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Robotic automation-based cycle time reduction for automotive radiator core assembly systems

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ABSTRACT

Manufacturing industries face increasing pressure to improve productivity and reduce cycle time amid global competition and the adoption of Industry 4.0 technologies. While lean manufacturing, quality management, and robotic automation have been widely applied, these approaches are often implemented independently. This study proposes an integrated manufacturing improvement framework that combines the 8 Steps problem-solving methodology, the 7 quality control (QC) tools, and robot-centric automation to reduce production cycle time below takt time in an automotive radiator core assembly system. A case-based industrial study was conducted using production data collected before and after improvement implementation. The proposed framework integrated bottleneck identification, root-cause analysis, workstation balancing, and robot-assisted automation supported by Pareto analysis, fishbone diagrams, control charts, and time studies. The implemented automation included robotic tube arrangement, automated knocking and rolling, programmable logic controller (PLC)-based auto-running control, automated fin transfer, and IoT-enabled production monitoring. The production cycle time decreased from 49.0 s/unit to 38.9 s/unit, representing a 20.6% reduction and achieving the takt time target of 41.7 s/unit, while productivity increased from 13.2 pcs/Mhr to 41.2 pcs/Mhr. The proposed framework provides a practical approach for improving productivity and operational performance in automotive assembly systems.

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1. INTRODUCTION

The manufacturing industry is undergoing rapid transformation driven by Industry 4.0 technologies and intensifying global competition. To remain competitive, manufacturers must continuously improve productivity, operational efficiency, and delivery performance while maintaining quality, cost, and delivery (QCD) objectives [1]–[3]. In automotive manufacturing, robotic automation, the industrial Internet of Things (IIoT), cyber-physical systems, and real-time process monitoring have become key enablers for improving manufacturing flexibility, reducing operational waste, and enhancing production consistency [3]–[7]. Consequently, manufacturers increasingly integrate automation and Lean 4.0 principles to strengthen assembly performance and supply chain competitiveness [8].

Despite these technological advances, automotive assembly systems continue to experience excessive cycle times, production bottlenecks, workload imbalances, and manual material handling,

particularly in manual and semi-automated environments. Repetitive operations, inefficient workstation synchronization, and non-value-added activities reduce throughput and operational stability [9]–[11]. Addressing these challenges requires integrated improvement strategies that combine structured problem-solving methodologies with robotic automation, intelligent process control, and robot-centric sensing technologies.

The industrial case investigated in this study concerns the radiator core assembly line of XYZ company, an automotive component manufacturer supplying original equipment manufacturers (OEMs). Increasing customer demand exposed operational limitations in core assy line #3, where the production cycle time exceeded the required takt time, resulting in bottlenecks and reduced production capacity. Root-cause analysis identified manual tube arrangement, repetitive material transfer, sequential machine operations, and inefficient human–machine interactions as the primary contributors, highlighting the need for robot-assisted material handling, programmable logic controller (PLC)-based control, and automated workstation coordination to improve productivity and process stability.

Previous studies have shown that lean manufacturing, line balancing, quality management, and simulation-based optimization improve manufacturing performance [8], [9], [11]. More recently, Industry 4.0 technologies—including robotic automation, IIoT, PLC-based control, sensor-enabled systems, and real-time monitoring—have further enhanced operational visibility, process consistency, and manufacturing flexibility [3]–[6]. However, most studies examine lean manufacturing, quality management, or robotic automation independently, with limited integration into a unified industrial framework. Moreover, existing research often emphasizes advanced optimization algorithms, digital twins, or large-scale smart manufacturing, while practical workstation-level robot-centric automation supported by structured problem solving and validated using industrial production data remains limited [3], [5]–[8].

To address these gaps, this study proposes an integrated manufacturing improvement framework combining the quality control circle (QCC), the 8 Steps problem-solving methodology, the 7-quality control (QC) tools, and robot-centric automation to reduce production cycle time in an automotive radiator core assembly system. The framework integrates systematic bottleneck identification, root-cause analysis, robot-assisted material handling, PLC-based control, sensor feedback, servo-driven motion, and IoT-enabled production monitoring into a unified workflow for automation planning, implementation, and performance validation.

This study makes three main contributions. First, it presents an integrated framework that combines structured quality improvement methodologies with robot-centric automation for manufacturing system optimization. Second, it demonstrates the practical implementation of robot-assisted tube arrangement, automated rolling, automated fin transfer, PLC-based control, and sensor-driven automation using empirical data from an actual automotive production environment. Third, it provides industrial evidence that integrating systematic root-cause analysis with intelligent automation improves production stability, reduces cycle time, and enhances manufacturing performance, offering a practical and scalable reference for similar automotive assembly systems.

2. METHOD

This study was conducted in the radiator core assembly line of an automotive component manufacturer supplying original equipment manufacturers (OEMs). The investigated production system consisted of five sequential workstations operating in a continuous assembly flow that combined manual operations, semi-automatic equipment, pneumatic actuators, and PLC-controlled machines. The research adopted an integrated manufacturing improvement framework that combined REFA work measurement, the QCC, the 8 Steps problem-solving methodology, the 7 quality control tools, and robot-centric automation [2], [8], [12]–[14]. The overall workflow, as shown in Figure 1, consisted of production system observation, time study measurement, bottleneck identification, root-cause analysis, automation design, implementation, and performance validation under actual industrial operating conditions.

Operational data were collected through direct shop-floor observation and stopwatch-based time studies. Thirty consecutive production cycles were recorded at each workstation under stable operating conditions to ensure measurement reliability [13], [15]. The collected data included cycle time, waiting time, operator movement, machine idle time, material transfer delay, workstation utilization, and defect occurrence. Pareto analysis was first employed to identify the production line requiring priority improvement, followed by Yamazumi charts to evaluate workstation balance against takt time requirements. Fishbone diagrams were subsequently used to identify dominant root causes of excessive cycle time based on the 4M1E framework [4], [15], [16]. The analytical outputs served as engineering inputs for workstation redesign and automation planning rather than solely for quality evaluation.

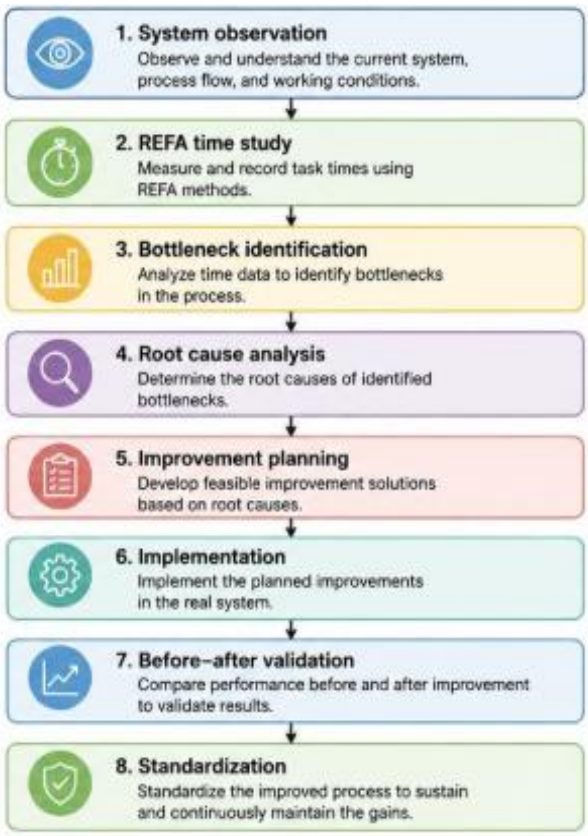


Figure 1. Research workflow of the integrated improvement framework

Based on the identified bottlenecks, an integrated robot-centric automation framework was developed to eliminate non-value-added activities and improve production flow [3], [5]–[7]. The framework combined structured root-cause analysis with robot-assisted material handling, PLC-based sequence control, cylinder sensor feedback, servo-driven rolling mechanisms, and IoT-enabled production monitoring. Automation solutions were implemented according to workstation-specific operational losses identified during the analytical stage. Robot-assisted tube arrangement reduced repetitive handling activities, PLC-triggered automatic machine operation eliminated unnecessary operator travel, servo-assisted rolling minimized repeated processing cycles, and automatic fin transfer synchronized upstream and downstream material flow. Rather than replacing the entire production line, the proposed framework emphasized low-cost, workstation-level automation integrated with the existing manufacturing system to improve productivity while maintaining operational flexibility [17].

The automation design also considered operator safety and ergonomics by reducing repetitive manual handling, minimizing direct human interaction with moving machine components, and maintaining safe operator working distances during automated operations. These considerations were incorporated to support safer working conditions while improving production efficiency, consistent with established industrial automation and ergonomic design principles [18], [19].

The system was designed as a workstation-level solution integrated with the existing production equipment to minimize implementation cost and production disruption. The automation architecture consisted of PLC-based sequential machine control, pneumatic cylinders for material positioning, servo-driven rolling mechanisms, and robotic transfer units for tube arrangement and fin handling. PLC logic employed a sequential interlock strategy in which each workstation operation was executed only after receiving completion signals from the preceding process, thereby preventing synchronization errors and unnecessary machine idle time. Photoelectric and cylinder proximity sensors continuously verified component presence and actuator positions to provide real-time feedback for automatic machine triggering and workstation synchronization. Prior to implementation, the sensing distance and response timing of each sensor were calibrated through repeated production trials to ensure stable, accurate, and repeatable operation under normal manufacturing conditions, consistent with established industrial automation commissioning practices.

The effectiveness of the proposed framework was evaluated using before-and-after performance comparisons. Manufacturing performance was assessed using cycle time, throughput, line efficiency, workstation utilization, and defect rate, while automation performance was evaluated through improvements in workstation synchronization, production stability, and human–machine interaction efficiency [13], [15]. Cycle time and takt time were used as the primary indicators of production capability, whereas throughput and line efficiency measured the effectiveness of workstation balancing after automation implementation. The proposed methodology provides a structured and reproducible approach for integrating quality improvement, robot-centric automation, and intelligent manufacturing technologies to improve the performance of automotive assembly systems [3], [5]–[7].

3. RESULTS AND DISCUSSION

Pareto analysis was first conducted to identify the production line requiring priority improvement. As presented in Figure 2, Core Assy Line #3 experienced the highest production demand increase (40.2%), contributing 38.8% of the cumulative production burden. This finding indicates that the production increase was concentrated on a single assembly line, making it the primary source of potential bottlenecks and throughput instability. Consequently, Core Assy Line #3 was selected for detailed investigation.

Cycle-time evaluation using the REFA method revealed that the required takt time during peak production was 41.7 s/unit, whereas Posts 2, 4, and 5 exceeded this limit with cycle times of 49.0 s, 46.7 s, and 48.4 s, respectively, as shown in Figure 3. The measurements were validated using 30 consecutive observations, resulting in a coefficient of variation of only 1.37%, indicating high measurement consistency. Based on these findings, the improvement target was established at 39.2 s/unit to ensure stable operation below takt time, as shown in Figure 4. Root-cause analysis using the fishbone diagram, as shown in Figure 5, identified five dominant method-related losses: manual knocking, manual machine triggering through the Nagara switch, manual rolling, manual tube arrangement, and manual fin-transfer operations. These repetitive manual activities were identified as the principal contributors to excessive cycle time and workstation imbalance.

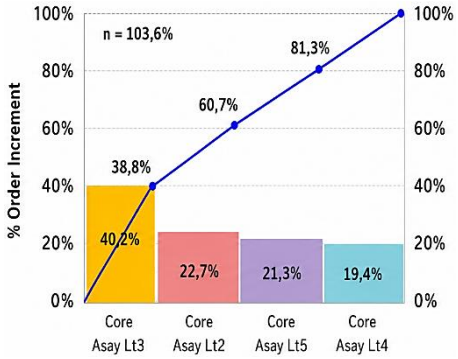


Figure 2. Pareto analysis of production order increase

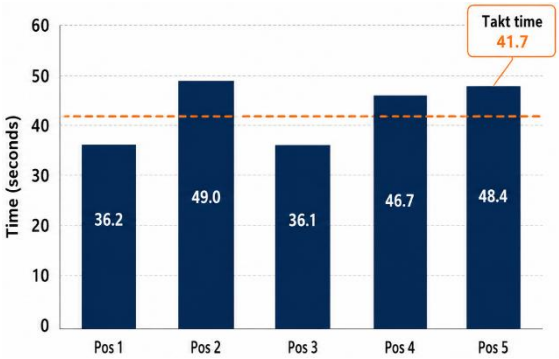


Figure 3. Workstation cycle times compared with the required takt time

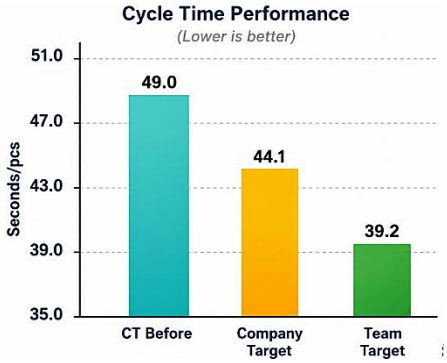


Figure 4. Target cycle time setting

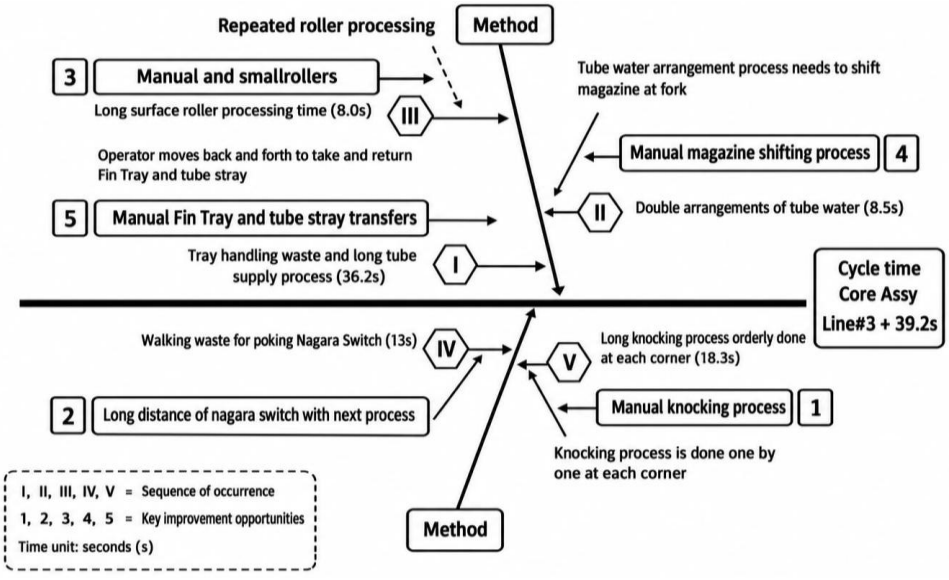


Figure 5. Improvement planning results: fishbone diagram for root cause analysis

To eliminate these bottlenecks, five targeted robot-assisted improvements were implemented (Figures 6 to 11). The interventions included automated knocking integrated with the compression process, PLC-based automatic machine triggering using cylinder sensors, robotic auto-rolling with a wider roller configuration, automated tube arrangement, and robotic fin-transfer with automatic tube supply. Rather than replacing the entire production system, these localized automation solutions reduced manual handling, eliminated unnecessary operator movement, synchronized machine operations, and improved workstation balancing. The integration of PLC control, sensor feedback, and robotic material handling also strengthened process consistency and supported real-time production monitoring within the existing manufacturing infrastructure.

The effectiveness of the proposed framework is summarized in Figure 10. The production cycle time decreased from 49.0 s/unit to 38.9 s/unit, representing a 20.6% reduction and exceeding the target of 39.2 s/unit while satisfying the takt-time requirement of 41.7 s/unit. Productivity increased from 13.2 to 41.2 pcs/man-hour, and workstation integration enabled manpower optimization from five operators to two operators in the improved production segment. These results demonstrate that the combined implementation of robotic automation and structured QCC methodology successfully eliminated bottlenecks, reduced non-value-added activities, and stabilized production flow under increased demand conditions.

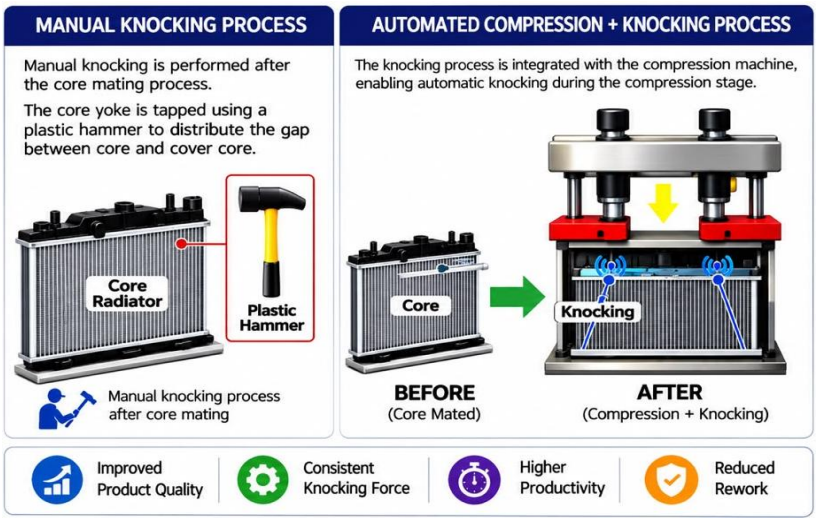


Figure 6. Automated knocking integrated with the compression



Figure 7. PLC-based automatic machine triggering using cylinder sensors



Figure 8. PLC-controlled automatic machine operation

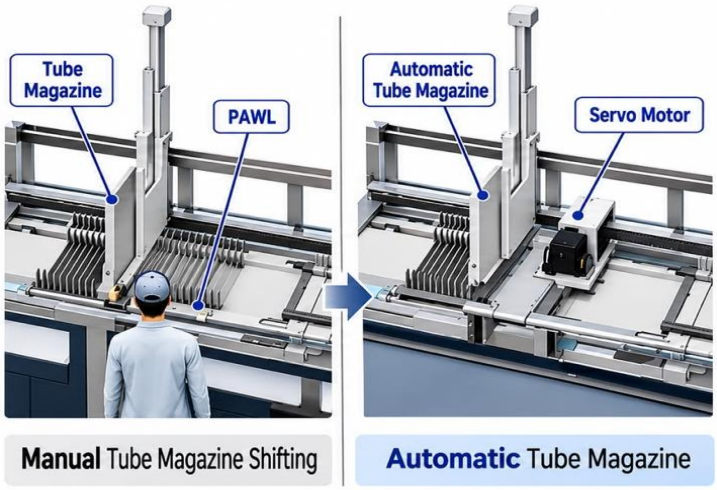


Figure 9. Robotic auto-rolling system

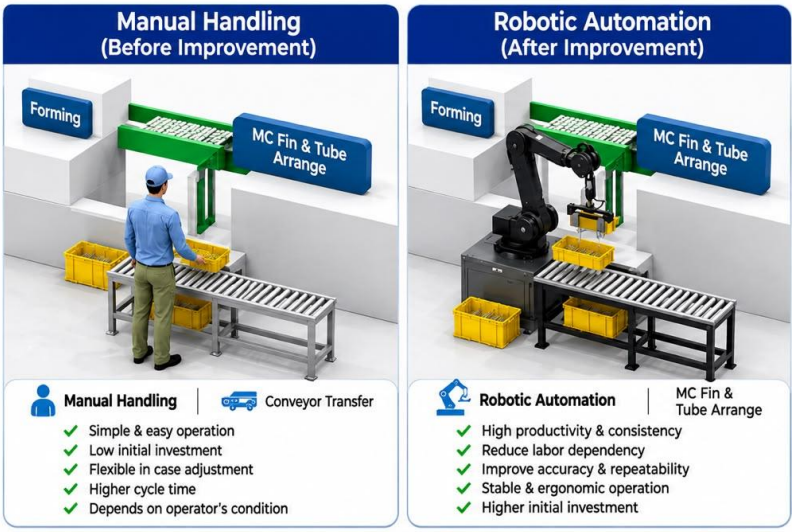


Figure 10. Robotic fin transfer and tube supply system

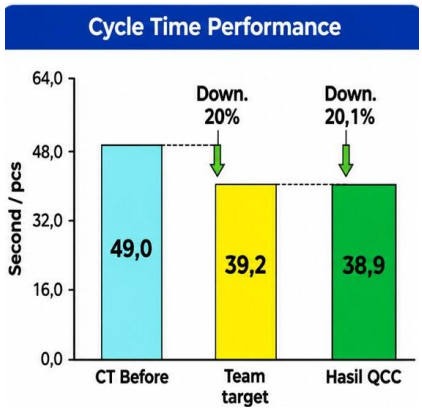


Figure 11. Automation outcome: before-and-after performance comparison

The performance improvement was achieved through the combined effects of robot-centric automation rather than any single intervention. PLC-based control with cylinder sensors eliminated unnecessary walking activities, robotic tube arrangement and auto-rolling reduced repetitive handling operations, while automated fin transfer synchronized material flow between adjacent workstations. These findings are consistent with previous Lean 4.0 and manufacturing automation studies, which reported that integrating targeted automation with systematic bottleneck analysis provides greater operational benefits than isolated process optimization [3], [5]. The present study extends previous work by demonstrating that automation decisions derived from QCC, 8 Steps, and the 7 QC Tools can effectively guide workstation-level robotic implementation using practical, low-cost automation technologies. Beyond improving cycle time, integrating sensor technologies and IoT-enabled monitoring supports sustainable manufacturing improvements by enabling real-time process monitoring, faster abnormality detection, and data-driven continuous improvement [20].

The robotic tube arrangement yielded significant performance gains by eliminating repetitive manual handling and inconsistent tube positioning. The servo-controlled automation replaced multiple manual alignment and transfer operations with a single synchronized movement, reducing non-value-added activities and improving workstation synchronization. As a result, processing time, operator-dependent variability, and idle time between workstations were reduced, leading to improved production flow and higher productivity [21].

These results also corroborate previous lean manufacturing studies showing that eliminating non-value-added activities and balancing workstation workloads are effective strategies for reducing production cycle time and improving manufacturing flow [22]. Likewise, recent Lean 4.0 research has emphasized that

digital technologies, including robotic automation, PLC-based control, and IIoT-enabled monitoring, enhance operational visibility, production flexibility, and process stability when integrated with continuous improvement methodologies [23]. The present study supports these observations through empirical evidence obtained from an actual automotive production line, where bottleneck-driven robotic interventions reduced cycle time by 20.6%, increased productivity from 13.2 to 41.2 pcs/Mhr, and enabled manpower optimization without requiring full production-line replacement. These findings therefore reinforce the growing consensus that incremental, workstation-level automation guided by structured lean problem-solving can achieve substantial operational improvements while maintaining relatively low implementation complexity [24].

Following implementation, all successful improvements were standardized through updated operating procedures and machine-control documentation in Table 1 to ensure long-term sustainability and facilitate replication across similar production lines through yokoten activities. In addition, quality analysis in Figure 12 identified Tube Dent as the dominant remaining defect, accounting for 79% of total non-conforming products. This issue was therefore selected as the next improvement theme, enabling future integration of productivity enhancement with product quality improvement.

Table 1. Standardized automation actions

No	Root Cause	Solution
1	Manual knocking process	Automate the knocking process
2	Machine uses nagara switch to start the process	Sequence modification program (machine plate fitting)
3	Manual roller process	Automate core rolling process
4	Tube water arrangement process is still manual	Automate tube arrangement process
5	Manual fin and supply tube transfer process are still manual	Automate fin and supply tube transfer process

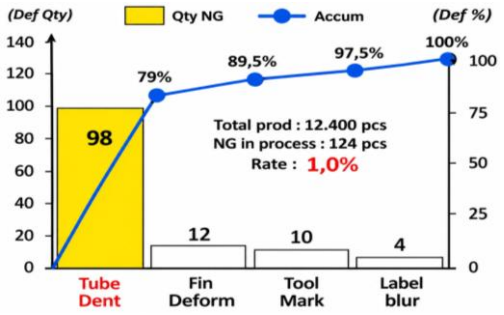


Figure 12. Pareto analysis of production defects for the next improvement priority

4. CONCLUSION

This study demonstrated that integrating the 8 Steps problem-solving methodology, the 7 QC tools, and robot-assisted automation effectively improved the performance of an automotive radiator core assembly system. Guided by systematic bottleneck identification and root-cause analysis, targeted automation—including PLC-based machine control, cylinder sensors, robotic tube arrangement, automated rolling, and automated fin transfer—reduced the production cycle time from 49.0 s/unit to 38.9 s/unit (20.6%), successfully meeting the takt time requirement of 41.7 s/unit. The improvements also increased productivity from 13.2 to 41.2 pcs/Mhr, reduced manual handling and manpower requirements, and enhanced production stability, demonstrating the practical effectiveness of combining structured quality management methodologies with robot-centric automation in industrial manufacturing.

Beyond these operational improvements, this study contributes to the manufacturing systems and robotics literature by demonstrating that integrating the QCC, the 8 Steps methodology, and the 7 QC Tools provides a systematic decision-making framework for implementing workstation-level robotic automation. By combining robotics, PLC-based control, sensor technologies, and IoT-supported monitoring, the proposed approach enables practical, scalable, and low-cost automation without requiring extensive production line redesign. Consequently, the framework can be readily adapted to other automotive assembly systems with similar production characteristics, providing a practical pathway for accelerating Lean 4.0 and Industry 4.0 adoption, particularly among Indonesian manufacturers seeking affordable and incremental manufacturing modernization.

From an industrial perspective, the proposed framework does not rely on proprietary hardware or high-end robotic platforms, allowing manufacturers to progressively automate bottleneck workstations while

maintaining existing production infrastructure. This modular implementation strategy improves the feasibility of replication across different automotive assembly systems with relatively low investment costs. Nevertheless, this study was limited to low-cost, workstation-level automation, and the performance of advanced robotic systems, such as AI-enabled robots or fully autonomous manufacturing cells, was not evaluated. In addition, workforce adaptation, including operator acceptance, training requirements, and long-term human–robot collaboration, was beyond the scope of this study.

This research was limited to a single automotive production line and evaluated short-term operational performance. Future studies should validate the proposed framework across multiple manufacturing environments and assess its long-term operational, economic, and sustainability impacts. Further research should also investigate the integration of artificial intelligence, digital twins, predictive maintenance, cyber-physical production systems, and advanced sensor analytics to further enhance autonomous decision-making, production flexibility, and smart manufacturing capabilities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Kriswanto			✓	✓		✓	✓	✓		✓	✓	✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there are no potential conflicts of interest with respect to the research, authorship, or publication of this article.

DATA AVAILABILITY

The datasets are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors confirm that there is no conflict of interest to declare for this publication.

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