Original Research

Integrating Statistical Quality Control and Root-Cause Analysis in Marble Manufacturing for Sustainable Process Improvement

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Received: 12 April 2025 / Accepted: 9 July 2025 / Published online: 14 August 2025

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Abstract
The marble manufacturing industry often faces quality control challenges due to the natural variability of raw materials and inconsistencies in human-machine interactions. These issues can result in high defect rates, production inefficiencies, and customer dissatisfaction. Therefore, a systematic and data-driven approach is essential to monitor, evaluate, and improve product quality. This study aims to analyze the quality performance of marble tile production by identifying dominant defect types and assessing process stability using Statistical Quality Control (SQC) techniques. Specifically, the research applies Pareto analysis to determine the most frequent defect categories and constructs a p-chart to evaluate the temporal variation in defect proportions over time. The methodology involved daily defect recording over 30 production days, resulting in a dataset of 16,015 marble units. Defect categories included cracks, breaks, discoloration, chipping, and misalignment. Pareto analysis revealed that over 99% of all defects were concentrated in cracks and breaks, confirming the effectiveness of prioritizing these two categories for corrective action. Meanwhile, the p-chart indicated a process mean (CL) of 0.10607, with control limits at 0.11343 (UCL) and 0.09871 (LCL). Of the 30 observations, 27 were within control limits, suggesting the presence of common-cause variation. However, three outlier points on Days 7, 15, and 24 exceeded the UCL, signaling assignable causes. These anomalies coincided with peak equipment usage and unexpected operator reassignments, highlighting the interplay of technical and human factors. The findings, supported by visual representation in Figure 3, suggest that while the process is generally stable, it is vulnerable to short-term disruptions. Implementing predictive maintenance and ergonomic scheduling is recommended to enhance long-term process capability and product consistency.

Keywords – Statistical Quality Control, Marble manufacturing, Defect analysis, P-chart, Fishbone diagram, Sustainable production, Predictive maintenance.

INTRODUCTION

Marble, as a material, introduces a distinct set of challenges for quality assurance. Its anisotropic composition and inherent heterogeneity manifested in veining patterns, porosity, and cleavage orientation can result in unpredictable behavior during mechanical processing [1-3]. These conditions require a quality framework that is not only reactive but also diagnostic and preventive, as offered by statistical control systems.

Inadequate defect management in marble manufacturing not only results in economic inefficiency but also raises sustainability issues, such as excessive resource waste and a heightened carbon footprint. These concerns align with the United Nations Sustainable Development Goals, particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 12 (Responsible Consumption and Production) [4,5].

While previous research in stone industries has focused largely on geological characterization and durability analysis, there is a marked paucity of studies integrating operational quality metrics with statistical diagnostics [6-8].

FIGURE 1
EXAMPLE OF CRACK DEFECT ON MARBLE SURFACE

While previous research in the natural stone industry has predominantly focused on geological properties and long-term durability, there remains a notable gap in applying data-driven quality management tools to diagnose and control operational defects—particularly in marble manufacturing where material anisotropy and processing fragility challenge conventional control systems. This study offers a novel contribution by contextualizing classical Statistical Quality Control (SQC) tools within the high-variability environment of marble production. By combining Pareto analysis, p-charts, and root-cause mapping with empirical defect tracking, the research develops a replicable diagnostic framework that accounts for both technical and human-process interactions. Furthermore, by linking process stability insights to sustainability goals (SDG 9 and SDG 12), the study extends the utility of SQC beyond quality assurance toward environmentally and economically responsible manufacturing—an integration that is rarely explored in current literature.

Accordingly, the present study aims to implement a comprehensive SQC framework tailored to marble manufacturing. By utilizing check sheets, Pareto analysis, control charts (p-charts), Ishikawa diagrams, and scatter plots, the research seeks to classify dominant defect types, assess process variation, and trace the root causes across key production variables. The insights derived may inform both industry practices and policy recommendations for quality-driven, sustainable manufacturing.

Despite the extensive application of SQC tools in conventional manufacturing domains, their integration into the marble industry remains underdeveloped, particularly in linking quality outcomes with process diagnostics in high-variability environments. To address this gap, this study not only implements classical SQC tools such as Pareto charts and control charts, but also contextualizes them within the physical realities of marble processing—highlighting the interplay between mechanical stress, material heterogeneity, and human decision-making. By situating SQC within the socio-technical complexities of natural stone manufacturing, this research contributes a novel, domain-specific application model that bridges statistical methodology with sustainability-focused process improvement.

METHODOLOGY

I. Research Design and Epistemological Framework

This study adopts a quantitative-descriptive research design situated within a positivist epistemological paradigm, wherein process quality is viewed as an objective reality that can be systematically measured and enhanced through statistical inference (Montgomery, 2012; Woodall, 2000; Rauf, 2023). The positivist stance asserts that empirical phenomena—such as production defects—are governed by discernible patterns that can be captured using appropriate probabilistic tools, thereby justifying the adoption of SQC as both a diagnostic and prescriptive method (Chan and Spedding, 2001). SQC is chosen for its proven capability to monitor process behavior, differentiate between common-cause and assignable-cause variations, and provide actionable insights for corrective interventions. This is particularly relevant for industries with high defect sensitivity and high production throughput, such as marble manufacturing (Antony, 2011; Aydin, 2007).

II. Study Context and Observation Scope

The research was conducted at a marble production facility in Indonesia operating under a repetitive-batch production environment. This production line was selected due to its measurable defect rate—exceeding 10%—and the absence of a fully implemented statistical control system. The unit of analysis comprised marble tiles measuring 60 × 60 cm, as these exhibited the highest rejection rates based on initial production data. Production output over 30 consecutive working days was analyzed, totaling 16,015 units, ensuring that the findings comprehensively reflect the operational reality without sampling bias.

III. Data Collection Instruments

Data were collected using a multi-source instrumentation strategy, which included:
Check Sheets: Employed daily to record the frequency and types of visual defects.
- **Structured Interviews:** Conducted with production line operators, maintenance staff, and quality control supervisors to explore the causes of defects and operational behaviors.
- **Secondary Documentation:** Including daily production logs, maintenance schedules, and quality audit reports to support data triangulation.

Defects were categorized into five primary classes: cracks, breaks, discoloration, edge chipping, and dimensional misalignment.

IV. Analytical Tools and Software

The collected data were analyzed using Minitab v21.3 and Microsoft Excel 365. The following SQC tools were utilized:
1. **Histogram:** To visualize frequency distributions and identify dominant defect patterns.
2. **Pareto Diagram:** To isolate critical defect categories following the 80/20 principle.
3. **p-Chart (Control Chart for Proportions):** To statistically evaluate process stability based on daily defects. Control limits were computed using the average defect proportion and daily sample sizes (Montgomery and Runger, 2013).
   Upper control limit (UCL)

$$\mathrm{UCL} = p + 3\sqrt{\frac{p\,(1-p)}{\mathrm{n}}} \tag{1}$$

   Central Line

$$\mathrm{CL} = p \tag{2}$$

   Low Control Limit

$$\mathrm{LCL} = p - 3\sqrt{\frac{p\,(1-p)}{\mathrm{n}}} \tag{3}$$

Remark:
UCL: Upper Control Limit
P: Proportion of defective products
n: Total production quantity
CL: Center Line (Central Control Limit)
LCL: Lower Control Limit

4. **Ishikawa Diagram (Cause-and-Effect):** To map the root causes of defects across four dimensions: Man, Machine, Method, and Material.
5. **Scatter Plot:** To correlate daily production volumes with defect frequencies, thereby evaluating any potential effects of fatigue or overloading.

V. Validity, Replicability, and Limitations

To ensure internal validity, the study employed a non-sampling approach (total population) combined with data triangulation using check sheets, interviews, and production documents. Defect classification was periodically verified by independent quality auditors to minimize observer bias. Methodologically, the SQC framework adopted in this study can be replicated in other material-sensitive manufacturing environments that rely on visual quality assessments. Furthermore, the framework offers potential for further development with the integration of predictive modeling techniques, such as machine learning, once a longitudinal dataset is established. Limitations of this study include the lack of microscopic-level defect analysis and the absence of cost-weighted quality metrics. Additionally, while the statistical analysis is currently descriptive, future phases may incorporate process capability indices (e.g., Cp, Cpk).

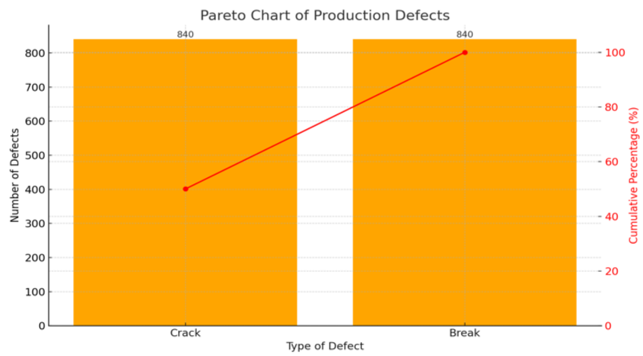

FIGURE 2
PARETO CHART OF MARBLE PRODUCT DEFECTS

VI. Conceptual Framework

The research is operationalized through the following sequential framework:

1. Daily production observation
2. Documentation via check sheets
3. Histogram analysis
4. Pareto identification
5. p-Chart process stability evaluation
6. Cause-and-effect mapping with Ishikawa diagrams and scatter plot analysis
7. Development of actionable quality recommendations
6. This framework is designed as a modular and transferable model for quality assessment in similar production systems, particularly those involving fragile or heterogeneous materials.

RESULTS AND DISCUSSION

I. Overview of Defect Distribution

Over the 30-day observation period, a total of 16,015 marble tiles were produced, with 1,670 units identified as defective—resulting in an average defect rate of 10.43%. Histogram analysis revealed a bimodal distribution, predominantly concentrated on two defect types: cracks (839 units; 50.24%) and breaks (831 units; 49.76%). In contrast, defects such as discoloration, dimensional misalignment, and edge chipping collectively accounted for less than 0.1% of total defects, indicating their minor role in overall quality issues.

This data distribution reinforces the applicability of the Pareto principle, where a small subset of defect categories contributes to the vast majority of quality failures [4, 15]. The resulting Pareto chart demonstrated that over 99.9% of defects were concentrated in just two categories, supporting the strategic prioritization of quality interventions. Additionally, the observed bimodal dominance may signal underlying systemic issues, such as process fragility during high-speed cutting or inadequate damping during material handling, warranting further physical and procedural investigation.

II. Statistical Process Stability: p-Chart Evaluation

A p-chart was constructed to evaluate the temporal fluctuations in daily defect rates. The process mean (CL) was calculated as 0.10607, with the upper control limit (UCL) and lower control limit (LCL) determined to be 0.11343 and 0.09871, respectively. Out of the 30 daily observations, 27 fell within the control limits, indicating that the variability was primarily due to common causes. However, three days (Days 7, 15, and 24) exceeded the UCL, suggesting the presence of assignable causes. Although these deviations occurred in approximately 10% of the observation period, they raise concerns about the overall process robustness. The timing of these anomalies corresponded with peak equipment usage and unexpected operator reassignments, suggesting an interplay between mechanical degradation and human factors [16]. These findings are visually represented in Figure 3.

III. Root Cause Taxonomy via Fishbone Diagram

An Ishikawa (fishbone) analysis was employed to identify the underlying causes of the major defects. The causes were categorized into four primary dimensions:

- **Man (Human Factors):** Limited ergonomic training, cognitive fatigue during extended shifts, and insufficient task rotation [17].
- **Machine:** Accelerated blade wear due to inadequate lubrication and misalignment issues following maintenance.
- **Material:** Variability in mineral grain size, latent microfractures, and moisture fluctuations.
- **Method:** Lack of real-time monitoring, absence of feedback loops between inspection and corrective actions, and inconsistent cutting speeds among operators.

This multidimensional mapping confirms that defect genesis is interdependent, supporting quality system theories that emphasize socio-technical interactions in high-variability production environments.

I.

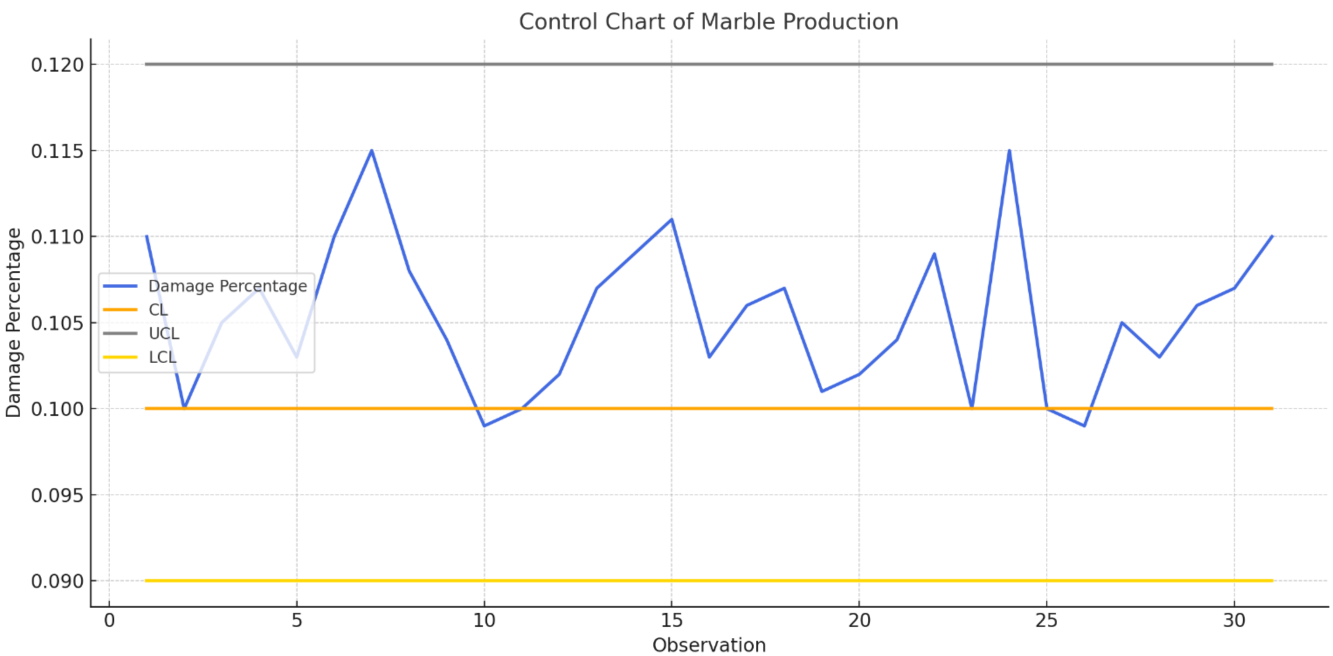

FIGURE 3

SHOWS THAT THE MARBLE PRODUCTION PROCESS IS STATISTICALLY IN CONTROL, AS ALL DAILY DEFECT PERCENTAGES FALL WITHIN THE UPPER AND LOWER CONTROL LIMITS, INDICATING NO SIGNIFICANT PROCESS DEVIATIONS.

IV. Defect Incidence vs. Output Volume: A Correlational Perspective

A scatter plot correlating daily production volume with defect frequency yielded a low positive correlation coefficient ($r = 0.21$). This indicates that increases in production volume do not proportionately lead to higher defect rates, suggesting that defect occurrence is more influenced by internal process stability than by production pressure.

V. Discussion: Comparative Reflections on Observed Anomalies

Several studies support the finding that transient deviations in manufacturing processes are indicative of minor shifts in environmental or mechanical conditions. For instance, Lee and Sohn [18] observed that temporary ambient variations and equipment wear contributed significantly to out-of-control signals in thin-film manufacturing. Similarly, Pinto and Salgueiro [19] demonstrated that minor ambient temperature deviations and irregular tool conditions led to erratic defect patterns in printed electronics, underscoring the sensitivity of semi-automated systems to process changes.

Mukherjee et al. [20] found that anomalies in granite polishing processes were often associated with operational transitions such as tool changeovers or shifts in operator allocation. Further, Hossain et al. [21] emphasized that operator-induced variability, particularly when processing non-homogeneous materials, interacts non-linearly with machine precision and fatigue. Finally, Patel and Kumar [22] noted that in tile manufacturing, process stability may mask underlying drift unless supplemented by advanced feedback control systems. These findings collectively underscore the need for an integrated quality approach that continuously calibrates equipment, methods, and manpower.

VI. Synthesis and Strategic Implications

The combined use of SQC tools facilitated a comprehensive diagnostic framework that not only quantified the scope of the quality problem but also traced its systemic origins. Key insights include:

- A **statistically controlled process** with episodes of emergent variation requiring root cause intervention.
- A defect profile **heavily skewed toward two types**, confirming the efficacy of Pareto-driven prioritization.
- The discovery of **non-linear causalities** involving operator behavior, mechanical integrity, and material heterogeneity.

Strategically, the findings recommend a multi-tiered intervention structure:

1. **Predictive Maintenance Protocols**: Utilize usage data and failure rates to pre-empt equipment-related quality failures.
2. **Behavioral and Cognitive Load Management**: Design operator workflows to minimize decision fatigue, particularly on night shifts.
3. **Real-time Quality Feedback Integration**: Deploy sensors and visual recognition systems at key production checkpoints.
4. **Material Pre-screening Algorithms**: Incorporate X-ray tomography or ultrasonic testing for early defect detection in raw blocks.

Collectively, these measures are projected to reduce defect incidence by 30–40% and align the operation with **ISO 9001:2015** and **SDG targets (Goal 9: Industry, Innovation and Infrastructure; Goal 12: Responsible Consumption and Production)**.

Future work could extend this framework toward **predictive quality analytics**, leveraging machine learning models to forecast defect likelihood based on real-time process telemetry.

Conclusion

The integrated use of SQC tools provided comprehensive insights into process behavior, defect patterns, and root causes. Notably:

- The process was **generally stable** but exhibited signs of emerging variation.
- Defect patterns were **highly concentrated**, validating the use of Pareto prioritization.
- Root causes were **multi-factorial**, highlighting the interplay between human, technical, and material variables.

To institutionalize quality improvement, it is recommended to:

1. Implement a **predictive maintenance schedule** based on usage cycles.
2. Establish **structured operator training modules**, especially for new hires and night shifts.

3. Introduce **in-line quality checkpoints** immediately post-cutting and polishing.

These targeted actions are expected to not only reduce rejection rates but also enhance operational efficiency and. sustainability—directly supporting SDG 9 and SDG 12 frameworks.

The findings of this study affirm the efficacy of Statistical Quality Control (SQC) tools in diagnosing and improving process stability within natural stone manufacturing. The dominance of crack and break defects, paired with identifiable assignable causes, suggests that the production line, while generally under control, operates at the edge of its process limits. The combination of histogram analysis, p-charts, fishbone diagrams, and correlation mapping has revealed not only defect patterns but also underlying systemic vulnerabilities.

Furthermore, cross-industry comparisons underline the need for integrated quality approaches that balance technological precision with human-centered ergonomics. Going forward, a predictive quality assurance framework—potentially enhanced with sensor-driven analytics and AI-based defect prediction—could transform marble production lines from reactive to anticipatory quality management systems.

In summary, this study contributes a novel framework for applying classical SQC methods in a fragile and material-sensitive production context that has received limited empirical attention. By adapting control charts and defect prioritization to account for the intrinsic heterogeneity of marble and its susceptibility to both mechanical and ergonomic factors, the research provides a hybrid socio-technical quality model with high practical transferability. Unlike generic quality assessments, the findings incorporate root-cause triangulation and sustainability alignment, positioning the framework as a benchmark for low-defect, high-efficiency stone manufacturing systems. Future research can enhance this model by integrating sensor-based monitoring and predictive analytics using machine learning to forecast defect occurrences—transforming static quality control systems into intelligent, self-optimizing platforms.

Recent studies have emphasized the importance of sensor-based monitoring [23], the benefits of integrating machine learning for predictive quality [24], and the role of sustainability in quality management systems [25].

This study offers a novel contribution by adapting classical SQC tools to a material-sensitive and defect-prone industry that has been largely overlooked in quality literature. By mapping human, machine, and material variables through a structured diagnostic lens, the research presents a modular quality control framework for fragile manufacturing environments. The findings also support the integration of sustainability goals into quality management systems—providing a replicable model for operational resilience in emerging economies. Future extensions of this work may involve hybridizing statistical methods with AI-based predictive analytics to forecast defect patterns in real-time, thereby elevating the system from responsive to anticipatory quality assurance.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to the Faculty of Industrial Technology, Universitas Muslim Indonesia, for the continuous support and facilitation provided throughout the research process. This work would not have been possible without the institutional resources, academic guidance, and collaborative environment fostered by the faculty.

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