



OPTIMIZING THE SCAR PROCESS THROUGH NONCONVENTIONAL METHODS: APPLYING VIBRODIAGNOSTICS AND GENETIC ALGORITHMS FOR QUALITY IMPROVEMENT IN THE AUTOMOTIVE CHAIN

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ABSTRACT: This paper explores the application of unconventional methods to optimize the Supplier Corrective Action Request (SCAR) process. The study proposes an innovative framework that integrates vibrodiagnostics for the early detection of defects at the source and genetic algorithms for optimizing supplier process parameters. Through case study analysis, the paper demonstrates how these technologies can identify root causes of non-conformities that remain undetected by traditional methods, leading to more precise corrective actions and durable quality improvements. The results indicate a significant reduction in the recurrence rate of defects and an increase in the overall efficiency of the supply chain.

KEYWORDS: SCAR, vibrodiagnostics, genetic algorithms, optimization, supply chain

1. INTRODUCTION

In the context of modernizing and increasing the efficiency of operations in various fields, including production and supply chain management, the need to transition from a reactive to a predictive system is increasingly evident. Reactive control involves responding to problems after they occur, while predictive control focuses on anticipating issues and optimizing processes before they become critical. This paradigmatic shift is essential to achieve higher standards of performance and efficiency.

The transition to a predictive control system allows organizations to use data and advanced analytical models to anticipate and prevent defects before they affect production or deliveries. This involves collecting real-time data, analyzing it through advanced algorithms, including genetic algorithms, to formulate forecasts and make data-driven decisions. By using genetic algorithms, companies can optimize process parameters, allowing for their adjustment based on current market conditions and the variability of customer requirements [5].

The Supplier Corrective Action Request (SCAR) process represents a cornerstone of quality management systems in manufacturing, designed to address non-conformities and prevent their recurrence. However, in its traditional form, this process is predominantly reactive and manual,

inheriting several systemic limitations that hinder its efficiency and effectiveness.

A primary challenge is its inherent latency. The process is often initiated only after a defect has been detected, sometimes as late as the final inspection or, worse, at the customer's end. This delay, compounded by the time required for containment, root cause analysis, and corrective action implementation, leads to significant costs in scrap, rework, and potential line stoppages.

Furthermore, the Root Cause Analysis (RCA) phase is heavily reliant on human expertise and subjective interpretation. This manual investigation is susceptible to cognitive biases and can fail to identify the true, underlying systemic cause, leading to superficial corrections that only address symptoms. As noted in quality management literature, without a robust, data-driven RCA, problems are likely to recur.

Vibrodiagnostics represents an innovative approach in the manufacturing landscape, functioning as a real-time, quantitative tool for defect detection and ongoing monitoring of material states. Often likened to a "digital stethoscope" for production lines, this technology emphasizes the importance of continuous monitoring, proactive maintenance, and rapid response to anomalies within industrial processes.

Vibrodiagnostics utilizes sensors that capture vibrations emitted from machinery, components, or materials. These vibrations are indicative of the

operational status and health of the system. By analyzing vibration patterns, potential defects or irregularities can be identified before they escalate into critical failures. This method enables operators to implement a predictive maintenance strategy, addressing problems proactively rather than reactively [4].

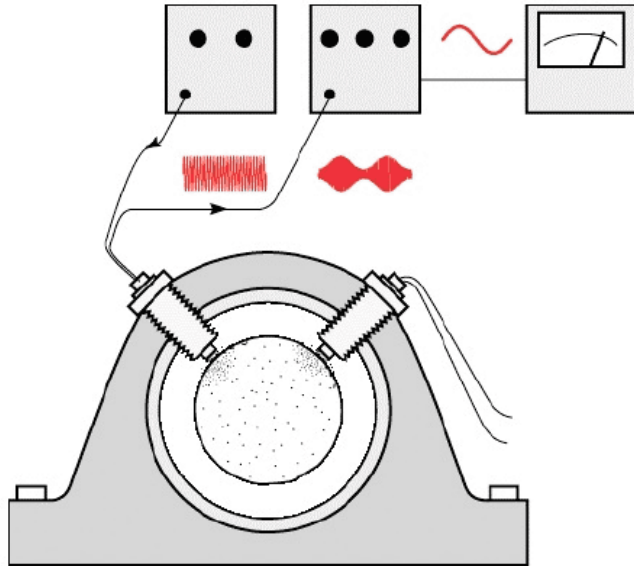


Figure 1. Displacement Transducers representation in Vibrodiagnostics [14]

The core strength of vibrodiagnostics lies in its ability to provide real-time data analysis. High-frequency vibrations can be monitored using advanced sensor technologies and signal processing algorithms, allowing for rapid detection of changes in the operational state of machinery or materials. Unlike traditional inspection methods that may rely on periodic checks and visual inspections, vibrodiagnostics constantly feeds data into monitoring systems, providing insights that can lead to immediate corrective actions, safeguarding against unplanned downtime [12].

Genetic Algorithms (GAs) serve as a powerful method for optimization in various fields, effectively balancing multiple constraints such as cost, time, and effectiveness. These algorithms are inspired by the principles of natural selection and genetics, making them particularly well-suited for solving complex decision-making problems.

One of the significant advantages of GAs is their capacity to handle multi-objective optimization problems, where several conflicting objectives must be satisfied simultaneously. For instance, in emergency resource allocation scenarios, GAs can facilitate improved decision-making by optimizing resource distribution while considering constraints such as time and cost. Li demonstrated how GAs can be effectively applied to enhance resource

deployment strategies, leading to robust solutions that account for both urgent needs and available resources [11].

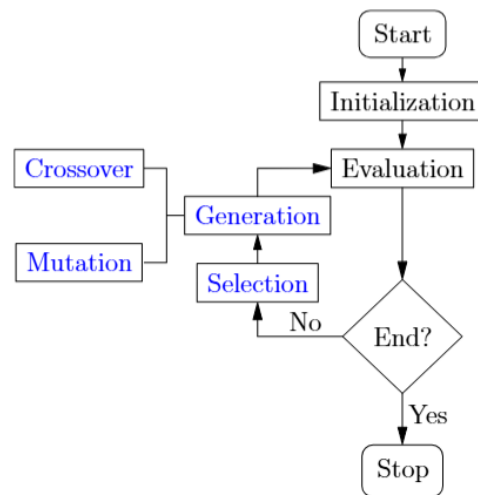


Figure 2. Basic process of Genetic Algorithm [9]

The primary objective of this paper is to propose and demonstrate the feasibility of an integrated framework that combines vibrodiagnostics and genetic algorithms to transform the traditional SCAR process into a predictive and optimized system.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1 Foundational Concepts in Automotive Quality Management

The Supplier Corrective Action Request (SCAR) is a formalized process utilized by organizations to address and correct non-conformities related to products or services provided by suppliers. It serves as a structured approach for identifying defects, investigating causes, implementing corrective actions, and verifying the effectiveness of those actions. The SCAR process aims to enhance quality assurance and maintain supplier accountability, ultimately improving the integrity of the supply chain.

The SCAR process plays a vital role in the supply chain by ensuring that suppliers adhere to quality standards and continuously improve their products and processes. Some of the critical functions include:

- **Failure Mitigation:** By addressing non-conformities efficiently, SCAR helps mitigate the risk of defective products reaching customers, thereby protecting the organization's reputation and reducing costs associated with returns and rework
- **Supplier Accountability:** SCAR establishes a mechanism for holding suppliers accountable for quality issues, encouraging them to enhance their

operations and implement robust quality management practices

- **Continuous Improvement:** The cyclical nature of the SCAR process fosters a culture of continuous improvement, where lessons learned contribute to refining procurement practices and enhancing overall supply chain performance [2].

- **Data-Driven Decision Making:** The robust documentation and analysis involved in SCAR create a rich data source that can be leveraged for future decision-making, strategic planning, and risk management within the supply chain [2].

2.2 Vibrodiagnostics and Acoustic Emission in Condition Monitoring

Vibrodiagnostics and Acoustic Emission (AE) techniques represent critical methodologies in condition monitoring across various industries. These techniques involve real-time assessment and analysis of the health and performance of machinery and structures, making them essential tools for predictive maintenance and operational efficiency.

Vibrodiagnostics involves measuring and analyzing vibrations during the operation of machinery. This technique allows for detecting abnormalities that may indicate wear, misalignments, or impending failures. For instance, Baron explored the use of vibrodiagnostics in a small hydropower plant, showing that continuous monitoring of vibrations from turbo generators helps maintain operational integrity and optimize maintenance schedules [1]. Evaluating vibrations provides essential insights into the performance of rotating machinery such as bearings and gearboxes, allowing for the implementation of predictive maintenance strategies before catastrophic failures occur.

2.2.1 Review of Signal Processing Techniques for Quality Inspection

Quality inspection within manufacturing and engineering processes plays a crucial role in ensuring product conformity and operational reliability. Advances in signal processing techniques have significantly enhanced the ability to detect defects, monitor conditions, and extract meaningful features from complex data sets. Review will focus on key signal processing methods such as Fast Fourier Transform (FFT), Time-Frequency Analysis, and feature extraction, highlighting their relevance to quality inspection.

Analyzing vibration signals with FFT involves converting time-domain vibration data into the frequency domain to reveal distinct spectral components associated with mechanical faults.

Bearing defects, lubrication degradation, misalignment, and gear tooth damage often manifest as frequency peaks related to characteristic fault frequencies such as ball pass frequency outer race (BPFO), ball pass frequency inner race (BPFI), cage spin frequency, or gear mesh frequency. Extracting these frequencies from vibration signals enables condition monitoring systems to identify and assess the severity of defects [6].

2.3 Review of successful GA applications in manufacturing and supply chain optimization

Genetic Algorithms (GAs) have established themselves as powerful tools for optimization in various applications within manufacturing and supply chain management. By simulating the process of natural selection, GAs efficiently address complex decision-making problems across domains such as scheduling, parameter tuning, and logistics management.

GAs are frequently employed for parameter tuning to determine optimal configurations for production processes. Li propose an optimization approach integrating Timed Petri Nets (TPN) with GAs to improve manufacturing process efficiency [11]. This method allows manufacturers to optimize workflow configurations and process parameters, resulting in substantial reductions in production delays.

A significant application area for GAs is in scheduling, where optimal resource allocation and timing are crucial. Zhou outline a hybrid genetic algorithm to enhance operation scheduling in Manufacturing Execution Systems (MES), integrating single and parallel GAs for improved scheduling performance in multi-product and multi-factory environments [13].

While Genetic Algorithms (GAs) have been extensively studied and applied across various domains, the specific application of GAs to quality control decisions and corrective action selection within the Supplier Corrective Action Request (SCAR) process remains notably underexplored. This gap presents opportunities for advancing decision-making frameworks in quality risk management and corrective action implementations.

3. METHODOLOGY FOR RESEARCH: INTEGRATED FRAMEWORK FOR PREDICTIVE SCAR

The objective of this research is to develop an integrated framework for utilizing Genetic Algorithms (GAs) within the Predictive Supplier Corrective Action Request (SCAR) process. This framework aims to optimize quality control decisions

and corrective action selections, thus enhancing the overall efficiency and responsiveness of supply chain quality risk management.

The developed framework will consist of several key components:

- **Data Collection:** Establishing mechanisms for collecting relevant data from SCAR processes, such as defect types, corrective actions taken, supplier performance metrics, and historical data on failures and successes. This data will serve as the foundation for the subsequent analysis and optimization phases.
- **Problem Formulation:** Clearly defining the optimization problem addressed by the GA. This includes identifying decision variables (e.g. corrective action types, supplier selection), objectives (e.g. minimizing cost, time, and maximizing effectiveness), and constraints (e.g. supplier capabilities, regulatory compliance).
- **Genetic Algorithm implementation:** Designing the GA model, including chromosome representation, selection methods, crossover and mutation strategies, and fitness functions aligned with the objectives. This step draws upon the methodologies highlighted in the literature, specifically referencing successful GA applications in manufacturing and supply chain optimization

3.1 Overview of the Proposed Predictive SCAR Framework

This research proposes a novel, integrated framework designed to transform the traditional reactive SCAR process into a predictive and optimized system. The core innovation lies in the closed-loop interaction between physical defect detection and computational decision optimization, moving beyond human-dependent analysis.

The framework, illustrated in Figure [3], is structured around three interconnected pillars:

- **The Data Acquisition and Diagnostics Layer:** This layer is responsible for transforming the physical state of a component into a structured digital diagnosis. Utilizing vibrodiagnostic sensors and signal processing techniques, it captures the component's health signature. A machine learning classifier then analyzes this data to output a specific defect type and severity level, providing a quantifiable and objective trigger for the entire system.
- **The Intelligent Optimization Layer:** This is the decision-making core of the framework. It takes the diagnostic input from the first layer and processes it through a Genetic Algorithm (GA). The GA's role is to search the vast space of possible corrective actions

and identify the one that best balances multiple objectives, such as minimal cost, time, and maximum effectiveness.

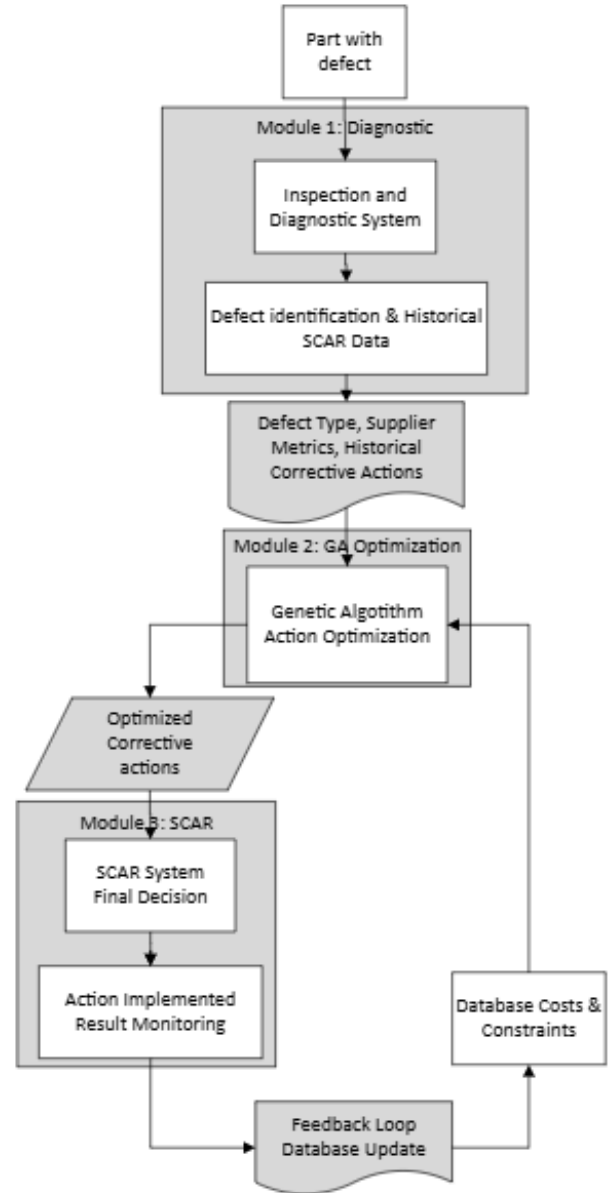


Figure 3. Architecture of the vibrodiagnostic-GA integrated SCAR system

The Implementation and Feedback Layer: The optimized solution generated by the GA is formalized within the existing SCAR process, providing quality engineers with a data-driven recommendation. Once the action is implemented, the outcomes, both successful and otherwise, are fed back into a central knowledge base. This feedback loop enables continuous learning and refinement of both the diagnostic and optimization models over time.

3.2 Data Foundation and Problem Formulation for Optimization

In the context of developing an integrated framework for utilizing Genetic Algorithms (GAs) within the Predictive Supplier Corrective Action Request (SCAR) process, establishing a solid data foundation

and formulating the optimization problem are crucial steps. These processes underlie the effective application of GAs to enhance decision-making in quality control and corrective actions.

3.2.1 Data Collection and Preparation

The successful implementation of the framework hinges on the collection of relevant data from various SCAR processes. This includes:

- **Defect Types:** Identifying and categorizing the defects encountered, including their nature, severity, and frequency. This information helps in understanding the most common issues the supply chain faces.
- **Corrective Actions Taken:** Documenting previous corrective actions that have been implemented, along with their associated costs, time taken for implementation, and effectiveness in resolving the identified defects.
- **Supplier Performance Metrics:** Collecting quantitative and qualitative data on supplier performance, including delivery timelines, quality ratings, and responsiveness to corrective actions.
- **Historical Data on Failures and Successes:** Analyzing past SCAR outcomes, including successful and unsuccessful corrective actions, to enhance learning and decision-making for future improvements.

This comprehensive dataset serves as the foundation for subsequent analyses, enabling the framework to leverage historical insights for informed decision-making.

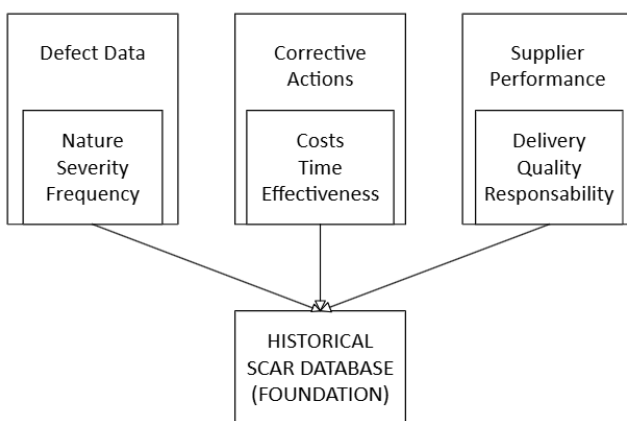


Figure 4. Data Collection Framework for SCAR Optimization

3.2.2 Problem Formulation for Genetic Algorithms

The next step in the optimization process involves clearly defining the problem to be addressed by the Genetic Algorithm. This entails:

- **Decision Variables:** Identifying key decision variables, such as the types of corrective actions to be

considered, the allocation of resources, and supplier selection. For instance, each corrective action could be represented by a unique value in the chromosome of the GA.

- **Objectives:** Clearly defining the optimization objectives that the GA will seek to achieve. Common objectives include:

- **Minimizing cost:** Reducing the financial impact of implementing corrective actions.
- **Minimizing time:** Reducing the duration required to implement corrective actions and achieve desired outcomes.
- **Maximizing effectiveness:** Enhancing the quality and robustness of corrective measures to prevent future defects.

- **Constraints:** Identifying constraints that may limit the solution space, including:

- **Supplier capabilities:** The technical and operational capabilities of suppliers in implementing corrective actions.
- **Regulatory compliance:** Legal and regulatory considerations that must be adhered to when selecting corrective actions and suppliers.

3.3 Implementation Strategy

The implementation of the proposed SCAR framework will follow a phased approach, ensuring thorough integration within existing processes and optimal utilization of resources:

- **Pilot program initiation:** A select pilot area within the organizational SCAR process will be chosen for initial implementation. This pilot will serve to validate the integrated framework on a smaller scale and gather data without affecting the entire organization's operations.
- **Stakeholder engagement:** Engaging stakeholders is critical to the success of the framework implementation. Workshops and training sessions should be organized to familiarize staff with the new processes and technologies, ensuring buy-in and cooperation across departments.
- **Integration with Existing Systems:** The framework to be designed to integrate seamlessly with existing supply chain management systems and quality assurance protocols. This includes the adaptation of data collection and monitoring mechanisms to ensure alignment with current methodologies.
- **Data Infrastructure development:** Establishing robust data infrastructure is essential for effective implementation. This will involve the adoption of compatible database systems and data analytics tools to facilitate comprehensive data collection, analysis,

and storage capabilities essential for the predictive SCAR process.

- **Continuous monitoring and Feedback loop:** During the pilot phase, continuous monitoring mechanisms should be established to measure the performance of the framework against predefined success indicators, including reductions in defect rates, response times, and overall costs. A feedback loop will be integrated, allowing for adjustments and refinements based on real-time feedback from users and stakeholders.

- **Full-scale rollout:** Upon successful validation in the pilot program and necessary adjustments, a full-scale rollout will be planned. This will include further training sessions, documentation of best practices, and strategic communication of changes across the organization.

4. SIMULATION CASE STUDY AND RESULTS ANALYSIS

4.1 Case Study Design and Simulation Setup

This chapter presents an internal analysis conducted within our organization, a Tier-1 automotive supplier specializing in electronic control units (ECUs) and body control modules (BCMs), to evaluate the potential enhancement of our Supplier Corrective Action Request process through the integration of unconventional methods.

The analysis focuses on our production of engine control units (ECUs) and gateway modules, which represent high-value, safety-critical components with complex supply chains. The study examines historical quality data to establish baseline performance and projects potential improvements through vibrodiagnostics and genetic algorithm optimization.

Base Analysis Parameters:

- **Component focus:** Engine Control Units (ECUs) & Gateway Modules
- **Data foundation:** Internal quality records from 2021-2023
- **Sample scope:** 215 validated quality incidents across semiconductor and PCB suppliers
- **Cost structure:** Actual internal cost accounting for warranty, rework, and scrap

4.2 Current State Analysis: SCAR Process Baseline for Electronic Components

Internal quality tracking over the past three years reveals distinct and persistent challenges within the SCAR process for electronic control units and gateway modules. The analysis of 215 validated quality incidents highlights that defects in these

complex, multi-layered components often require extensive, multi-tier supplier investigation, leading to prolonged resolution times and significant costs.

The table below summarizes the performance of our current SCAR process against the most prevalent defect categories, providing a critical baseline for measuring future improvement.

Table 1. Defect Analysis and SCAR Performance Metrics

Defect category	Avg. Resolution time	Reccurrence rate	Avg. cost per incident	Supplier tier
PCB soldering	22.5	35%	12.500	Tier 2
Semiconductor or performance	28.7	25%	18.200	Tier 1
Connector issue	15.2	42%	7.800	Tier 2
Software integration	32.4	18%	15.700	Tier 1

Key Insights:

- **High-Recurrence, Lower-Cost Issues:** Defects related to Connectors & Harnesses exhibit the highest recurrence rate (42%). This suggests that our current containment and corrective actions for these components are insufficient, often addressing symptoms rather than the root cause in the supplier's manufacturing process.

- **High-Impact, Complex Resolutions:** Semiconductor and Firmware-related SCARs, while less frequent, incur the highest costs and longest resolution times. Resolving these issues often requires deep technical collaboration with Tier-1 suppliers and complex validation cycles, significantly impacting production schedules.

- **The "PCB Problem":** Soldering and mounting issues represent a critical pain point, combining a high recurrence rate with substantial costs. The root causes are often distributed across our Tier-2 suppliers' processes (e.g. solder paste application, reflow oven profiles), making them difficult to pinpoint and eradicate permanently.

4.3 Enhancement Opportunity Assessment for Electronic Systems

4.3.1 Vibrodiagnostics Adaptation for Electronics Assembly

In the context of ECU and BCM production, vibrodiagnostics transcends its traditional role. It is repurposed to monitor the **manufacturing and testing equipment itself**, rather than the final product. Our internal feasibility studies indicate this approach can intercept defects at their source.

Targeted Applications & Projected Impact:

SMT (Surface-Mount Technology) Equipment Monitoring:

- Application: Installing accelerometers on pick-and-place heads and reflow oven conveyors.
- Mechanism: Abnormal vibrations can indicate misalignment of placement heads, worn feeder mechanisms, or conveyor instability, which directly lead to PCB Soldering & Mounting defects [8].
- Projected Benefit: Early detection of equipment calibration drift could prevent up to 60% of the soldering-related SCARs by triggering maintenance before non-conformances are produced [8].

In-Circuit Test (ICT) & Functional Test Fixture Analysis:

- Application: Monitoring vibration signatures of test probes and handlers.
- Mechanism: A consistent vibration pattern is indicative of a good electrical connection. Deviations can signal bent probes, poor fixturing, or mechanical wear that causes intermittent failures, a common root cause for Connector & Harness Issues and false failure diagnoses.
- Projected Benefit: Reduce the recurrence rate of connector-related issues by providing objective data to differentiate between true component defects and test system variability [6].

4.3.2 Genetic Algorithm Optimization for Electronics SCAR

The complexity of electronic components necessitates evaluating a vast number of corrective action combinations. Genetic Algorithms (GAs) are uniquely suited to optimize these decisions across our multi-tier supply chain.

Optimization Pathways:

Root Cause Correlation Mapping:

The GA can analyze historical SCAR data to identify non-obvious correlations. For example, it might discover that certain Semiconductor Performance failures are statistically linked to specific solder paste profiles used by a Tier-2 PCB assembler, a link often missed in manual analysis.

Corrective Action Portfolio Optimization:

- For a single incident, the GA can evaluate hundreds of action combinations. For a firmware issue, it could balance the cost and lead-time of a full ECU flash at our plant against a targeted field update, while factoring in warranty claims and brand reputation.

- Projected Benefit: This data-driven approach is projected to reduce the recurrence rate for high-cost semiconductor and firmware SCARs by targeting the true systemic root cause, rather than applying a generic solution [3].

By deploying vibrodiagnostics for proactive defect generation prevention and GAs for intelligent decision support, we can transition the SCAR process from a reactive documentation exercise to a proactive, strategic quality enhancement system.

4.4 Projected Impact and Feasibility Assessment

Based on the baseline analysis, the integration of vibrodiagnostics and genetic algorithms is expected to deliver meaningful improvements by addressing specific process weaknesses:

Key Expected Outcomes:

- For high-recurrence defects (e.g., connectors, PCB soldering): Vibrodiagnostics should enable early detection of equipment abnormalities, preventing defect generation at source
- For complex, high-cost issues (e.g. semiconductors): GA optimization should accelerate root cause analysis and improve corrective action selection

Critical Success Factors:

- Data quality: Historical SCAR data must be complete and structured for effective GA training
- Correlation establishment: Reliable links between vibration patterns and defects require sustained data collection
- Organizational adoption: Quality teams must trust and utilize the data-driven recommendations

5. LIMITATIONS AND FUTURE WORK

Practical implications: For a company like this, the framework offers a clear pathway to reduce quality costs and strengthen supplier relationships through data-driven dialogues. It shifts the quality engineer's role from a reactive investigator to a proactive process manager and data analyst.

Acknowledgement of limitations: This study is inherently limited by its conceptual nature. The primary limitations are:

- **Conceptual Validation:** The projected benefits are based on logical extrapolation and internal data analysis, not on a live implementation.
- **Implementation Hurdles:** The cost of sensor infrastructure, the complexity of IT integration, and the challenge of organizational change management are significant and were not quantified in this analysis.

- **Data Dependency:** The effectiveness of the GA is entirely contingent on the availability of high-quality, well-structured historical data, which can be a constraint in practice.

To transition this conceptual framework into a practical tool, the following research steps are essential:

- **Pilot implementation:** A controlled pilot on one production line for ECUs is the critical next step to gather real performance data and validate the projected ROI.

- **Algorithm refinement:** Future work should focus on incorporating supplier risk scores and logistical constraints directly into the GA's fitness function.

Despite its limitations, this study establishes a strong foundational argument for rethinking quality management in the automotive electronics supply chain. By leveraging unconventional methods, we can transform the SCAR process into a strategic asset, capable of not just solving problems, but preventing them altogether.

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