IMPLEMENTATION OF A CAMERA–LASER SENSOR TO SUPPORT THE SMART FACTORY CONCEPT IN AUTOMATED TURBOCHARGER MANUFACTURING

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The paper presents the design, implementation, and experimental verification of a hybrid camera–laser sensor (Keyence IX-080) integrated into an automated turbocharger assembly line. The study addresses the limitations of traditional optical and inductive sensors when detecting small metallic components with high reflectivity, variable orientation, and sensitivity to changing lighting conditions. A systematic methodology was developed, including sensor placement design, configuration of image- and height-based detection tools, and integration with the PLC control system. Long-term testing under real production conditions was conducted over 18,000 assembly cycles, covering natural variability in lighting, handling, and surface reflections. The implemented system achieved a detection success rate of 99.89%, with a Wilson confidence interval of 99.80–99.94%, and demonstrated 100% Poka-Yoke performance for deliberately introduced errors. The results confirm the high reliability, robustness, and suitability of the hybrid sensor for automated inspection of critical components in turbocharger manufacturing. The findings also highlight opportunities for further optimization of detection tools to increase resilience against reflections and geometric deviations. The study demonstrates that intelligent sensing technologies significantly enhance process stability, product quality, and the overall effectiveness of Smart Factory systems.

KEYWORDS

Camera–laser sensor, Kyence IX-080, automated inspection, turbocharger assembly, Smart Factory, hybrid sensing, Poka-Yoke, industrial vision, height profiling, measurement system reliability, Wilson confidence interval, component detection

1 INTRODUCTION

Contemporary industrial manufacturing is undergoing a dynamic transformation that fundamentally changes the way production processes are designed, controlled, and optimized. Within the ongoing industrial revolution, there is an intensive interconnection of physical devices with digital systems, extensive use of data, and the implementation of intelligent technologies capable of autonomously responding to changes in operation [Abu Ebayyeh 2022]. The result is the emergence of highly adaptive production environments in which machines, sensors, information systems, and workers are integrated into a single coherent whole. Such an environment—often referred to as an intelligent or smart factory—enables higher efficiency, quality, and reliability of production.

The automotive industry is among the sectors that benefit most significantly from this technological transformation. High demands on assembly precision, quality monitoring, and error minimization require the use of advanced sensor systems capable of reliably identifying even small components with high variability in shape or surface properties. One of the critical stages in turbocharger assembly is the inspection of the presence of small elements such as circlips or springs, whose absence may lead to serious failures of the final product. Traditional optical or inductive sensors, however, often fail to ensure sufficient detection accuracy in environments with changing lighting conditions, vibrations, or reflections from metallic surfaces.

Hybrid camera–laser sensors represent a promising solution to these limitations. The combination of two-dimensional imaging and laser-based height measurement enables reliable identification of components even in cases where conventional sensors fail. Thanks to their ability to be integrated into production line control systems, these sensors can significantly contribute to reducing the number of nonconforming products, improving overall equipment effectiveness, and strengthening elements of intelligent manufacturing.

In recent years, the issue of automated inspection of assembly operations has become the subject of intensive research, particularly in connection with the emergence of intelligent sensor systems and the requirement for zero-defect manufacturing. Modern measurement systems are increasingly based on a combination of optical and laser technologies, which allow reliable detection of small components even in environments with high variability of surfaces and lighting conditions. Significant works in this field highlight the need for precise evaluation of measurement systems, including the analysis of repeatability, reproducibility, and measurement uncertainty. Lashkari and Chenouri [Lashkari 2025] present a comprehensive framework for the statistical evaluation of measurement systems, encompassing variance component analysis, ICC coefficients, and Wilson confidence intervals. Similarly, the VDA 5.3 [VDA 2024] and AIAG MSA [AIAG 2010] standards emphasize the importance of attribute studies, bias analysis, and linearity assessment in the evaluation of optical sensors in the automotive industry, with practical recommendations for MSA implementation also supplemented by the CPQP methodology [Barth 2021].

In the field of industrial vision and defect detection, attention is focused primarily on the use of advanced image-processing algorithms and artificial intelligence methods. Jia and Wang [Jia 2022] demonstrate that a combination of U-Net architecture and morphological operations enables high accuracy in detecting surface defects in industrial production. The most recent studies from 2024–2025 show that the application of convolutional neural networks and hybrid sensor systems can achieve accuracy levels of 97–99.9% in the inspection of assembly components in the automotive industry [Ribeiro 2025], including the detection of small metallic elements, incorrect orientation, or missing parts. Particular attention is paid to studies focused on the automated inspection of turbochargers, where high-resolution cameras and laser profiling are used to verify the correct positioning of blades, retaining rings, and other critical assembly elements [Zhang 2025].

Hybrid camera–laser systems, such as the Keyence IX-080, represent a technological trend that combines the advantages of two-dimensional imaging with precise height measurement. Al-Ashwal et al. [AlAshwal 2023] report that the combination of laser profiling and AI-supported image analysis enables accuracy exceeding 99.8% in detecting small metallic components under dynamic production conditions. Industrial applications published in 2024–2025 further confirm that laser sensors and camera systems are capable of reliably identifying components even in the presence of reflections, vibrations, or variable lighting [QuellTech 2024, Winkler 2022, Kobayashi 2021]. Official Keyence sources document the use of camera and laser systems in automotive manufacturing, including the inspection of assembly elements, position measurement, and ensuring zero-defect production [Barodi 2025]. The latest analyses also point to the rapid development of AI-supported sensor technologies in the Keyence portfolio, particularly in connection with edge-computing architecture and automated configuration of detection tools [Kitishian 2025].

In the context of intelligent manufacturing, research activities focused on the integration of sensor systems, intelligent control, and production process monitoring also play an important role. Pitel et al. [Pitel 2015] highlight the importance of intelligent control systems in increasing the stability and flexibility of automated lines. Yaqub et al. [Yaqub 2023] emphasize the significance of sensor systems in production process monitoring and data fusion. Although Mey et al. [Mey 2021] do not work with camera systems, their approach to multisensor diagnostics and data fusion is analogous to trends in industrial vision, where the combination of 2D imaging and 3D profiling enhances detection reliability.

The aim of this paper is to present the design, implementation, and experimental verification of the Keyence IX-080 camera–laser sensor in automated turbocharger manufacturing at a partner company. The paper focuses on the methodology for integrating the sensor into an existing production line, optimizing its settings for the detection of critical components, and evaluating its contribution from both technical and application perspectives.

The results confirm that intelligent sensing represents an effective tool for modern digitalized manufacturing and significantly contributes to increasing the quality and reliability of assembly processes.

2 THEORETICAL AND TECHNOLOGICAL BACKGROUND

Contemporary manufacturing is characterized by an increasing degree of digitalization, connectivity, and automation, which fundamentally changes the way production processes are monitored and controlled. Modern production systems rely on the ability to continuously acquire and process information from various parts of the technological chain. A key element of this transformation is sensor devices, which provide accurate data on the condition of components, equipment, and assembly operations. Without reliable data acquisition, it would not be possible to achieve a high level of automation or ensure stable product quality.

In automated assembly processes, sensors play a crucial role, as they enable verification of the correctness of individual steps and prevent errors that could lead to product damage or production interruptions. However, when inspecting small metallic components, traditional sensors often reach their limits. Components with small dimensions, low contrast, or reflective surfaces can cause unreliable results, especially in environments with variable lighting conditions or vibrations. Optical sensors are sensitive to reflections and lighting changes, while inductive sensors are unable to distinguish shape or precise positioning of elements. These limitations create a need for technologies capable of reliably identifying components even under demanding production conditions.

Vision systems provide detailed information about the shape and visual features of objects, enabling identification of contours, orientation, or the presence of characteristic elements. Their accuracy, however, may be affected by changes in illumination or surface reflections. Laser sensors, by contrast, measure height differences and object profiles, making them suitable for detecting elements based on their spatial position. On their own, however, they do not provide sufficient information about shape or visual details. The combination of both technologies in a single device therefore represents a significant advancement in the field of industrial detection.

Hybrid camera–laser sensors combine the advantages of two-dimensional imaging and precise height measurement, enabling reliable identification of components even in situations where traditional sensors fail. As a result, they can recognize small metallic elements even when they are partially obscured, positioned in different orientations, or produce reflections. Measurement stability is ensured by the fusion of visual information and spatial profiling, which increases resistance to environmental disturbances.

In turbocharger assembly, reliable detection of small components is particularly critical. Components such as circlips or small springs are essential for the correct functioning of the assembly, and their absence can lead to serious failures. As these are small metallic parts with high reflectivity, their inspection is a demanding task. Moreover, the production environment is dynamic, with the presence of vibrations, rapid movements, and variable lighting conditions. For this reason, it is necessary to employ a sensing solution capable of reliably identifying both the presence and precise position of these components in real time. Hybrid camera–laser sensors provide an appropriate response to these requirements, as they combine the accuracy of spatial measurement with detailed visual analysis. Their implementation makes it possible to increase the reliability of assembly operations, reduce the number of nonconforming products, and support the stability of the entire production process. Consequently, they represent an important element of modern automated lines that emphasize high quality and repeatability of production.

3 METHODOLOGY AND RESULTS OF TESTING THE IMPLEMENTATION OF A CAMERA–LASER SENSOR FOR COMPONENT INSPECTION

The implementation of an intelligent sensing system into an existing automated line requires a systematic approach that includes analysis of the production process, selection of suitable equipment, design of its placement, configuration of measurement tools, and subsequent experimental verification. This chapter describes the methodological framework used in introducing the Keyence IX-080 camera–laser sensor into a turbocharger assembly line. The objective was to create a reliable tool for detecting the presence of small metallic components that are critical to the proper functioning of the assembly.

The first step was an analysis of the assembly operation in which components with small dimensions and high reflectivity are inspected. From a sensing perspective, this is a demanding task, as these elements may be partially obscured, positioned in different orientations, or produce reflections that complicate their identification. Based on the conducted analysis, it was decided to use a hybrid sensor that combines visual information with height measurement. The Keyence IX-080 device was selected for its ability to operate reliably in environments with metallic surfaces, for its high measurement repeatability, and for its ease of integration into the existing control architecture of the line.

Figure 1. Camera–laser sensor Keyence IX-080 (Source: author's own processing)

The design of the sensor placement was carried out with regard to the mechanical constraints of the workstation, the trajectory of the manipulator, and the accessibility of the assembly space. The sensing head was mounted on a rigid holder to ensure a stable view of the inspected area and to minimize the influence of vibrations. An important aspect was maintaining an appropriate distance between the sensor and the object, enabling optimal use of the laser triangulation measurement range. After mechanical installation, position calibration was performed to compensate for minor deviations caused by mounting.

Sensor configuration was carried out in several steps. First, a reference image representing the correct assembly state was created. This image serves as the basis for comparison with current measurements. Subsequently, detection zones were defined in which the inspected components are located. For each zone, measurement tools combining image analysis and height profiling were configured. This ensured that the sensor could distinguish the presence of a component not only by its shape but also by its spatial position. The configuration also included setting illumination parameters, time delays, and filters to eliminate noise caused by reflections or minor surface irregularities.

After the configuration was completed, the sensor was connected to the line control system. Communication was realized via digital outputs signaling OK or NOK status. These signals were subsequently processed by the PLC, which controls the further course of the assembly operation based on them. The integration was designed so as not to require major interventions into the existing line logic and to allow the sensor to be easily reconfigured if necessary.

The final phase of the implementation was experimental verification of functionality. Testing was carried out under conditions simulating real operation and included several scenarios, including correctly installed components, missing parts, and deliberately introduced positional deviations. The test results made it possible to optimize the settings of the detection tools and to confirm that the sensor is capable of reliably identifying both the presence and absence of the inspected elements. This verified its suitability for long-term deployment in automated manufacturing.

The Keyence IX camera–laser sensor uses a set of specialized tools that enable analysis of height, shape, and brightness of the scanned object. These tools can be combined with one another, increasing detection reliability even under demanding production conditions. Each tool is designed to address a specific type of measurement task, and their correct configuration enables accurate identification of components with small dimensions or low contrast. The fundamental tool is Height, which is used to measure the height of a point within a defined area. The sensor allows selection of the measurement point size according to the required accuracy—small points with a diameter of 1.0 mm, standard points with a diameter of 1.5 mm, or larger points with a diameter of 3.0 mm. The measurement range depends on the type of sensing head used; for example, the IX-150 head can measure height over a range of approximately 150 mm with a measuring span of ±50 mm. This tool is particularly suitable for detecting the presence of a component based on its height profile.

The Height Difference tool is intended for comparing the heights of two points and evaluating their relative height difference. It enables identification of deviations that may indicate incorrect insertion or a missing component. When multiple tools of this type are used, normalization with respect to a common reference point can be applied, reducing the number of measurement points and shortening measurement time. Normalization also increases result stability in repeated measurements.

Another tool is Monochrome Area, which is used to analyze brightness within a defined image region. This tool compares the current brightness of the object with a reference image (master) representing the correct state. Evaluation is based on a histogram, allowing reliable identification of changes in illumination or the presence of an object with different optical properties. Monochrome Area is particularly suitable in cases where components need to be distinguished based on visual contrast.

The Position Adjustment tool is used to correct displacement of the scanned object relative to the reference image. It utilizes characteristic object contours, which can be adjusted so that only those contour parts relevant for detection are retained. This tool ensures that other measurement tools function correctly even when the object position slightly varies due to handling tolerances or production line vibrations.

The MAX/MIN tool enables evaluation of the maximum or minimum height within a defined window. After defining the area in which the component should be located, the sensor evaluates whether a point with a height within the specified range is present in this area. If the sensor cannot find any point that meets the required parameters, the result is evaluated as nonconforming. This tool is particularly suitable for detecting components that have a characteristic height structure or create a pronounced height profile.

The final tool is Height Area, which allows the combination of area-based analysis with height measurement. It enables evaluation of height characteristics over a wider region, which is useful for detecting components with irregular shapes or for inspecting larger areas where overall height differences need to be assessed.

Together, these tools form a flexible system that enables accurate and reliable component detection in automated assembly processes. Their appropriate combination ensures high measurement stability even in environments with variable conditions, which is essential for high-quality and repeatable production.

After a detailed study of the configuration options and application modes of the IX-080 camera–laser sensor, a strategy for its experimental verification under real production conditions was defined. The sensing head will be rigidly mounted on a holder designed and manufactured using additive 3D printing technology (Fig. 2). The holder was subsequently mounted on an extension performing vertical motion via a pneumatic cylinder, enabling precise positioning of the sensor close to the turbocharger area to be inspected. This solution ensures stable sensor positioning, minimizes the influence of vibrations, and allows repeatable sensing under identical conditions.

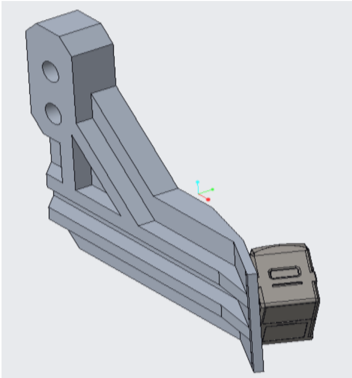

Figure 2. 3D model of the holder for mounting the camera–laser sensor (Source: author's own processing)

The testing strategy was designed to provide a sufficiently extensive and representative data sample from real operation. Over three weeks of continuous production, all images and measurements from the sensor were systematically collected, with this period covering various changes in lighting conditions, tool wear, handling variability, and other operational influences that may affect detection stability. The resulting dataset made it possible to verify not only the basic functionality of the sensor but also its long-term reliability and resistance to disturbing factors.

3.1 Implementation Procedure for Sensor Configuration in the Assembly Application

The configuration process of the camera–laser sensor is conceptually simple; however, its successful application in an automated production process requires a detailed understanding of the available functions and measurement tools. A key prerequisite for reliable detection is the proper setting of image quality and the creation of a reference (master) image, which serves as a standard for subsequent comparisons (Fig. 3).

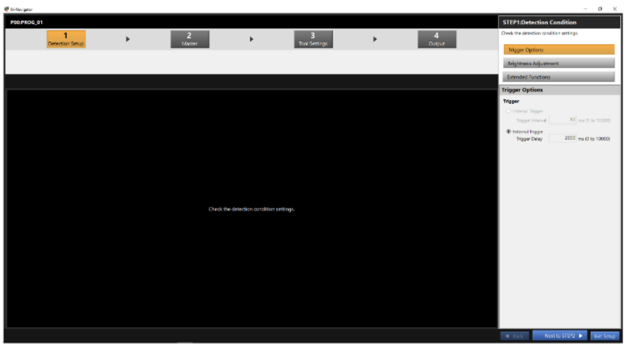

Figure 3. Initial detection setup in the IX-Navigator application environment (Source: author's own processing)

The first step in the configuration is setting the capture start delay. The sensor is connected to a PLC device, which generates an external trigger pulse at the moment when the inspected component is within the camera's field of view. The time delay was set to 2000 ms after receiving the PLC pulse, ensuring synchronization of image capture with communication between the sensor and the supervisory PC (Fig. 4).

Next is the configuration of image quality. The image brightness is adjusted using the Brightness tool, with correct selection of the capture mode being essential for achieving optimal focus. The system also allows adjustment of the illumination intensity, which is particularly important when imaging reflective metallic surfaces (Fig. 5).

In the final phase of setting image quality, it is possible to choose between a preference for higher capture speed or higher sensitivity. In the current application, higher sensitivity was selected, as the priority is to obtain the highest-quality image for reliable detection of small components.

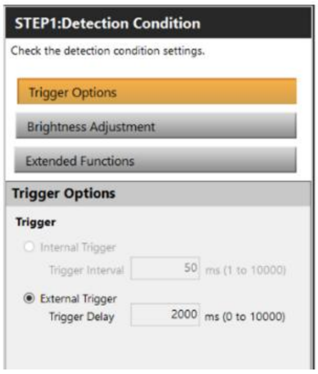

Figure 4. Configuration of the image capture start delay (Source: author's own processing)

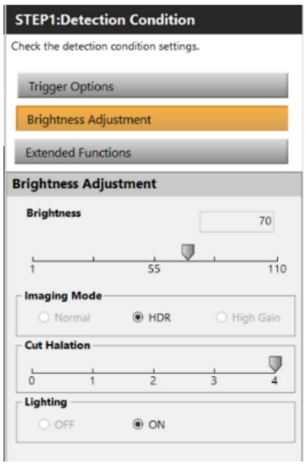

Figure 5. Image brightness and illumination settings (Source: author's own processing)

The next step is creating the master image (Fig. 6), which represents the correct assembly state. In the image, a red-colored area can be identified, indicating a zone outside the measurement range of the sensing head. Since the inspected components - the circlip and the spring - are located within the allowable range, the sensor is able to capture them reliably.

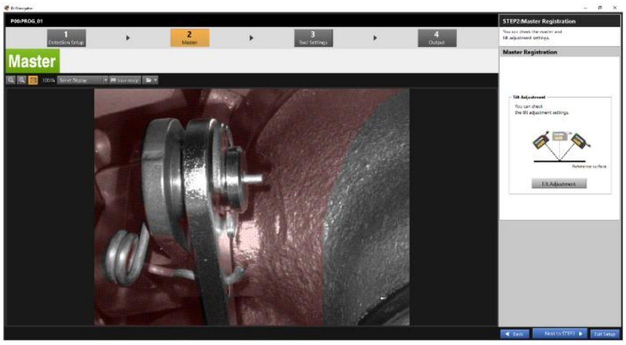

Figure 6. Creation of the master image (Source: author's own processing)

After creating the master image, the **Tilt Adjustment** tool can be used to verify the correct distance of the sensor from the object. The color scale provides immediate visual feedback. Warm colors (red) indicate that the object is too close, while cool colors (blue) indicate that the object is too far (see Fig. 7). This behavior is consistent with other Keyence visualization tools, which use the same color logic to display deviations (e.g., in Height Difference or Step Tool).

In the next step, the measurement tools for detecting individual components are configured. In this application, the MIN/MAX and Position Adjustment tools were used. The first configured tool was MIN/MAX in MAX mode, which was used to detect the lower protrusion of the spring. For this purpose, a tolerance range from +20 mm to –10 mm was defined. The same procedure was applied for detecting the upper protrusion of the spring.

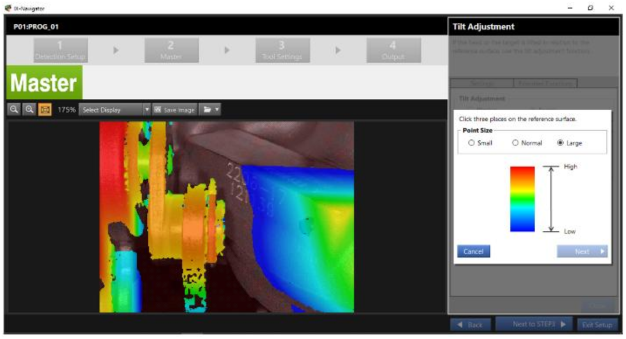

Figure 7. Sensor distance verification (Source: author’s own processing)

Detection of the circlip was more challenging, as its position varies depending on how it is placed by the operator. By analyzing typical variations during placement, a stable reference point was identified where the circlip can be reliably detected. In this case, the MIN/MAX tool was also used, with the tolerance range set from +5 mm to –2.5 mm (Fig. 8).

The final detection tool used was Position Adjustment, which compensates for variability in the component’s position. This tool allows a fixed reference point to be defined, from which the positions of all detection zones are subsequently derived (Fig. 9).

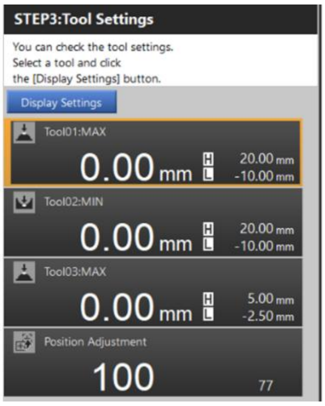

Figure 8. MIN/MAX tool settings for detecting the spring and circlip (Source: author’s own processing)

Figure 8. Configuration of the Position Adjustment tool (Source: author’s own processing)

The final step in configuring the sensor was setting the output signals to the PLC, which ensure correct interpretation of the detection results within the production line control system.

3.2 Testing Results of the Keyence IX-080 Camera–Laser Sensor

For the successful integration of the Keyence IX-080 camera–laser sensor into the production process, extensive experimental testing under real operational conditions was essential. The goal of the testing was to verify the reliability of detecting critical components (the circlip and the spring) under full production load and in an environment with natural variability in handling, lighting, and surface reflections.

Testing was conducted over three weeks of continuous production, with the sensor deployed on the assembly line without any modifications to the production cycle. In total, 18,000 assembly cycles were evaluated, providing a sufficiently large sample for statistical assessment of detection reliability. The testing also included deliberately introduced error conditions (missing circlip, missing spring, various circlip rotations) to verify the Poka-Yoke functionality of the system (Figs. 10–12). Achieving 100% Poka-Yoke is critical, as it eliminates the possibility of defective parts proceeding to subsequent production stages, thereby significantly increasing process safety and final product quality.

Of the total images, 17,980 were evaluated as correct (OK) and 20 as incorrect (NOK). The detection success rate thus reached:

$$p = \frac{17980}{18000} = 0.9989\ (99.89\ \%) \qquad (1)$$

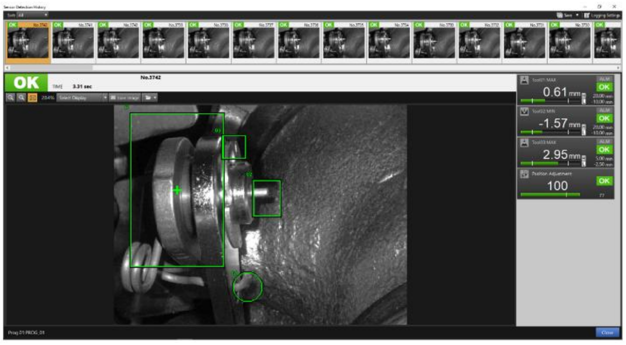

Figure 10 Example of a correctly evaluated image – all measurement tools within tolerance, result OK (Source: author’s own processing)

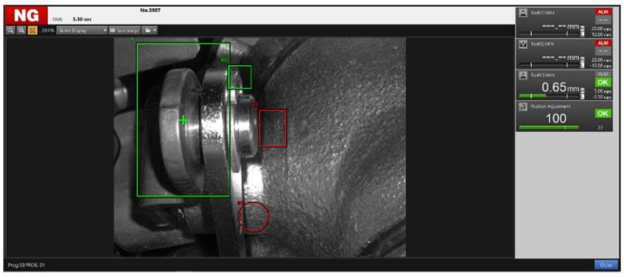

Figure 11 Example of a deliberately introduced error – missing components evaluated as NG using the MAX/MIN tools (Source: author’s own processing)

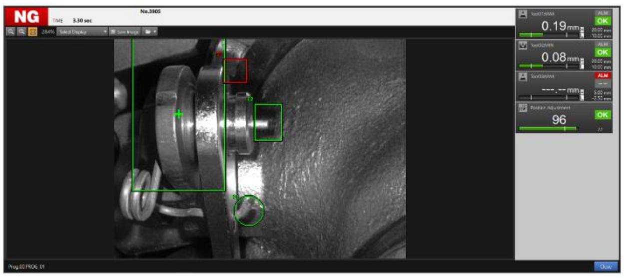

Figure 12 Example of an incorrectly evaluated image – alarm at Tool03, despite correct values at Tool01 and Tool02 (Source: author’s own processing)

Since each assembly cycle represents an independent trial with two possible outcomes (correct detection/incorrect detection), this constitutes a typical binomial experiment. The success rate is therefore an estimate of the true probability of correct sensor detection in the population of all possible assembly cycles.

The binomial model is particularly suitable because:

- each trial occurs under the same conditions,
- the outcome is dichotomous,

- the number of trials is large (n = 18,000),
- the probability of success is high, allowing for precise interval estimates.

To estimate the confidence interval for the success rate, the Wilson confidence interval was used, which is preferred over the classical Wald interval, especially for high success rates and a low number of failures. The Wilson interval provides a more stable and less biased estimate, as it corrects for the issues of symmetry and extreme values.

Classical Wald interval:

$$\hat{p} \pm z\sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \quad (2)$$

is unreliable for high values of p and a small number of failures because:

- assumes symmetry around $\hat{p}$
- may produce intervals outside the [0,1] range
- is biased at extreme values

For this reason, the Wilson interval is used, which has the following form:

$$\widehat{p_w} = \frac{\hat{p}+\frac{z^2}{2n}}{1+\frac{z^2}{n}} \quad (3)$$

$$ME_w = \frac{z}{1+\frac{z^2}{n}}\sqrt{\frac{\hat{p}(1-\hat{p})}{n} + \frac{z^2}{4n^2}} \quad (4)$$

where:

- z=1.96 for a 95% confidence interval,
- $\widehat{p_w}$ is the center of the interval
- ME_w je margin of error.

Resulting interval:

$$p \in (0.9980, 0.9994)$$

(99.80%, 99.94%) (5)

This interval indicates that the true probability of correct sensor detection lies within the specified range with 95% confidence. The interval is very narrow, which is a result of the large sample size and the high stability of the measurements.

4 DISCUSSION

The results of the experimental verification of the Keyence IX-080 camera–laser sensor confirmed its high reliability in detecting critical components in the turbocharger assembly process. The achieved success rate of 99.89% across a sample of 18,000 assembly cycles meets the requirements for automated inspection systems in the automotive industry. The narrow Wilson confidence interval (99.80%, 99.94%) further demonstrates that the sensor exhibits stable performance even under the natural variability of production conditions.

Deliberately introduced error conditions were detected with 100% accuracy, confirming the system's capability to function as a Poka-Yoke. This feature is extremely important, as it prevents defective parts from entering subsequent production stages, significantly reducing the risk of faults in the final product. From a process engineering perspective, this represents a major contribution, supporting the stability and predictability of the assembly process.

The incorrectly evaluated cases (20 out of 18,000) exhibited common characteristics, highlighting the limitations of the current measurement tool settings. Most frequently, these involved local reflections on metallic surfaces, contrast changes caused by variable lighting, or slight shifts of the reference point during handling. These phenomena are typical of a dynamic production environment and pose a challenge for all optical and hybrid sensing systems.

The results suggest that further reliability improvements could be achieved by optimizing the MAX/MIN tool settings, expanding the set of reference contours for Position Adjustment, and adding adaptive thresholds in the Monochrome Area tool. These adjustments could reduce the system's sensitivity to reflections and minor geometric deviations, further enhancing detection robustness.

Overall, it can be concluded that the implemented sensor system demonstrated a high technical level, stability, and suitability for long-term deployment in automated production. The results also provide valuable insights for the further development of sensor applications in a Smart Factory environment.

5 CONCLUSIONS

This article presented the design, implementation, and experimental verification of the Keyence IX-080 camera–laser sensor in automated turbocharger production. The hybrid sensor system, combining two-dimensional imaging with laser height measurement, demonstrated high reliability in detecting small metallic components that are critical for the proper function of the assembly.

Experimental testing under real production conditions confirmed that the sensor achieved a success rate of 99.89%, with deliberately missing components detected with 100% accuracy. These results demonstrate that the implemented system meets Poka-Yoke requirements and significantly contributes to reducing the risk of assembly errors.

The Wilson confidence interval confirmed measurement stability even with a large data sample and variable operational conditions. The identified mis-evaluations provide important input for further optimization of the measurement tool settings, particularly in areas sensitive to reflections and positional deviations.

The implementation of hybrid sensor technology represents a significant step toward intelligent and digitized manufacturing. The results show that modern camera–laser systems can effectively support assembly process quality, enhance process stability, and contribute to the fulfillment of Smart Factory principles. Future research may focus on expanding the sensor architecture with additional elements, integrating advanced image processing algorithms, and utilizing adaptive models based on artificial intelligence.

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