A scenario-based framework for strategic inspection decision-making in high-volume production environments

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A scenario-based framework for strategic inspection decision-making in high-volume production environments

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Abstract

Purpose – This study bridges the gap in quality control strategies for high-volume production by balancing the cost and effectiveness of inspection strategies. Using the cost of quality (CoQ) to manage cost and external failures (EF) to gauge effectiveness, this research introduces an innovative inspection strategy chart that serves as a decision-making tool for optimizing inspection processes.

Design/methodology/approach – This paper presents a scenario-based framework designed to support strategic decision-making in inspection processes by integrating empirical data analysis with inspection strategy charts. This approach allows for a dynamic assessment and visualization of the relationship between CoQ and EF, facilitating more informed decision-making in quality management. Notably, it contrasts the traditional models with a novel approach that more accurately captures the uncertainty and correlation among key quality indicators, showcasing its potential for more refined decision-making in quality management.

Findings – Application of the framework illustrates its effectiveness in offering a nuanced understanding of the cost implications and effectiveness of various quality control strategies. This facilitates enhanced strategic decision-making, optimizing inspection processes and reducing external failures in high-volume production settings.

Research limitations/implications – The study focuses on a single industry case study, limiting the generalizability of findings across different high-volume production contexts. Future research could explore the framework's applicability in other sectors and refine the model based on additional empirical data.

Originality/value – The research introduces a versatile framework that navigates the unique challenges of high-volume manufacturing environments. Diverging from models optimized for low-volume settings, this approach provides a valuable tool for adapting inspection strategies to complex production demands, marking a significant contribution to quality management and control literature.

Keywords Quality control, Inspection strategy, High-volume production, Cost of quality, External failures, Decision-making

Paper type Research paper

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1. Introduction

In the evolving landscape of high-volume production, the need for innovative quality control strategies is increasingly evident. Existing models often struggle to meet the diverse demands of high-volume contexts like automotive electronics and consumer goods, highlighting a gap in the literature. Smart manufacturing under the Industry 4.0 paradigm has intensified the complexity of products and processes, making the integration of advanced quality control systems essential (Colledani *et al.*, 2014; Zhou *et al.*, 2011). Quality inspection activities, traditionally viewed as non-value-adding, are crucial in supporting value-adding processes, requiring careful planning and execution (Kukulies *et al.*, 2014; Verna *et al.*, 2022; Verna *et al.*, 2022). The planning phase, known as Inspection Strategy (IS) definition, involves assigning inspection locations and equipping these stations with necessary instructions and resources (Defeo, 2016). This complex process, involving many operational alternatives, constraints, and cost factors, underscores the intricate nature of developing effective inspection solutions (Mandroli *et al.*, 2006). A robust IS must address the demands of various stakeholders, balancing trade-offs among its objectives and discerning among multiple viable inspection alternatives (Verna *et al.*, 2022), highlighting the dual challenge of minimizing costs while maximizing quality conformance as critical in this process (Khozein *et al.*, 2013).

During the manufacturing stage, the dynamic nature of quality situations necessitates regular revision of the established IS to ensure product quality, reduce failure costs from ineffective inspections, and minimize appraisal costs by adjusting inspection processes (Kukulies *et al.*, 2014, 2016). Investments in better inspection equipment or improvements in the production process to reduce failure rates are typical responses to these challenges (Verna *et al.*, 2021a), reflecting the ongoing tension between quality assurance and cost management within the production process (Khozein *et al.*, 2013).

Alternative scenarios for inspection strategies, compared to the current models, can be effectively evaluated using Inspection Strategy Maps (ISM), as proposed by Verna *et al.* (2021b). These maps offer a comprehensive framework to analyze inspection strategies from both cost and effectiveness perspectives. Incorporating mathematical modeling to estimate quality costs and inspection effectiveness, they also serve as practical tools for assessing the adequacy of alternative inspection strategies by plotting their joint cumulative probability distribution in a chart. Sousa and Nunes (2021a), and Zaklouta and Roth (2012) further emphasize the role of ISMs in decision-making, advocating for an economic balance in inspection efforts. However, the ISM model primarily suited for low-volume productions necessitates adaptation to high-volume settings. The exploration of different methods to define confidence regions within these maps is crucial, particularly in understanding which approach best fits each scenario. This aligns with recent calls for more research on Cost of Quality (CoQ) assessment, an area that remains under-researched yet holds significant potential for development (Omachonu *et al.*, 2004; Psarommatis *et al.*, 2020; Psomas *et al.*, 2021; Reis *et al.*, 2023; Saihi *et al.*, 2023).

In response to this need, the current study introduces a novel framework for scenario-based strategic mapping. By integrating advanced analytical methods with practical evaluation tools, this framework adapts to a range of high-volume production settings. Although the methodology is exemplified through a case study in the automotive industry, its principles and tools are designed for broad applicability across various sectors. The proposed approach provides a comprehensive solution for strategic quality control, focusing on the balance between cost of quality and inspection effectiveness, which is related to external failures, and innovating in defining and representing confidence regions within inspection strategy charts.

This versatile approach is poised to make significant contributions to the field of quality and reliability management, offering a model that is applicable to various high-volume manufacturing contexts and paving the way for future research in quality control strategies across multiple industries.

The remainder of the paper is organized as follows. Section 3 presents the proposed methodology, expanding upon the theoretical foundation laid out in Section 2. In Section 4, the proposed methodology is applied to a case study in the automotive industry. Section 5 discusses the findings, and Section 6 concludes the paper with a summary of the main implications and limitations of the study, offering directions for further research.

2. Literature review

Since the introduction of the CoQ concept by Juran (1951) and Feigenbaum (1956), various approaches have been proposed to estimate quality costs, typically divided into four main categories: Prevention, Appraisal, Internal Failure, and External Failure (PAF). These categories help quantify the quality of a production system through the costs incurred in attaining that same quality. Many inspection strategy models (ISMs) are based on this PAF classification. For instance, Farooq *et al.* (2017) and Zaklouta and Roth (2012) explored ISMs in the context of automotive assemblies using this framework. However, alternative approaches such as Crosby's "quality as conformance to requirements" (Crosby, 1979), the process cost approach by Porter and Rayner (1992), and activity-based costing (ABC) by Cooper and Kaplan (1988) have also been significant.

Inspection strategy is a critical component impacting quality costs, especially in the context of Industry 4.0. Traditional ISMs often face challenges in practical application, struggling to incorporate real-world data and adapt to dynamic manufacturing environments. The recent study by Sousa and Nunes (2021a) developed a CoQ-based ISM to assist in decision-making for inspection revision and improvement, addressing gaps in practical application through the use of historical production data.

The integration of ISMs with Industry 4.0 technologies offers new opportunities for real-time data acquisition and dynamic adjustment of inspection strategies. Reis *et al.* (2024) highlighted the need for continuous improvement practices in IS, advocating for the regular evaluation and adaptation of inspection strategies to ensure product quality and cost efficiency. This approach contrasts with traditional models that often oversimplify the complexity of industrial environments.

While the literature provides various models and approaches for CoQ and ISMs, there remains a significant gap in the practical adoption of these models in industry. The complexity of mathematical models and the challenge of acquiring reliable quality cost estimates in real-world conditions often inhibit their use (Sousa and Nunes, 2021b; Zaklouta and Roth, 2012). Additionally, the process cost approach, proposed by Porter and Rayner (1992), and the activity-based costing (ABC) model by Cooper and Kaplan (1988) have provided alternative methods for determining CoQ. Juran's early concepts of "quality costing" and "economics of quality" laid the groundwork (Juran, 1951), further developed by Feigenbaum's categorization of PAF costs, suggesting that investments in prevention and appraisal reduce failure costs (Feigenbaum, 1956).

Estimation of cost variables in ISMs may not be straightforward in real cases, but prior knowledge of the production process and historical data can aid this process (Verna *et al.*, 2022). To utilize quality cost data effectively, it must be gathered and reported to relevant stakeholders in a timely manner. An effective assessment method should be flexible, sensitive, fair, and fast (Sousa and Nunes, 2019a). Meeting these requirements makes quality cost data a powerful tool for ISMs and quality management. A robust IS must consider the needs of various stakeholders, making reasonable trade-offs between objectives (Mandroli *et al.*, 2006). These stakeholders, spanning different companies and departments, must coordinate to achieve the right balance between conflicting quality-cost goals (Colledani *et al.*, 2014). However, IS often relies on the experience of the quality planner or on traditions, standards, and procedures that do not optimize the balance of quality assurance versus cost and time (Filz *et al.*, 2021; O'Connor, 2001).

Academic research on the "real-world" implementation of ISMs considering quality costs is limited. It is challenging to account for all user requirements and contextual variables in real manufacturing processes (Hamrol *et al.*, 2020). Often, models underestimate or ignore some real-world aspects, resulting in unrealistic or unfeasible solutions that do not capture domain-specific characteristics (Rezaei-Malek *et al.*, 2019). Consequently, errors and uncertainties in estimated process variables can affect result accuracy, emphasizing the need to consider the sensitivity of assessments to the inherent uncertainty and vagueness in real environments (Sousa and Nunes, 2019b).

There are several ISMs based on CoQ modeling across different sectors. For example, Sousa and Nunes (2019b) applied their ISM to automotive assemblies, while Farooq *et al.* (2017) evaluated inspection strategies in consumer goods manufacturing. However, these models often face implementation challenges due to their mathematical complexity and the difficulty of incorporating real-world data (Reis *et al.*, 2024). Verna *et al.* (2021b) proposed Inspection Strategy Maps (ISM) to analyze inspection strategies from both cost and effectiveness perspectives, but these models are primarily suited for low-volume productions and require adaptation for high-volume settings. Additionally, Dimitrantzou *et al.* (2020) and Psomas *et al.* (2021) emphasized the need for robust CoQ assessment methods that can handle the uncertainty and variability inherent in modern manufacturing processes.

By integrating advanced analytical methods with practical evaluation tools, this study seeks to develop a dynamic framework applicable across various high-volume production settings. The innovative Inspection Strategy Chart introduced in this research addresses the limitations of traditional ISMs, offering a comprehensive solution for strategic quality control that balances cost and effectiveness. The proposed framework not only applies to high-volume manufacturing contexts but also provides a decision-making tool that dynamically assesses and visualizes the relationship between CoQ and EF, marking a significant advancement in quality and reliability management.

Recent calls for more specific and dynamic frameworks in CoQ assessment, such as those by Verna *et al.* (2021b) and Psomas *et al.* (2021), highlight the need for methods that can adapt to the changing conditions of modern manufacturing environments. This study aims to fill these gaps by providing a robust and adape model that can be applied in real-world settings, thereby contributing significantly to the field of quality and reliability management.

3. Methodology

This section introduces the methodology for creating Inspection Strategy Charts that map two critical indicators: the External Failure Indicator (see Section 3.1) and the Cost of Quality Indicator (see Section 3.2). Section 3.3 details the application of @RISK for Monte Carlo simulation, highlighting its role in managing uncertainties and correlations between the indicators. Section 3.4 elaborates on the development of Inspection Strategy Charts, utilizing rectangular and elliptical models to represent uncertainty and correlations between the two indicators.

3.1 External failures indicator

In high-volume manufacturing environments, the ubiquity of variability and the inevitability of defects are accentuated, making the management of external failures a critical aspect of quality control (Psarommatis *et al.*, 2022). It is virtually impossible to have incoming material, in-process material, and final products defect-free every time (Psarommatis *et al.*, 2022). The proposed framework in this article introduces the External Failures (*EF*) indicator as the first key metric, specifically tailored to address the complexities of high-volume production settings.

Unlike lower volume environments where defects can be more meticulously controlled, high-volume settings often deal with a larger scale of production where perfect inspection is practically unattainable. In these scenarios, even with advanced inspection methods, some level of defectiveness persists due to the limitations of measurement systems (Psarommatis *et al.*, 2022; Shirodkar and Rane, 2021). An ideal measurement system, devoid of any errors, is a theoretical concept rather than a practical reality (Shirodkar and Rane, 2021). Consequently, the *EF* indicator becomes essential in quantifying the impact of these imperfections in high-volume manufacturing.

Judging produced features close to the specification limits, a reliable decision on whether the feature lies within or outside the specification cannot be made depending on the measurement uncertainty during an inspection (Mueller *et al.*, 2020). Therefore, during the inspection operation, two types of error may be generated by the inspection procedure: Type I error, and Type II error. An acceptable part being rejected is a Type I error, and a defective part being accepted is a Type II error (Shirodkar and Rane, 2021). The Type II error is also known as the consumer risk and is usually more serious (Shetwan *et al.*, 2011), as it can lead to significant losses associated with the loss of customer trust and loss of prestige.

Considering the Type II error, the inspection effectiveness of an inspection strategy may be represented using the External Failures (*EF*) indicator, defined as the probability of defective outputs that are erroneously not detected post-inspection. Thus, it indicates the number of defective outputs that may be detected by customers, defined as follows (Franceschini *et al.*, 2018; Galetto *et al.*, 2020; Genta *et al.*, 2018):

$$EF = P_d \cdot \beta \tag{1}$$

where:

(1) P_d is the probability of occurrence of defective outputs under optimal operating conditions;

(2) β is the probability of erroneously not detecting a defective output (Type II error). This error is particularly consequential in high-volume production as it can lead to significant losses due to decreased customer trust and prestige (Shetwan *et al.*, 2011).

It is critical to acknowledge that the *EF* indicator does not capture the entirety of defects that might reach customers, particularly in high-volume production settings. Beyond undetected defects in production processes, the emergence or identification of defects post-production can result from several factors. These include poor product design, inaccurate identification of characteristics in the planning phase (where inspections are designed to detect only those defects that have been defined as controlled characteristics), and issues in subsequent product operations such as improper handling during logistical delivery, material contamination, product packaging, and storage. Furthermore, certain failures may be latent or present functional problems undetectable through regular internal inspections, emerging only during more comprehensive product audits (Sanchez-Marquez *et al.*, 2020).

For instance, as highlighted by Cerqueira (2021), in the assembly of electronic boards, many defects that exist during production may not be apparent for various reasons. Firstly, testing during production might be less rigorous than that available to customers, hence failing to reveal certain defects. Secondly, the intermittent nature of some defects means they might only become apparent during customer usage under specific operational conditions. The perception of external defects also varies based on customer expectations and the severity of the defect. While some defects are critical due to their serious consequences, others might be deemed less significant and overlooked if they do not drastically impair the product's functionality or safety (Tuominen, 2012).

In high-volume manufacturing environments, therefore, the *EF* indicator offers a nuanced perspective on inspection effectiveness. It recognizes that some defects may manifest only under specific conditions or be perceived differently by customers, depending on the defect's nature and severity. This understanding is vital for quality control in high-volume production, where the scale and complexity of operations add layers of challenges in maintaining consistent product quality (Tuominen, 2012).

3.2 Cost of quality indicator

In high-volume production, quantifying the Cost of Quality (CoQ) involves categorizing costs into Prevention, Appraisal, and Failure (PAF), crucial for managing operational scale impacts (Psomas *et al.*, 2021).

Accurately measuring CoQ offers benefits like cost reduction and improved market competitiveness. However, estimating CoQ variables is challenging due to the scale and variability of production processes, necessitating adaptable and accurate methods (Sousa and Nunes, 2019a; Verna *et al.*, 2022). While computational models for CoQ estimation are diverse and sector-specific (Davrajh and Bright, 2013; Farooq *et al.*, 2017; Jafari-Marandi *et al.*, 2019; Sousa and Nunes, 2019a; Tansurat and Chattinnawat, 2019), they highlight the absence of a one-size-fits-all solution in high-volume production contexts. This article suggests exploring a new computational model for assessing CoQ in such settings, drawing on the PAF approach to address its unique cost categories:

(1) Prevention costs ($C_{prevention}$). These are investments made to avert the occurrence of defects in products. This category encapsulates expenses related to the design and implementation of quality control systems, training programs for employees, and procurement of high-quality materials. The assessment of prevention costs entails a detailed analysis of all proactive measures taken to ensure product quality, including the amortization of quality management systems and the cost of quality audits. Additionally, it includes the costs related to process engineering improvements and supplier quality assurance.

(2) Appraisal costs ($C_{inspection}$). These costs are attributed to the activities undertaken to evaluate products and ensure they meet quality standards. Notably, appraisal costs cover both inspection and reinspection processes. Despite being conducted using the same equipment, and therefore initially considered to have identical cost estimates, these activities are differentiated by the context in which they are applied. To accurately estimate these costs, an analysis of both fixed and variable expenses is essential. Fixed costs might include the depreciation of inspection equipment and software, while variable costs could encompass labor costs associated with operating the equipment. Collaboration with the accounting department is vital to accurately assess these costs, integrating considerations of both hardware maintenance and operational labor. This category also includes costs related to routine testing, calibration of inspection equipment, and the creation of quality reports.

(3) Failure-related costs (C_{repair}, $C_{analysis}$, $C_{reinspection}$, and C_n). This category aggregates costs associated with rectifying defects, including repair (C_{repair}), failure analysis ($C_{analysis}$), reinspection ($C_{reinspection}$), and the expenses linked to forwarding defective units to subsequent production stages (C_n). Each of these components demands a tailored approach for cost estimation:

- Repair Costs (C_{repair}) involve both the labor costs of repairs and the expenses related to scrapping and replacing defective parts. Historical data on defect types and associated costs are invaluable for deriving a weighted average cost per unit, necessitating close coordination with the production and manufacturing departments. This includes the costs for rework and the disposal of non-repairable items.

- Analysis Costs ($C_{analysis}$), which have not previously been explicitly accounted for, are estimated in conjunction with the accounting department. This estimation parallels that for other operations requiring manual labor, emphasizing the need for a collaborative approach to capture the comprehensive expenses involved. It includes costs for defect investigation and root cause analysis.

- Reinspection Costs ($C_{reinspection}$), though part of failure costs, require a distinct estimation approach due to their occurrence post-repair. Like inspection costs, they involve an assessment of fixed and variable components, albeit in a different operational context.
- Costs of Passing Defective Units (C_n) are estimated predominantly through expert judgment within both the corporate and academic realms. This subjective estimation underscores the challenges of quantifying the indirect costs associated with quality failures. It covers the costs for handling customer complaints, warranty claims, and potential loss of reputation.

Therefore, the total CoQ for a 100% inspection scenario (namely $CoQ_{100\%\,\mathrm{insp}}$) can be formulated as:

$$CoQ_{100\%\,\mathrm{insp}} = \begin{array}{c} C_{prevention} \cdot N_p + \\ C_{inspection} \cdot N_p + \\ C_{analysis} \cdot N_p \cdot (P_d + \alpha - \alpha \cdot P_d - P_d \cdot \beta) + \\ C_{repair} \cdot N_p \cdot P_d \cdot (1 - \beta) + \\ C_{reinspection} \cdot N_p \cdot (P_d + \alpha - \alpha \cdot P_d - P_d \cdot \beta) + \\ C_n \cdot N_p \cdot P_d \cdot \beta \end{array} \quad [€] \tag{2}$$

where:

(1) N_p is the number of units passing through the inspection station;

(2) P_d is the probability of defective outputs in the inspection station;

(3) α is the type I error (false defectives);

(4) β is the type II error (false compliant);

(5) $C_{inspection}$ is the unitary inspection cost (€/unit);

(6) $C_{analysis}$ is the unitary analysis cost (€/unit);

(7) C_{repair} is the unitary repair cost (€/unit);

(8) $C_{reinspection}$ is the unitary reinspection cost (€/unit);

(9) C_n is the unitary cost of passing a defective unit to the next process (€/unit).

(10) $C_{prevention} \cdot N_p$ is the total prevention cost;

(11) $C_{inspection} \cdot N_p$ is the total cost of 100% inspection;

(12) $C_{analysis} \cdot N_p \cdot (P_d + \alpha - \alpha \cdot P_d - P_d \cdot \beta)$ is the total cost of analysis;

(13) $C_{repair} \cdot N_p \cdot P_d \cdot (1 - \beta)$ is the total cost of repair;

(14) $C_{reinspection} \cdot N_p \cdot (P_d + \alpha - \alpha \cdot P_d - P_d \cdot \beta)$ is the total cost of reinspection;

(15) $C_n \cdot N_p \cdot P_d \cdot \beta$ is the total cost of passing defective units to the next station.

The unitary CoQ for 100% inspection ($Unitary\ CoQ_{100\%\ insp}$) refers to the cost incurred per unit of product, i.e. represents the financial impact of the above listed quality-related issues on individual units produced, and is expressed by:

$$Unitary\ CoQ_{100\%\ insp} = \frac{Total\ CoQ_{100\%\ insp}}{N_p} \left[\frac{€}{\text{unit}}\right] \tag{3}$$

In high-volume production environments, the vast amount of real-time and historical data enhances the decision-making for selecting an economically optimal Inspection Strategy (IS). This data enables precise estimation of cost components critical for CoQ calculations, such as inspection ($C_{inspection}$), reinspection ($C_{reinspection}$), repair (C_{repair}), analysis ($C_{analysis}$), and costs associated with passing defective units to the next stage (C_n). Large data sets from high-volume systems, which can be regularly updated to mirror current operations, ensure the relevance and accuracy of these cost estimates.

Similarly, the estimation of key parameters like the number of units passing through the inspection station (N_p), the probability of defective outputs (P_d), and the probabilities of Type I (α) and Type II (β) errors benefits from the depth and breadth of data typical in high-volume settings. Real-time monitoring and historical analysis enable a more accurate and dynamic understanding of these parameters, allowing for adjustments in inspection strategy that are closely aligned with actual production conditions.

3.3 Monte Carlo Simulation using @RISK

The Monte Carlo simulation in this study is conducted using @RISK, a widely adopted software tool renowned for its robust capabilities in probabilistic modeling and risk analysis. @RISK is particularly suited for the analyses in this paper due to its ability to handle complex scenarios involving uncertain variables and correlations between them. @RISK integrates seamlessly with spreadsheet applications such as Microsoft Excel, providing a user-friendly interface that facilitates the creation and manipulation of probabilistic models (Prakash and Ambekar, 2024). This integration allows the incorporation of probabilistic distributions for the External Failure and Cost of Quality Indicators directly into the proposed framework. Besides the application in Quality Management (Sousa and Nunes, 2021b), other studies that utilized @RISK include Project Management (Kuru and Artan, 2024), Supply Chain Managament (Tayyab *et al.*, 2024).

3.4 Developing an inspection strategy chart

The indicators of *EF* and *CoQ* can be concurrently represented on an inspection strategy chart, delineating a specific inspection strategy. Unlike traditional approaches that might represent inspection strategies as mere points of intersection between *EF* and *CoQ* values on a two-dimensional chart, this method recognizes each strategy as encompassing a region, reflecting the inherent uncertainties of these indicators. To accurately define this region, two innovative approaches are employed, each enhancing the strategic decision-making process by more precisely capturing the uncertainties related to *EF* and *CoQ*.

The first approach, Approach 1, employs a rectangular representation to outline the current inspection strategy as detailed by Verna *et al.* (2021b). Through this method, a rectangle is constructed on the chart to signify the IS, with its dimensions determined by the independent 95% Confidence Intervals (CI) of each indicator. Yet, while this rectangular approach serves as a benchmark, as established by Verna *et al.* (2021b), it presents notable limitations, potentially curtailing its applicability across diverse scenarios.

One of the primary limitations is its foundational assumption that both *CoQ* and *EF* follow normal distribution patterns. This assumption is a critical constraint because it does not accommodate the complex and often non-normal multivariate data typically encountered in practice. Data related to quality control and the incidence of external failures can exhibit a variety of distribution shapes, including skewed, leptokurtic, or multimodal distributions, which are not well-represented by a normal distribution framework.

Moreover, the approach assumes independence between the *CoQ* and *EF* indicators, which may not accurately reflect the realities of production and quality assurance processes. *CoQ* and *EF* are likely interrelated, as improvements or degradations in quality control processes can directly impact the frequency and severity of external failures. Ignoring the potential correlation between these indicators can lead to an oversimplified representation of the inspection strategy, potentially resulting in strategic decisions that do not fully account for the complex interplay between quality costs and the risk of external failures.

Thus, while Approach 1 provides an initial framework for depicting inspection strategies, its reliance on normal distribution assumptions and the independence of *CoQ* and *EF* indicators may not adequately capture the intricate and variable nature of real-world data. These limitations highlight the necessity for more sophisticated and flexible modeling techniques, such as those offered by copula-based approaches proposed in Approach 2, to more accurately represent and navigate the complexities of inspection strategy planning and execution.

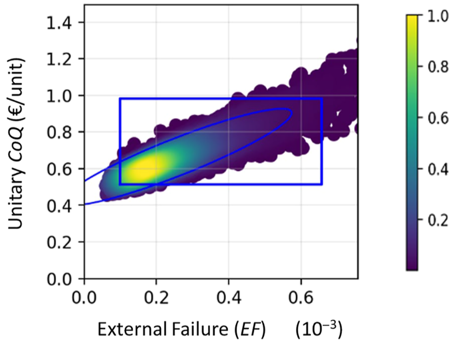
Approach 2, on the other hand, introduces a more sophisticated representation through an elliptical copula, addressing the shortcomings of the first approach. This method crafts a confidence region depicted by an ellipse, offering a more flexible and accurate depiction of the joint variability and correlation between *CoQ* and *EF*. The ellipse is defined by its semi-major and semi-minor axes and inclination angle, parameters that collectively provide a precise identification of the distribution's positioning with a 95% CI. This approach is particularly advantageous in modeling a variety of non-normal data distributions, overcoming the limitations inherent in the first approach.

The exploration of copula-based methods, as opposed to the rectangular regions predominantly used in prior studies, marks a pivotal shift towards more adaptable and nuanced models. Copulas, as mathematical constructs, articulate the joint cumulative probability distribution of multiple variables (Tootoonchi *et al.*, 2022), enabling a more refined analysis of the interconnectedness and mutual influence of *CoQ* and *EF* indicators. This is particularly relevant in high-volume production settings, where the complexity of operations and quality control necessitates dynamic and versatile analytical approaches.

The inspection strategy chart, central to this methodology, visualizes the relationship between *CoQ* and *EF* through a dense scatterplot derived from actual production data. The inclusion of an elliptical confidence region, calibrated to contain the 95% CI of the data, marks a significant advancement over traditional rectangular models. Through this elliptical approach, the intricate relationships between *CoQ* and *EF* are more accurately captured, paving the way for more informed and effective decision-making in quality control strategies.

Figure 1 presents an example of the above-mentioned inspection strategy chart. This chart delineates the relationship between the *CoQ* and the *EF* indicator for a generic inspection strategy. The chart displays a dense scatterplot where each point represents a unique combination of *CoQ* and *EF* values derived from actual production data acquired during regular production. The color gradient within the scatterplot indicates the density of data points, with warmer colors representing higher concentrations of data. This density visualization is pivotal in high-volume production contexts, where the sheer amount of data requires an effective method to discern patterns and trends. Central to this chart is the depiction of confidence regions, both rectangular confidence regions (see the established Approach 1 (Verna *et al.*, 2021b)) and elliptical confidence region (see the newly proposed Approach 2), which are constructed based on the variability of the *CoQ* and *EF* indicators. As the figure clearly shows, the ellipse offers superior coverage, encapsulating a greater proportion of the data points and thus providing a more sensitive and encompassing visualization of the inspection performance.

This innovative representation allows decision-makers to visually assess which strategies fall within acceptable quality and cost parameters, symbolized by their placement within the confidence regions. The proposed inspection strategy chart facilitates strategic decision-making by enabling the selection of an inspection strategy that effectively balances *CoQ*



Source(s): Figure created by authors

Figure 1. Inspection strategy chart: scatterplot of cost of quality (*CoQ*) vs. external failure (*EF*) with indication of confidence regions for a generic inspection strategy

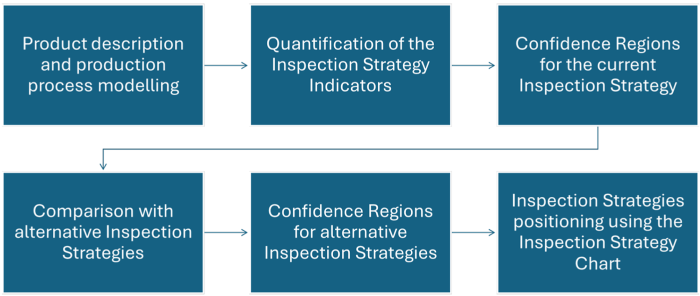
against the risk of external failures, tailored to the demands and risk profiles of high-volume production settings.

The ideal strategy, in this context, is one that seeks to minimize both *CoQ* and *EF*. By plotting alternative strategies on the chart, decision-makers can evaluate their relative cost of quality and effectiveness in preventing external failures. The choice of which strategy to implement depends on various factors, including the nature of the product, market demands, and the decision-maker's risk tolerance (Colledani *et al.*, 2014; Schmitt *et al.*, 2014). In scenarios where the impact of failures is particularly severe, reducing *EF* takes precedence. Conversely, in situations where the stakes are lower, a higher *CoQ* might be acceptable, reflecting a strategic compromise between quality costs and operational risks.

To clarify the methodological process used, Figure 2 shows a detailed flowchart of the methodological approach applied for the analysis of inspection strategies. This flowchart outlines the steps from production process modeling to the quantification and comparison of inspection strategies, and the determination of confidence regions.

3.5 Validation of the proposed framework

To ensure the robustness and reliability of the proposed framework for estimating the Cost of Quality (CoQ) and External Failures (EF) indicators, the following validation steps should be undertaken:



Source(s): Figure created by authors

Figure 2. Methodological flowchart for inspection strategy analysis

(1) Literature Review and Comparison: Conduct a thorough literature review to benchmark the framework against established practices and industry standards. This review facilitates the refinement of confidence regions within the Inspection Strategy Maps (ISM) and the enhancement of previous methodologies.

(2) Expert Consultation: Engage with domain experts within the company, including testing engineers, production line managers, and quality assurance professionals, as well as scholarly experts. Their feedback is instrumental in validating the assumptions and parameters used in the framework, confirming its relevance and applicability to the specific industrial context.

(3) Data Validation: Rigorously validate the input data, including historical records of inspection costs, repair expenses, analysis costs, defect proportions, and other production-related parameters. This process involves cross-referencing data from multiple sources, verifying data consistency, and conducting sensitivity analyses using @RISK to assess the robustness of the results.

(4) Model Verification: Verify the mathematical and computational aspects of the model by testing it against known scenarios and comparing the simulated outcomes with expected results. Any discrepancies or anomalies should be thoroughly investigated and addressed to enhance the model's validity.

The validation of the framework involves a comprehensive and iterative process, integrating inputs from multiple sources, rigorous data validation, mathematical verification, sensitivity analyses, and external peer review. These efforts ensure the reliability and accuracy of the framework for estimating CoQ and EF indicators and assessing uncertainties in the context of the study.

4. Case study

The case study's host company is a branch of a large international German company that operates in several business domains, including consumer goods, energy and building technology, industrial technology, and mobility. The case study's focus is on the mobility sector, specifically automobile multimedia and automotive electronics, and the company produces a broad range of electronic products, such as Driver Information and Infotainment Systems, Instrumentation Systems, 2-Wheeler and Power Sports, and Chassis Systems.

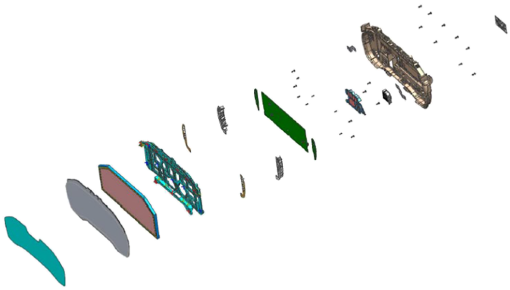
In this context, an explanatory single-case study was performed (Saunders *et al.*, 2016) focusing on a specific inspection station, which is part of the production line of an Infotainment System (Reis *et al.*, 2023).

This section is organized into six sub-sections according to the schematization presented in Figure 2.

4.1 Product description and production process modeling

The product object of the present study consists of an Infotainment System and has been associated with the largest number of complaints and internal failures. It consists of a multi-functional interactive hardware and software device that provides information (e.g. fuel level, door security, parking assistance), communication (e.g. phone calls using voice control technology, Bluetooth), and entertainment (e.g. audio/video, radio, rear-seat entertainment) services (Yin, 2018). To familiarize the reader with the product, the parts that comprise the final assembly of a complete device are shown in Figure 3.

The majority of the parts and subassemblies that make up the entire device are produced internally. In essence, different production chains exist, such as the ones for assembling Printed Circuit Boards (PCBs), bonding glass and displays, and assembling and adhering this set to the carrier frame. The primary purpose of printed circuit boards (PCBs), which are



Source(s): Figure created by authors

Figure 3. Complete device isometric exploded view

electrically insulating boards composed of intricate printed circuits, is to electronically connect and support a vast number of components by means of signal, electric current, and other qualities. The first part, an unassembled PCB, is sent by conveyor belts to a printer at the start of the PCB manufacturing process. There, lead-free solder paste is applied using stencil printing. Afterward, discrete parts like resistors, capacitors and microchips are mounted forming an Assembled PCB (PCBA), which is finally soldered by a reflow oven.

To create a finished product, further assembly components like covers and screws are put together on the Final Assembly Line (Reis *et al.*, 2023). Following component insertion and soldering procedures, the product measurements are acquired at different phases of manufacture. Nineteen workstations make up the Final Assembly line, one of which is the Function Tester (FCT), an automated inspection station that functionally evaluates the PCBA once it has been joined to the other product elements that make up the complete device.

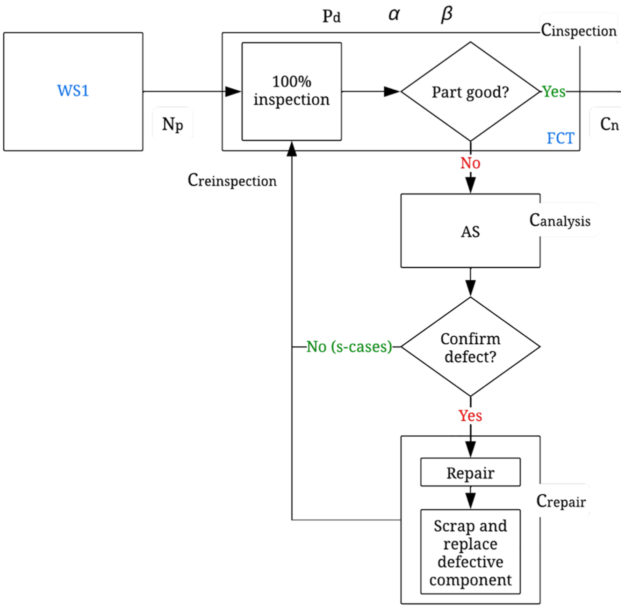
The parts that the FCT deems defective are sent to the offline technical Analysis Station (AS), where an analysis technician determines whether the rejected part is, in fact, defective; if not, the part is labeled as "s-case" and returned to the FCT, i.e. the workstation where it was previously deemed to be unsuccessful for further inspection; if confirmed to be defective, the device is disassembled, component by component, until the defective part is eliminated.

In certain situations, such as when replacing a foil that was put together incorrectly, the technician can complete this repair with the tools she/he possesses. In other situations, the part is sent to the electrical laboratory if more investigation or complex rework is required. The part returns to the process, as in the S-cases, after being repaired.

The described handling process of a defective part from the FCT is summarily represented in Figure 4, which also encompasses the elements pertinent to model the CoQ regarding (1) the product inspection and the respective inspection errors, (2) the analysis of the failed products, (3) operations for repairing/replacing the identified defective parts, (4) the reinspection of the s-cases and repaired products, and (5) the cost of passing a defective product to the next process (Reis *et al.*, 2023). The FCT is represented between two workstations (WS), named WS1 and WS2.

4.2 Quantification of the inspection strategy indicators

This section outlines the estimation process for each cost element ($C_{inspection}$, $C_{reinspection}$, C_{repair}, $C_{analysis}$, and C_n) and parameter (N_p, P_d, α, and β), crucial for calculating the External Failure (*EF*) and Cost of Quality (*CoQ*) indicators as delineated in Eqs. (1) and (3) within Sections 3.1 and 3.2, respectively. The methodology for deriving these estimates is detailed, highlighting refinements and advancements made relative to the approach utilized in a preceding study by Reis *et al*. (2023), which analyzed the same testing station. The assumptions about the distributions of variables describing the dynamic framework were made based on a careful



Source(s): Adapted from Reis *et al.* (2023). Figure created by authors

Figure 4. Conceptual model of the current defect handling at FCT along with the model costs and parameters (see Section 3)

consideration of available data (Verna, 2024), expert insights, and industry standards. These assumptions were essential for conducting the Monte Carlo simulations in the software @RISK and generating probability distributions for the key parameters involved in the analysis and to capture the range of potential values for each cost parameter, taking into account both deterministic factors and inherent variability.

In the PAF CoQ framework, inspection costs fall under the Appraisal category, typically assessed by calculating the return on investment (ROI) for the required equipment (Yin, 2018). A Company Testing Engineer highlights the goal of designing efficient test chains for cycle time, line balancing, and cost. Since inspection and reinspection use the same equipment, their costs ($C_{inspection}$ and $C_{reinspection}$) are considered identical, based on the sum of fixed (e.g. machinery, software licenses) and variable (e.g. labor) costs. Some costs, either because considered negligible or difficult to estimate, are not considered in the model, e.g. energy and maintenance costs. The estimated unitary $C_{inspection}$ and $C_{reinspection}$ costs resulted in 0.43 €/unit. The uncertainty for both parameters was obtained by considering a uniform distribution ranging from 0.40 to 0.50 €/unit.

Within the PAF CoQ framework, repair costs are categorized under Failure costs, representing Internal Failures. This classification is due to repair being an activity addressing defects identified prior to product delivery to customers. The cost of repair (C_{repair}) encompasses the labor costs for repairs and the expenses for scrapping and replacing defective parts. This estimate is based on historical data on various defect types and their costs, recorded in the database by production line managers. After consulting with the Manufacturing Department, a weighted average repair cost of 2 €/unit was calculated. The uncertainty of this cost is modeled with a uniform distribution, ranging from 1.5 to 4 €/unit.

The analysis cost ($C_{analysis}$) had not previously been evaluated by the Company and was estimated in collaboration with the Accounting Department. Drawing on analyses similar to those for operations requiring human operators, the cost was determined to be 0.50 €/unit.

The uncertainty associated with this parameter was calculated using a uniform distribution, ranging from 0.35 to 0.75 €/unit.

The cost of passing a defective unit to the next station (C_n) was estimated at 20 €/unit, based solely on expert opinion from within the Company and academia. Due to the significant uncertainty associated with this parameter, a uniform distribution ranging from 15 to 30 €/unit was used to capture this variability.

This study chooses uniform distributions for estimating uncertainty in cost parameters, prioritizing simplicity and clarity in its modeling approach. While alternatives exist, such as normal distributions for prevention and appraisal costs suggested by Su *et al*. (2009) and triangular distributions by Reis *et al*. (2023), this choice seeks to maintain model straightforwardness without dismissing the relevance of other methods. It's important to acknowledge that the appropriateness of any cost assessment method is context-dependent, closely tied to the specific industrial environment (Reis *et al.*, 2023), underscoring the tailored nature of this approach.

The parameters are based on a database containing the results of tests carried out, i.e. secondary data already available at the company. The secondary data refers to the 310 producing days of the year 2020 in which 1,328,907 single units of the analyzed product (i.e. an Infotainment System) were tested within the FCT. Given these data, the N_p value considered in the simulation was 4,314, and the P_d value was 5.1%, which are the realistic typical daily production quantity and proportion of defectives, respectively, according to the analysis performed at @RISK. The uncertainty associated with N_p and P_d was obtained experimentally according to the real distribution of the data, as seen in Table 1. In the previous work proposed by Reis *et al*. (2023), on the other hand, the average production daily value was considered for N_p in their model, and P_d was estimated as the geometric mean between the failed and produced products, both without defining an associated uncertainty.

The proportion of false defectives (α) (type-I error) was empirically estimated based on the count of s-cases within the failed devices, i.e. the cases which the analyst spotted improper rejections by the inspection/test system. The average of s-cases for the year 2020 in this station and this production line was 1.8%. The uncertainty associated with α was also obtained experimentally according to the real distribution of the data, as seen in Table 1.

The Company usually defines product specifications tighter than initial customer specifications so that errors are forced on one side of the specification. The testing stations measure several quality characteristics, and whenever one of them happens to be outside the tight-imposed tolerance limits, the product will "fail" at the station. This can increase false defectives given by the measurement system, while reducing false compliant (β). The β values were adopted from similar quality inspections in the electromechanical sector (Galetto *et al.*, 2020), with its standard deviation assumed to be 5% of β mean value. Contrarily, Reis *et al*. (2023) equated type-I and type-II errors, opting for a uniform distribution to determine the uncertainty of both indicators, diverging from the approach of utilizing distribution data.

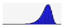
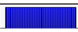
The graph, distribution type, mean value, and the 95% CI for the mean, of the parameters used in the proposed approach were derived by using the software @RISK by LUMIVERO for Monte Carlo Simulation, of the parameters used in the proposed approach and are presented in Table 1. These values were used for the current 100% inspection strategy, denoted as IS-0.

4.3 Confidence regions for the current inspection strategy

A Monte Carlo Simulation-based approach was used to obtain the distributions of the two indicators *EF* and *CoQ* (see Eq. (1) and (3) of Section 3.1 and 3.2) derived from the model parameters and CoQ elements listed in Table 1.

The authors made the complete dataset publicly available via the Harvard Dataverse platform (Verna, 2024). From the distributions, the estimate of the mean values and related 95% CI are obtained. As above mentioned, the adopted tool is @RISK, which is an Excel add-in developed by LUMIVERO for performing a Monte Carlo Simulation. In total, 10,000

Table 1. Model parameters and *CoQ* elements for the 100% inspection strategy (IS-0)

	Graph	Distribution	Minimum	Maximum	Mean	Std. Deviation
N_p		Gumbel Minimum Extreme Value	0	7273	4314	1279
P_d		Pearson type 5	0.012	0.716	0.051	0.032
α		Log-logistic	0.001	0.239	0.018	0.011
β		Uniform	0.005	0.005	0.005	0.000
$C_{inspection}$		Uniform	0.40	0.50	0.43	0.030
C_{repair}		Uniform	1.50	4.00	2	0.72
$C_{analysis}$		Uniform	0.35	0.75	0.5	0.12
$C_{reinspection}$		Uniform	0.40	0.50	0.43	0.03
C_n		Uniform	15.00	30.00	22.50	4.33

Source(s): Table created by authors

simulations were performed until no changes were observed in the parameters such as mean, median and percentiles. Figures 5 and 6 present the histograms obtained from the Monte Carlo Simulation results.

The *Unitary CoQ* resulted in 0.60 €/unit for the $I_{100\%}$, which can be found between 0.513 and 0.983 €/unit within a 95% CI, as shown in Figure 5. This value was absent from the Company's data for the testing station since there are just overall estimates for the whole manufacturing line, however, it is reasonable according to specialists of the Company. The simulation for the External Failure Indicator resulted in $0.257.10^{-3}$, which can be found between $0.099 \cdot 10^{-3}$ and $0.658 \cdot 10^{-3}$ within a 95% CI for the $I_{100\%}$ (Figure 6).

The relationship between the *CoQ* and *EF* for the 100% inspection strategy (IS-0) is presented graphically in Figure 7(a), as per the methodology presented in Section 3.4. As there are many data points with a high level of overlap, the density of the data points is represented in the scatterplot using the displayed colors.

Rectangular confidence regions, according to the established Approach 1 discussed in Section 3.2, are showcased in chart (b) of Figure 7. The dimensions of these rectangles are established by the independent 95% Confidence Intervals (CI) for each indicator, providing a straightforward, albeit limited, visualization of uncertainty. In contrast, chart (c) of Figure 7 introduces an elliptical copula approach (as per the newly proposed Approach 2 presented in Section 3.2). This method employs the geometrical parameters of the ellipse—namely, the semi-major axis, the semi-minor axis, and the inclination angle—to more accurately represent the distribution's positioning within a 95% CI. This elliptical model offers a nuanced understanding of the data, highlighting the interdependencies and correlations between indicators that the rectangular model may overlook.

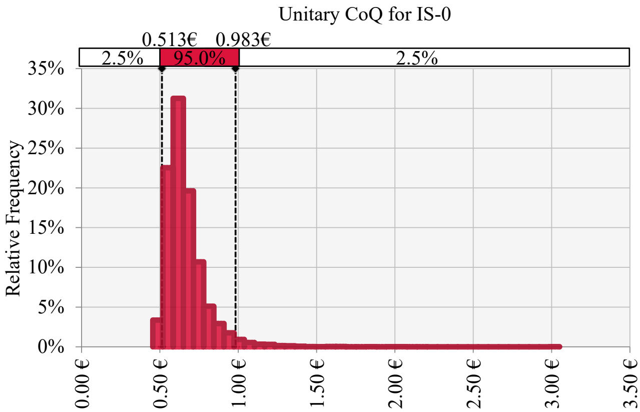


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Figure 5. *Unitary CoQ* distribution with indication of the mean and its 95% CI, for the 100% inspection strategy (IS-0)

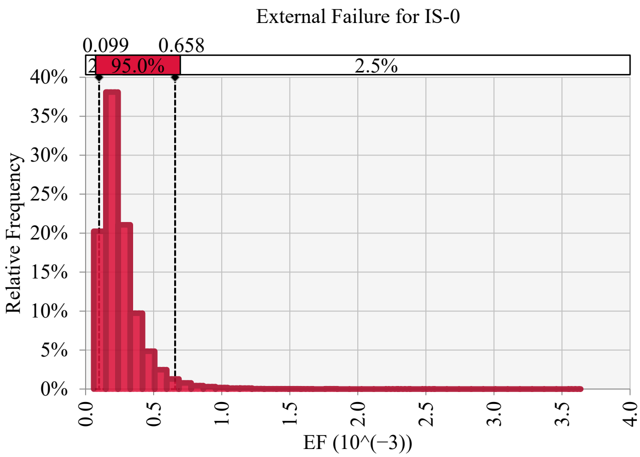

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Figure 6. External failure (*EF*) distribution, with indication of the mean and its 95% CI, for the 100% inspection strategy (IS-0)

In Figure 8(a), the scatterplot is presented alongside the rectangle and the ellipse, all within a single chart, offering a comprehensive visual comparison. Figure 8(b) provides a closer look at both the rectangle and the ellipse, zooming in to accentuate the differences between these two depicted regions. This magnified view facilitates a detailed examination of the contrasting approaches to representing uncertainty and correlation within the data.

Given the parameters fit to data according to a model, the probability that the confidence region will include (or "cover") the true value is called the coverage, which is an important factor to be assessed by decision-makers to choose an inspection strategy considered safe or within which an adverse effect is unlikely to occur in terms of the desired *CoQ* and *EF*. A sensible confidence region should contain the best fit point, be consistent and efficient, contracting around more data is obtained. It is undesirable to come up with procedures that

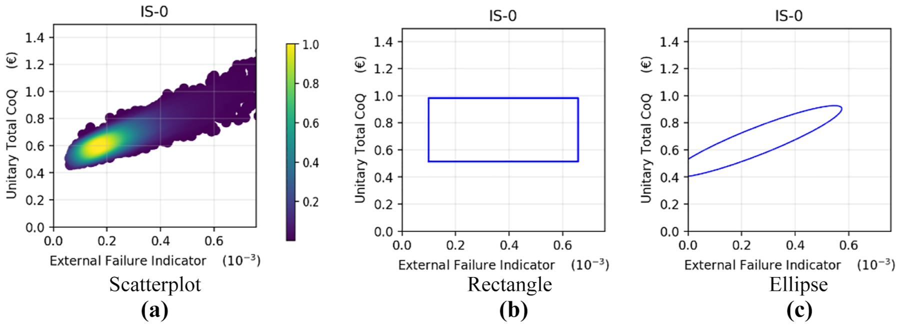

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Figure 7. Inspection strategy chart for 100% inspection strategy (IS-0): (a) Scatterplot of cost of quality (*CoQ*) vs. external failure (*EF*), (b) rectangular confidence region using the established Approach 1, and (b) elliptical confidence region using the newly proposed Approach 2

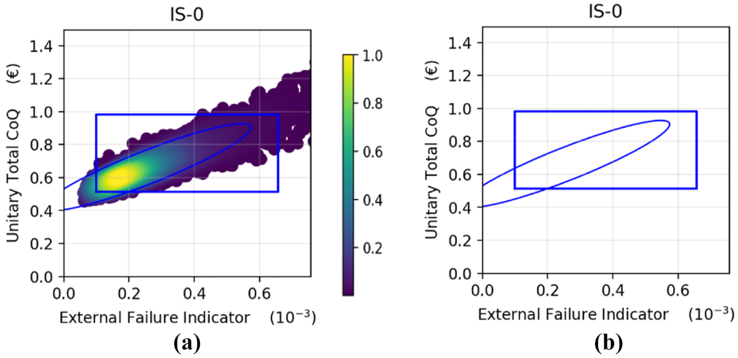

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Figure 8. Comparison of confidence regions for the 100% inspection strategy (IS-0) using Approach 1 and Approach 2

result in regions without these properties, as they may cause faulty confidence regions and therefore provide an incorrect description of the inspection strategy mapping. Figure 8 shows that the coverage of the regions enclosed by the rectangle and the ellipse are different, with the ellipse being the most sensitive, as it covers 95% of all points of the scatterplot, while in the rectangle, the upper left corner and the lower right corner do not contain scatterplot points.

4.4 Comparison with alternative inspection strategies

The aim of this section is to apply scenario-based planning in order to design alternative options and provide foresight or ex-ante impact assessment in terms of *CoQ* and *EF*. Accordingly, the two IS indicators of total *CoQ* and *EF* are evaluated for the current company strategy (IS-0) and used as the benchmark to be compared against, and then two other alternative scenarios (IS-1 and IS-2) are tested with scenario or "what-if" analyses, through which it is possible to explore the performance of the simulated systems by tweaking the initial conditions. Data pertaining to IS-1 and IS-2 are accessible via the Harvard Dataverse platform (Verna, 2024). The three strategies compared are:

(1) IS-0: Current Company Strategy

The current inspection strategy (IS-0) employed by the company serves as the baseline scenario. This strategy involves the existing inspection tools and procedures, with their associated costs and error rates (α and β). The performance metrics (total CoQ and EF) derived from this strategy provide a benchmark for assessing the impact of alternative strategies.

(2) IS-1: Investment in More Accurate Inspection Tools

One way to provide better quality is to use more accurate inspection tools for detecting nonconformities. Precise machining equipment and accurate inspection tools can offer better quality control but are often more expensive to acquire and operate (Reis *et al.*, 2023).

In IS-1, we propose investing in higher-precision inspection equipment. The primary changes in this scenario include:

(1) decreased error rates (α and β): With more accurate inspection tools, the probability of Type I (false positives) and Type II (false negatives) errors decreases. This results in fewer products being incorrectly classified as defective or compliant.

(2) increased inspection costs ($C_{inspection}$ and $C_{reinspection}$): The investment in better equipment increases the unitary costs of inspection and reinspection due to higher acquisition costs, maintenance expenses, and potentially longer inspection times.

The expected impact of this strategy is a reduction in the overall defect rate (P_d) and improved product quality, but at a higher inspection cost. This trade-off needs to be carefully evaluated to determine if the reduction in external failure costs (EF) justifies the increased CoQ.

(3) S-2: process improvement and enhanced machining capabilities

Another way to improve quality is to decrease the probability of defects (P_d) in the production process. This can be achieved through process improvements or by using more precise machining equipment with higher process capabilities (C_p and C_{pk}) when creating product quality characteristics (Karimi-Mamaghan *et al.*, 2020).

In IS-2, we propose implementing process improvements and enhancing machining capabilities. The primary changes in this scenario include:

(1) decreased probability of defective outputs (P_d): By improving the production process or using more precise equipment, the inherent defect rate of the production process decreases.

(2) potential changes in costs: While the primary focus is on reducing defects, there may also be associated costs for process improvements, such as investments in new machinery, training for employees, and adjustments in production procedures.

The expected impact of this strategy is a reduction in the number of defective units produced, which subsequently lowers both internal and external failure costs. Unlike IS-1, this strategy may not significantly increase inspection costs but requires investments in process improvements and equipment upgrades.

These current and the two alternative scenarios explore the joint impact of various uncertainties, changing some variables at a time (i.e. P_d, α, β, $C_{inspection}$ and $C_{reinspection}$), the ones highlighted in bold in Table 2. The Mean values and 95% CI of inspection performance indicators *CoQ* and *EF* for the three scenarios are also presented in Table 2.

4.5 Confidence regions for alternative inspection strategies

Following the considerations of Approach 1 and Approach 2 presented in Section 4.3, the strategy maps for the scenarios IS-1 and IS-2 are presented in Figures 9 and 10. The focus is to emphasize the fundamental requirements and limitations of applying copulas for these scenarios.

Table 2. Inspection scenarios and their respective indicators

Inspection strategy	Description	P_d	α	β	$C_{inspection}$ and $C_{reinspection}$ (€/unit)	$C_{prevention}$ (€/unit)	EF (10^{-3})	95% CI for EF (10^{-3})	CoQ (€)	95% CI for CoQ (€)
IS-0	100% inspection (current inspection scenario)	5.14%	1.80%	0.50%	0.43	0	0.257	(0.099; 0.658)	0.600	(0.513; 0.983)
IS-1	Investment in better inspection equipment	5.14%	1.00%	0.10%	1.00	0	0.051	(0.020; 0.132)	1.194	(1.094; 1.606)
IS-2	Investment in the production process resulting in P_d decline	2.5%	1.80%	0.50%	0.43	0.40	0.125	(0.115; 0.135)	0.921	(0.895; 1.032)

Source(s): Table created by authors

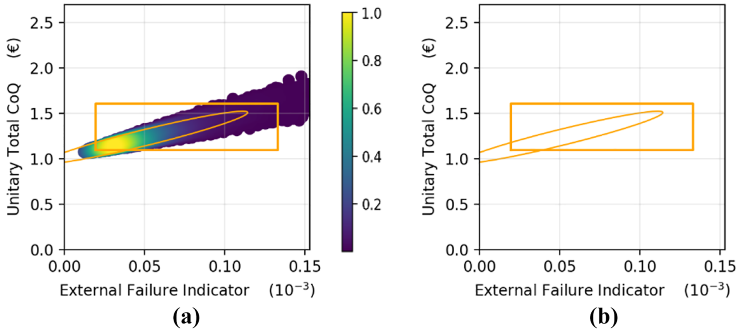

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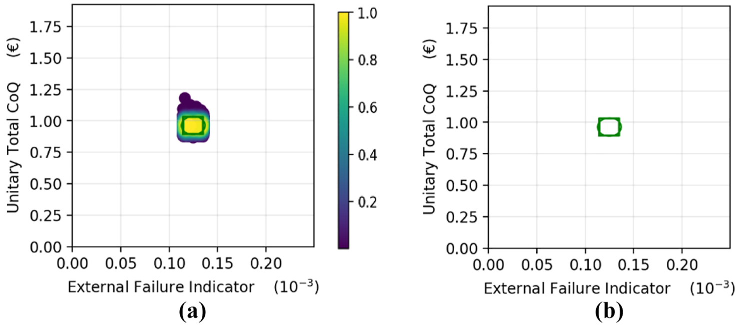
Figure 9. Comparison of confidence regions for IS-1 using Approach 1 and Approach 2



Source(s): Figure created by authors

Figure 10. Comparison of confidence regions for IS-2 using Approach 1 and Approach 2

The confidence regions for IS-1, presented in Figure 9, are graphically similar to the results in IS-0: the coverages of the regions enclosed by the rectangle and the ellipse are different, with the ellipse covering all points of the scatterplot, while in the rectangle, the upper left corner and the lower right corner do not contain scatterplot points.

For IS-2, however, the rectangle and the ellipse are comparable in terms of fit to the data points within the scatterplot. Both shapes exhibit sensitivity to the distribution of the data, with the rectangle closely hugging the denser area of the scatterplot, while the ellipse encompasses a more restricted range. Indeed, the horizontal extremities of the ellipse slightly extend beyond the dense cloud of scatterplot points, yet this does not significantly detract from its comparative alignment with the actual data distribution.

4.6 Inspection strategies positioning using the inspection strategy chart

Figure 11 illustrates the comparison between the scenarios IS-0, IS-1 and IS-2 on the same inspection strategy chart, plotting the two approaches (Approaches 1 and 2) for the confidence regions for each scenario.

Based on the analysis of the inspection strategy chart, performing the current 100% inspection (IS-0) leads to a significant increase in the indicator *EF* when compared to the other two scenarios, leaving comparatively more defects in the device.

On the other hand, from an economic point of view, the two alternative proposed scenarios, IS-1 and IS-2, lead to higher costs when compared to the current IS-0. Although part of IS-2 is

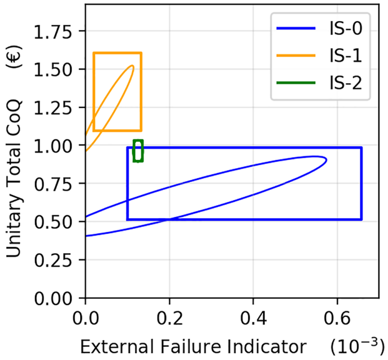


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Figure 11. Comparison of inspection strategies IS-0, IS-1 and IS-2 using the inspection strategy chart

located within the upper left corner of the rectangular confidence region of IS-0, it was seen that the referred region of IS-0 actually does not contain scatterplot points, being the ellipse the contain the best fit for the IS-0 data.

It can also be said that the inspection indicators *Unitary CoQ* and *EF* obtained for IS-2 are affected by less uncertainty compared to those obtained for IS-0 and IS-1.

The choice of inspection strategy by the company depends on its strategic priorities. If the goal is to minimize both CoQ and EF, IS-2 may be the most suitable despite its higher costs, as it offers reduced uncertainty and a better fit within the confidence region. Alternatively, if minimizing costs is the primary objective, the company may opt to continue with IS-0, accepting a possible higher EF as a trade-off. The company's decision may also be influenced by the degree of uncertainty it is willing to tolerate, with IS-2 providing the least uncertainty among the options.

5. Results and discussion

5.1 Inspection scenarios

While this study only compares the current IS-0 with IS-1 (investment in better inspection equipment), and IS-2 (investment in the production process), explored dimensions of inspection strategies may also include scenarios such as reinspection of accepts (Zaklouta and Roth, 2012), a mid-ground strategy between 100% and no inspection, i.e. sampling inspection, and even the no-inspection scenario.

Nevertheless, is important to be aware that the scenarios go beyond objective analyses and include subjective interpretations. For example, although the hypothetical scenario of no-inspection is interesting, it is important to state that some quality characteristics must be mandatorily inspected during the production process, e.g. those related to safety, legislation, and customer requirements. Therefore, it is assumed that these characteristics would be inspected in another testing station in this supposed situation of not inspecting in FCT. Even for characteristics that are inspected at the initiative of the company rather than by external requirements, the complete absence of control is probably not the best solution, especially in cases of processes that are not as robust.

Considering the context of the automotive electronics industry, inspection followed by analysis and repair activities helps to explain why some type of quality problem occurs, which is a useful source of information for product and process improvement. By working on these tasks, i.e. analyzing defects and performing root cause investigations, quality engineers gain valuable information. However, when the product and the process are robust, it is plausible to assume that some characteristics can only be controlled during the pre-production phase, where product samples are manufactured, instead of being inspected at 100% during the mass production phase. In addition, as shown in scenarios IS-1 and IS-2, the selection of the inspection equipment has an impact on both the effectiveness and the cost of quality.

In summary, inspection strategies are meticulously tailored to address unique product specifications, production environments, and customer requirements. Nevertheless, this study highlights the significance of customization, scalability, and continuous improvement within the employed inspection strategy. Moreover, it illustrates the strategy's capability to scale effectively in response to varying production volumes and evolving manufacturing technologies. Integration of feedback loops and performance metrics ensures ongoing refinement and optimization of the inspection approach using real-time data and industry best practices.

Therefore, this research contributes substantively to ongoing research and development endeavors aimed at advancing quality management practices. The detailed documentation of methodology and comprehensive presentation of outcomes establish a robust foundation for future studies to explore advanced statistical models in other inspection scenarios, leverage emerging technologies, and innovate approaches in the domain of quality assurance.

5.2 Inspection strategy charts

Integrating scenario analysis with a structured methodology for developing inspection strategy charts could significantly benefit organizations. This integration yields a topology that quantifies the causal relationships between critical variables, such as the *CoQ* and *EF*. Such diagrams enable businesses to navigate various inspection strategies, offering a framework to comprehend the comparative positioning of different strategies effectively.

It is crucial to verify the properties of the confidence region for each approach, as not all regions may accurately represent the level of confidence achievable with certain distributions of *CoQ* and *EF*. Choosing the right approach to depict the confidence region is a pivotal step in employing a copula method for the analysis of multivariate data. This choice ensures that both the structure of dependence and the strength of dependence between variables are accurately captured. The dependence structure is indicated by the selected copula family, whereas the strength of dependence is determined by the copula parameters. Therefore, careful selection of the copula family and precise estimation of copula parameters are imperative.

This paper advocates for a straightforward graphical technique involving the creation of a scatterplot that displays rank-transformed pairs, also referred to as an empirical copula. This visual comparison facilitates a better evaluation of tail dependence, guiding the subsequent selection of appropriate copula families. Through such methodologies, organizations can achieve a deeper understanding of the interrelations between *CoQ* and *EF*, enhancing strategic decision-making in the context of inspection strategies. In detail, the strategic decision on which inspection strategy to adopt depends on the company's priorities. If minimizing CoQ and EF is crucial, the most balanced strategy may be preferred despite higher costs and lower uncertainty. For those prioritizing cost minimization, a strategy with lower inspection costs might be more suitable, accepting a higher EF as a trade-off.

5.3 Outcomes and implications

The results of the study are directly related to the gap defined in the literature review, which highlighted the need for a robust and dynamic framework that integrates the Cost of Quality (CoQ) and External Failures (EF) to optimize inspection strategies in high-volume manufacturing environments. These outcomes demonstrate the effectiveness of the proposed Inspection Strategy Chart in addressing the identified gaps. Specifically, the results showcase how the dynamic adjustment of inspection strategies based on real-world data can lead to significant improvements in both cost efficiency and quality control.

By using the elliptical confidence region approach, companies can dynamically adjust their inspection strategies to better align with actual production conditions. This results in more accurate and timely inspections, reducing unnecessary costs associated with over-inspection and minimizing the risk of external failures. The proposed framework significantly enhances quality control by providing a comprehensive understanding of the relationship between CoQ and EF. This allows for more targeted and effective inspections, ultimately leading to a reduction in the incidence of external failures and an improvement in overall product quality.

The study utilized data from a functional testing station of an Infotainment System, demonstrating that the proposed framework can be practically applied to real-world scenarios. The outcomes confirmed that the elliptical approach provides a more faithful representation of the data trajectory compared to traditional rectangular methods, supporting more reliable decision-making processes. Furthermore, the framework's ability to consider the needs of various stakeholders and make reasonable trade-offs between objectives was validated through this practical application. This aligns with the identified gap that traditional ISMs often fail to incorporate stakeholder perspectives adequately, leading to suboptimal decision-making.

Additionally, the framework was validated through a comprehensive and iterative process, as outlined in Section 3.5. This included literature review and comparison, expert consultation, rigorous data validation, and model verification. These steps ensured the robustness and reliability of the framework, confirming its applicability and effectiveness in estimating CoQ and EF indicators, and assessing associated uncertainties in high-volume production settings.

6. Conclusions

In the context of evolving high-volume production environments, the integration of effective quality control strategies remains a pivotal challenge, marking a discernible gap in existing literature. This study endeavors to bridge this divide by introducing scenario-based inspection strategy charts, which elucidate the dynamic interplay between inspection effectiveness and associated costs. By leveraging real-world data and innovative analytical approaches, this research marks a significant stride towards addressing the underexplored domain of comprehensive Cost of Quality (*CoQ*) assessments and External Failures (*EF*) analysis within the sphere of production engineering.

This work advances research in inspection models incorporating *CoQ* and *EF* by grounding its analysis in real-world data—a notable departure from the historical reliance on hypothetical scenarios or models not corroborated by historical data. By utilizing data from a functional testing station of an Infotainment System, this study directly addresses the recent demand for more thorough research on *CoQ* assessments, an area marked by significant under-exploration and ripe for further scholarly exploration (Psarommatis *et al.*, 2020; Psomas *et al.*, 2021).

In detailing the construction of confidence regions for the inspection strategy charts, two distinct approaches were used. Approach I employs a user-defined rectangular shape for the region, with its size dictated by distributions and confidence interval (CI) values. Approach II introduces a more innovative methodology, allowing both the shape and size of the confidence region to be dynamically determined by the underlying data distribution, resulting in an elliptical form. These methodological advancements not only enhance the toolset available for quality control analysis but also introduce a nuanced perspective on assessing the reliability of inspection strategies.

The case study integral to this research critically evaluates various inspection strategies in light of CoQ and EF considerations. It underscores the importance of context in determining whether the traditional rectangular approach or the novel elliptical approach is more suited to specific production scenarios. The findings from the case study suggest a significant advantage of the elliptical confidence region approach, which tends to offer a more faithful representation of the actual data trajectory, thereby facilitating more reliable decision-making processes. This empirical evidence underscores that the elliptical model, by capturing the complex interdependencies and correlations between various indicators, provides a more nuanced understanding of the data, an aspect that might be overlooked by the simpler rectangular model.

The practical implications of the proposed approach are underscored by its tailored applicability to the industrial context of the case study. The study draws attention to the prevalent challenges in acquiring accurate cost data within companies, often necessitating reliance on expert estimations and consequently introducing a degree of uncertainty into the analysis. From a managerial perspective, the research highlights the absence of a structured framework for decision-making regarding inspection strategies within the case study company. By proposing a model that integrates often-overlooked quality-related cost components, such as the analysis and handling of defective units, the study calls for enhanced cross-departmental collaboration and continuous CoQ assessment.

Future research should explore the use of formal goodness-of-fit tests to improve the accuracy and applicability of the model, with a focus on removing copula families that do not accurately represent empirical data. Additionally, incorporating qualitative methods such as interviews, focus groups, and expert panels will help to gather diverse perspectives on the factors influencing external failure and cost of quality elements. Expanding the scope to include multiple case studies from different industries will validate the findings across various contexts and enhance the generalizability of the results. By using multiple data sources and methods, future research can achieve triangulation, thereby increasing the validity and reliability of the research findings. This comprehensive approach will extend existing methods and open new avenues for investigating inspection strategy optimization in high-volume production settings.

6.1 Implications for research, practice and society

The proposed framework for inspection strategy, which integrates CoQ and EF, has several significant implications.

For research, this study bridges the gap between theoretical models and practical applications in high-volume manufacturing environments. By incorporating real-world data and dynamic adjustments based on empirical findings, the framework advances the body of knowledge in quality management and provides a robust foundation for future studies. Researchers can build on this methodology to explore its applicability in other industries and refine the model to handle various manufacturing complexities.

In practical terms, the Inspection Strategy Chart offers a valuable tool for practitioners in the manufacturing sector to optimize inspection processes. This can lead to significant cost savings by reducing unnecessary inspections and focusing resources on critical areas. The dynamic nature of the framework allows for continuous improvement and real-time decision-making, enhancing overall production efficiency and product quality. Companies implementing this framework can expect lower production costs and higher product reliability, improving their competitive edge and customer satisfaction.

The economic and commercial impact of this framework is substantial. By reducing external failures and optimizing inspection strategies, companies can achieve higher product reliability and lower production costs. This not only improves their market position but also fosters customer trust and loyalty. The framework’s adaptability ensures its broad applicability across various production contexts, making it a versatile tool for different manufacturing settings.

Socially, improved quality control and reduced external failures ensure the reliability and safety of manufactured products, which is crucial in industries such as automotive and consumer electronics. Enhanced product quality contributes to higher consumer confidence and overall quality of life, as reliable and safe products lead to fewer incidents and better user experiences.

These implications underscore the practical benefits and broader impact of the proposed framework, aligning with the study’s findings and conclusions. By addressing the dynamic and complex nature of modern manufacturing environments, the framework provides a comprehensive solution for strategic quality control that balances cost and effectiveness.

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