characterized by both enhanced centering and reduced variability. Notably, the study's measurement-driven DMAIC framework offers a substantial and transportable methodological contribution, creating a systematic logic for improving economic performance and process stability across a variety of material-intensive industrial sectors.

From a managerial standpoint, this scenario shows that Gauge R&R should not be viewed as a supporting element of capability studies or statistical process control. Rather, it is the fundamental underpinning for reliability that validates all future statistical conclusions. A practical framework for attaining more stable and financially feasible output is provided by the integrated use of measurement systems analysis, SPC, root-cause verification, and standardized control procedures for extrusion operations plagued by chronic thickness instability.

Despite the improvements observed, this study has several limitations that should be explicitly acknowledged. This study uses a single-case design, concentrating on a blown-film extrusion process for a 31 μm LLDPE product, in accordance with Yin's [23] view that comprehensive investigation of representative cases can offer high explanatory value for typical industrial settings. Nonetheless, the results are still limited by particular material rheology and machine setups. It is still challenging to determine the independent effect size of each action because the improvement interventions were assessed as an integrated package during a rather short follow-up period. Consequently, the observed gains in Cp, Cpk, and defect reduction are context-dependent and may fluctuate under different polymer rheologies, mechanical configurations, and operating conditions. Furthermore, it is impossible to accurately separate the independent effect size of each individual action because the implemented treatments were assessed as a unified package. Instead of a long-term, multi-season control horizon, the post-improvement data represents a brief follow-up period.

Above, future studies could incorporate online sensing, automated control logic, or predictive analytics to improve real-time thickness management. These developments would be in line with the changing relationship between digital manufacturing and quality engineering [7,14], leading to more independent and proactive process control.

Acknowledgement: We acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

Conflict of Interest: The authors declare no conflict of interest. All authors have approved the final manuscript and its authorship order, and all eligible contributors have been appropriately included.

Declaration: This manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

REFERENCES

[1] R. Rana *et al.,* "Plastics and the environment: Challenges, impacts, and pathways to sustainability," *Integrated Environmental Assessment and Management*, Art. no. vjaf193, 2025, doi: https://doi.org/10.1093/inteam/vjaf193

[2] B. Bamps, M. Buntinx, and R. Peeters, "Seal materials in flexible plastic food packaging: A review," *Packaging Technology and Science*, vol. 36, no. 7, pp. 507–532, 2023, doi: https://doi.org/10.1002/pts.2732

[3] A. Chiarini, "Improvement of OEE performance using a Lean Six Sigma approach: An Italian manufacturing case study," *International Journal of Productivity and Quality Management*, vol. 16, no. 4, pp. 416–433, 2015, doi: https://doi.org/10.1504/IJPQM.2015.072414

[4] D. A. Desai and B. N. Prajapati, "Competitive advantage through Six Sigma at plastic injection molded parts manufacturing unit: A case study," *International Journal of Lean Six Sigma*, vol. 8, no. 4, pp. 411–435, 2017, doi: https://doi.org/10.1108/IJLSS-06-2016-0022

[5] M. M. U. Z. Siddiqui and A. Tabassum, "Application of Six Sigma methodology for enhancement of soft plastic extrusion process," *Memoria Investigaciones en Ingeniería*, no. 28, pp. 193–221, 2025, doi: https://doi.org/10.36561/ING.28.14

[6] J. de Mast and J. Lokkerbol, "An analysis of the Six Sigma DMAIC method from the perspective of problem solving," *International Journal of Production Economics*, vol. 139, no. 2, pp. 604–614, 2012, doi: https://doi.org/10.1016/j.ijpe.2012.05.035

[7] Z. Abd Elnaby *et al.,* "Improving plastic manufacturing processes with the integration of Six Sigma and machine learning techniques: A case study," *Journal of Industrial and Production Engineering*, vol. 41, no. 1, pp. 1–18, 2024, doi: https://doi.org/10.1080/21681015.2023.2260384

[8] J. Antony, R. Snee, and R. Hoerl, "Lean Six Sigma: Yesterday, today and tomorrow," *International Journal of Quality & Reliability Management*, vol. 34, no. 7, pp. 1073–1093, 2017, doi: https://doi.org/10.1108/IJQRM-03-2016-0035

[9] D. Skalli *et al.,* "Industry 4.0 and Lean Six Sigma integration in manufacturing: A literature review, an integrated framework and proposed research perspectives," *Quality Management Journal*, vol. 30, no. 1, pp. 16–40, 2023, doi: https://doi.org/10.1080/10686967.2022.2144784

[10] K. S. Boparai, R. Singh, and H. Singh, "Modeling and optimization of extrusion process parameters for the development of Nylon6–Al–Al_2O_3 alternative FDM filament," *Progress in Additive Manufacturing*, vol. 1, pp. 115–128, 2016, doi: https://doi.org/10.1007/s40964-016-0011-x

[11] C.-N. Wang *et al.,* "The performance analysis using Six Sigma DMAIC and integrated MCDM approach: A case study for microlens process in Vietnam," *Journal of Engineering Research*, vol. 13, no. 2, pp. 538–550, 2025, doi: https://doi.org/10.1016/j.jer.2024.04.013

[12] Automotive Industry Action Group, *Measurement Systems Analysis*, 4th ed. Southfield, MI, USA: AIAG, 2010.

[13] W. de O. S. Soares *et al.,* "Gage R&R studies in measurement system analysis: A systematic literature review," *Quality Engineering*, vol. 34, no. 3, pp. 382–403, 2022, doi: https://doi.org/10.1080/08982112.2022.2069505

[14] A. Razumić *et al.,* "A review of methods for assessing the quality of measurement systems and results," *Applied Sciences*, vol. 15, no. 17, Art. no. 9393, 2025, doi: https://doi.org/10.3390/app15179393

[15] B. Runje, A. Horvatić Novak, and A. Razumić, "Measurement system analysis in production process," in *Proc. XVII International Scientific Conference on Industrial Systems (IS'17)*, Novi Sad, Serbia, 2017, pp. 274–277

[16] R. K. Burdick, C. M. Borror, and D. C. Montgomery, "A review of methods for measurement systems capability analysis," *Journal of Quality Technology*, vol. 35, no. 4, pp. 342–354, 2003, doi: https://doi.org/10.1080/00224065.2003.11980232

[17] N. F. Hubele, "Encyclopedia and Handbook of Process Capability Indices: A Comprehensive Exposition of Quality Control Measures, Series on Quality, Reliability and Engineering Statistics". *Journal of Quality Technology*, vol. 39, no. 2, pp. 175–177, 2007, doi: https://doi.org/10.1080/00224065.2007.11917685.

[18] M. Z. Anis, "Basic process capability indices: An expository review," *International Statistical Review*, vol. 76, no. 3, pp. 347–367, 2008, doi: https://doi.org/10.1111/j.1751-5823.2008.00060.x

[19] C. Saikaew, "An implementation of measurement system analysis for assessment of machine and part variations in turning operation," *Measurement*, vol. 118, pp. 246–252, 2018, doi: https://doi.org/10.1016/j.measurement.2018.01.008

[20] T. Munir *et al.,* "Effect of measurement uncertainty on combined quality control charts," *Computers & Industrial Engineering*, vol. 175, Art. no. 108900, 2023, doi: https://doi.org/10.1016/j.cie.2022.108900

[21] D. C. Montgomery, *Introduction to Statistical Quality Control*, 8th ed. Hoboken, NJ, USA: Wiley, 2020.

[22] J. Arumun, V. Ekanem, and E. Ashigwuike, "Review of gauge repeatability and reproducibility for dimensional measurements," *Scholars Bulletin*, vol. 10, no. 7, pp. 186–194, 2024, doi: https://doi.org/10.36348/sb.2024.v10i07.003

[23] R. K. Yin, *Case Study Research: Design and Methods*, 5th ed. Thousand Oaks, CA, USA: SAGE Publications, 2014.