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# Re-design of the Quality Control System in the Lighting Industry

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**Abstract**

Nowadays, manufacturing companies face the challenge to maintain low prices, products with customised quality, and a low scrap rate. The case study is focused on one of the global enterprises in the lighting industry.
This study has aimed to analyse and minimize scrap using re-designing the quality control system transferring the end-of-line to an in-process quality approach (in-process inspection).
The quality inspector only checks the finished products; thus, certain components must be discarded. The goal is to minimize the discarding of components in the final step, after they have gone through all processes, by stopping them as early in the process as possible.
After all the implementation was done, in a month of production the decreasing of the scrap has led to an economic reduction in total with 4.661 euro cumulated in different parts of assembly (aluminium, metal and polymer) and the other areas (surface treatment, die casting, mould injection).

**Keywords:** quality; cost reduction; process; assembly, production.

## 1. Introduction

Manufacturing companies are faced with the challenge of producing their products in a short time, at low cost and with high quality to remain competitive [1,2]. In recent years, the transition toward smart manufacturing and Industry 4.0 paradigms has intensified this pressure, requiring the integration of data-driven decision-making and adaptive systems within production environments [3,4]. The importance of product quality as a differentiating factor is growing steadily. As a result, the quality requirements for products are becoming ever more stringent and quality inspection is therefore becoming increasingly important [5,6].
Consequently, for a holistic view of manufacturing, not only individual manufacturing processes but also the inspection steps for checking component quality must be considered, which is why a consideration of the entire manufacturing process and inspection sequence (MPIS) is necessary [7]. MPIS comprises the combined consideration of sequential manufacturing and inspection processes and are used to represent or model the production process of components [8]. In addition, modern approaches integrate big data analytics and cyber-physical systems to enhance transparency and traceability across production systems [9,10].
As a result of increasing quality requirements and thus increasing complexity of production, the risk of scrap increases, which has a negative effect on productivity [11]. A possibility to increase productivity and thus profitability is to identify scrap at an early stage in the manufacturing process sequence. This aligns with recent research that emphasizes the importance of managing product variety and system complexity in modern manufacturing environments [12].
In this way, scrap can be eliminated from the manufacturing process sequence, thus saving costs in subsequent steps. Particularly for electrical articles, there is great potential for cost reductions, since manufacturing and inspection costs are comparatively high due to the production of safety-critical and high-quality products [13]. For early identification of scrap, quality control of component characteristics during production is required in addition to the final inspection of the finished component. This can be further supported by structured Industry 4.0 frameworks that classify and guide the integration of advanced monitoring systems into manufacturing processes [14].
This can be achieved by including physical component inspections, but these are associated with additional costs. For this reason, more prediction models are currently being used for quality control during production, which can also be used for early scrap identification [15]. With the aid of prediction models, it is possible to predict an output (e.g. component characteristics such as surface roughness) based on input (e.g. process variables such as process forces or times) and thus also to identify scrap [16]. Furthermore, integrated production-quality system modelling approaches have shown that combining production planning with inspection strategies leads to improved overall system performance [17].

In mass production industries, the concept of massive scraps is of prime importance. Undetected defects could affect thousands, if not millions, of finished or semi-finished products. Tardy detected defects or failures often lead to product recalls, returns or massive scraps, which are nightmare for industrialists and marketing managers [18]. Recent studies highlight the integration of machine learning with SPC techniques to enhance process monitoring and anomaly detection in complex manufacturing environments [19].

These catastrophic events are not well publicized as they generate losses due to re-manufacturing costs, logistics costs, systematic shrinking of their market share, and severe damage to their image. The consequences for customers concerned can also be catastrophic, ranging from product shortage, injury or death [20]. In this context, statistical process control techniques have been widely extended beyond manufacturing, demonstrating their applicability in complex and high-risk environments [21].

Almost every major event, like massive scraps or equipment breakdown, has different origins. However, they share a common characteristic: their causes, even known, have not been detected by the control system and the failure whatever its origins, has affected a lot of products before being detected. In case of massive scraps, quality control plan fails its mission. Modern continuous improvement methodologies such as Lean Six Sigma emphasize the importance of early detection and systematic prevention of such failures [22].

Recent advances in sampling strategies and adaptive control charts further support efficient inspection planning under uncertainty [23]. Additionally, integrated inspection and production planning models highlight the importance of considering inspection costs and capacity constraints [24]. Practical industrial case studies confirm that structured methodologies and teamwork approaches contribute significantly to scrap reduction and process improvement [25].

**Brainstorming**

It is a generally accepted phenomenon that a group of people interacting with each other to collaboratively solve a problem have almost always had a better outcome than the average of the outcomes of each person working on the same problem individually. This is the reason brainstorming is such a useful tool when approaching a new problem: the contribution of each person helps subconsciously cue other people's brains to think in a higher gear, and this has a multiplying effect that greatly increases the productivity of the group over the individual.

Brainstorming can be conducted in a variety of ways, some more formal than others, but some basic guidelines apply no matter what the structure:

1. Establish the purpose of the meeting: Spend a certain amount of time generating ideas surrounding a particular question or problem.
2. Do not criticize or compliment ideas as they are presented: doing so discourages the multiplying affect desired in the process.
3. Do build and expand on the ideas already presented.
4. Do not stop immediately if the flow of ideas slows down; some lulls are to be expected.
5. Record every idea presented so they can be evaluated later. Some groups find it useful to write each note on a post it notes and stick them up around the room so they can be seen and referenced.
6. After the established time has expired, or the ideas seem to have run dry, the ideas can be categorized and evaluated for quality or usefulness, depending on the situation. Following these guidelines ensures the optimum environment for producing ideas but still leaves plenty of room for customizing the session to the company, group, and problem being evaluated. Brainstorming can be used any time ideas are needed to proceed with a project [14].

### 1.2. Quality Management Concepts

Quality Assurance (QA) is a process-driven method focused on building quality into the process itself to prevent defects from occurring in the first place. This includes defining standards, training staff, and establishing quality management systems.

Quality Control (QC) is a reactive process that involves testing and inspecting the output of a process to identify and fix any defects before the product is released.

In-Process Quality Control (IPQC) is the monitoring and inspection of products at various stages of production to identify and correct deviations in real time.

### 1.3. Research Gap and Research Objectives

Although there is extensive literature addressing quality control, defect prediction, and scrap reduction in manufacturing processes [1–13], several gaps remain insufficiently explored.

Most existing studies focus either on statistical quality control methods or on machine learning prediction models for identifying defective components. However, the integration of these models into real-time production planning and inspection allocation strategies, especially for mass production systems where inspection capacity is limited, is often treated only conceptually and lacks practical validation.

Furthermore, while many authors discuss the benefits of early defect's detection or in-process inspection, few studies provide a quantitative evaluation of the economic impact associated with transitioning from end-of-line inspection to in-process inspection within a real industrial case. This gap is particularly evident in industries with high product complexity and safety-critical requirements, such as the electrical or lighting industry, where inspection costs and scrap losses are substantial.

**The research presented in this paper aims to fill these gaps by:**

Designing and implementing a quality inspection reallocation strategy, shifting from end-of-line to in-process inspection;

Evaluating the economic and operational impact of this transition in a real-world manufacturing environment;

Demonstrating how early defect identification and process-based inspection planning can reduce massive scrap generation and improve overall process efficiency.

Hence, this study contributes to the literature by providing an integrated methodological and empirical framework that supports smart inspection planning, combining production dynamics, risk assessment, and quality control optimization.

## 2. Materials and Methods

### 2.1. Research Context and Case Study Description

This study is based on an industrial case analysis conducted at Glorious Lighting, a member of the LITING UNIVERSAL Group from Hong Kong, a company with more than 20 years of experience in the manufacture of lighting fixtures.
The Romanian company, established in Brăila in 2019, produces lighting equipment primarily for the European IKEA market. By 2024, the company exceeded 900 employees and represents a significant contributor to regional economic development.
The company has several production areas: polymer injection, die casting, metal workshops, surface treatment and assembly.
In each of these areas the inspection method is different as will be explained in the following lines.
In the plastic injection, die casting and metal workshop area, batches are checked according to the number of parts on the pallet.

### 2.2 Methodological Framework

The research follows up industrial engineering methodology, merging process examination, data analysis, and practices of continuous improvement. The objective of the paper is to assess and improve the efficacy of quality control by transforming it from end-of-line inspection to a quality in process system.

### 2.3 Before Implementation

Initially, the company applied for an end-of-line inspection, where a limited number of components were checked depending on the batch size and production area, also this verification was made after all the processes were done.
Quality control way of sampling (Table 1) was based on:

- Number of components per pallet
- Fixed sampling size per batch
- Visual inspection and basic functional checks
- This approach had several limitations, like:
- Delayed defect detection
- Risk of large quantities of non-conforming products
- Limited process feedback

**Table 1.** Way of working for quality control before quality in process.

| Area | Number of components/pallets | Number of components verified |
|---|---|---|
| Plastic injection | <200 | 5 |
| | >200 | 10 |
| Die casting | <300 | 10 |
| | >300 | 15 |
| Metal workshop | <100 | 5 |
| | >100 | 10 |
| Surface treatment | <100 | 10 |
| | >100 | 15 |
| Assembly | On each line of production | One first products + auxiliary materials (the functionality and the assembly of the product as the final customer are visually checked) – that is left assembled in front of each line<br>5 boxes of packaged products + auxiliary materials |

After the brainstorming of the management team was done, the decision was to concentrate on quality improvement.
In the following pages we will see some examples for the quality in process for each area.
The transition from an end-of-line quality control approach to an in-process quality management system has delivered significant improvements across all manufacturing areas of the lighting equipment company, including plastic injection molding, die casting, metal processing, surface treatment, and assembly.
After, quality verifications are made as is shown in the following pages from Table 2 to Table 4.

### 2.4 Implementation by Production Area

#### 2.4.1 Quality in process for polymer injection

**Table 2.** Quality in process for polymer injection area.

| First product verification | Others verification |
|---|---|
| 1 piece from each cavity of the mold (ex: 4 cavities result 4 pcs verified) from the pallet/box where operator place the finish good components that will be found at each equipment that is in function<br>If the product is ok will write with a market on a dot of the component “ok” and sign , after the first product will be put on the equipment<br>If the first product is NOk the quality inspector will check 9 more pieces from each cavity that was NOK.<br>From 9 pieces verified if it is found 2 more pieces NOK from the same cavity will put a stop label on all the production on that shift on the same equipment and will announce the shift leader<br>If all 9 pieces are ok from the same cavity quality inspector will just announce like an warning | 2 pieces from each cavity that are on the pallet/ box. where the operator put the good components that will be found at each equipment that is in function.<br>If both of pieces from each cavity are good will just put the components back in the pallet/box<br>If will find 1- or 2-pieces defect from 2 they will verify 8 more pieces from each cavity that was NOK<br>If will find 2 more pcs NOK from 8 pieces verified will put a stop label on all the production on that shift on the same equipment and will announce the shift leader<br>If all 8 pieces are ok from the same cavity quality inspector will just announce like an warning |

As shown in Table 2, the quality in plastic injection area is done evaluated based on several key process indicators.
If a test is necessary, the quality inspector and line leader will put a stop label on all the quantity produce and will announce to the group that, after the test, a decision will be made. After the test is provided and a decision is made – if the components are ok, quality inspector with the line leader will take the stop from the pallets/boxes.
Special tasks:
1. For the plastic cases the diameter when they are cold should be 235 mm. If they are not like this quality inspector will announce, like a remark.
2. For lamp holder cap, quality inspector needs to verify if the operator does not put the components on top of each other when they are still warm, because it expands.
3. In injection, because we have three shifts, what is produced on third shift will not be verified by quality
4. When injection employees change the mold, shift leader has the responsibility to announce quality inspector, so the quality inspector will come and verify the first product as soon as possible.
5. For concreate bases (had plastic cases), all the verification will be done in old way
- Secure if they use the correct recipe
- Recipe for concrete bases: Slag - 79%, concrete - 12%, water - 9%

#### 2.4.2 Quality in process for die casting and metal workshop

**Table 3.** Quality in process for die casting and metal workshop.

| First product verification | Others verification |
|---|---|
| 1 piece from the pallet/box where operator place the finished good components that will be found at each equipment that is in function<br>If the first product is OK, the quality inspector will write with a marker on outside of the component “ok” and sign and the first product will be put on the equipment or near on a table.<br>If the first product is NOK, the quality inspector will check 9 more pieces<br>If will find 2 pcs NOK from 10 pcs verified will put a stop label on all the production on that shift on the same equipment and will announce the shift leader<br>If it remains just with the first product NOK, quality inspector will just announce like a warning | will take from each process 5 pieces from each pallet/box where operator place the good components<br>If pieces are good will just put the components back in the pallet/box<br>If will find 1 piece defect from 5 they will verify 5 more pieces<br>If will find 2 pieces defect from 10 they will put a stop label on all the production on that shift from the same operator and will announce<br>If will not find any more defects they will just announce like a warning |

Table 3 shows how quality checks are done in die casting and metal workshop areas with the steps of verifications that should be made.

If a test is necessary, the quality inspector and line leader will put a stop label on all the quantity produced before by the same operator and will announce at the group that after the test a decision will be made (and tag the line leader and the responsible of the area). After the test is provided and a decision is made – if the components are ok, quality inspector with the line leader will take the stop from the pallets/boxes.
Special tasks:
1. When metal or die casting employees change the mold, shift leader has the responsibility to announce quality inspector, so the quality inspector will come and verify as soon as possible the first product.
2. Die casting responsible need to provide some rules for the kick of the components for the extra aluminum – quality inspector needs to verify if the rules are respected by the operators, if the rules are not respected quality inspector will announce on the group and tag the responsible of the area.
3. For the first day quality inspectors will receive from feeder for die casting some special cotton gloves and for the metal will receive 2 types of gloves to be protected from scratches
4. When the quality inspector will need new pair of gloves, the quality inspector needs to come to the feeder with the pair of gloves that is damaged, and they will receive a new one.

5. For Die casting when quality inspector will find defects, if they need to announce problems on the WeChat group, they will tag just the responsible of the area, if they need to put stop, they will speak with the technician of the shift in die casting
6. For Die casting, because we have three shifts, what is produced on third shift will go without quality verification.

**2.4.3 Quality in process for liquid paint in surface treatment**
Figure 1 gives an overview of how quality operators should check in surface treatment area for liquid paint.

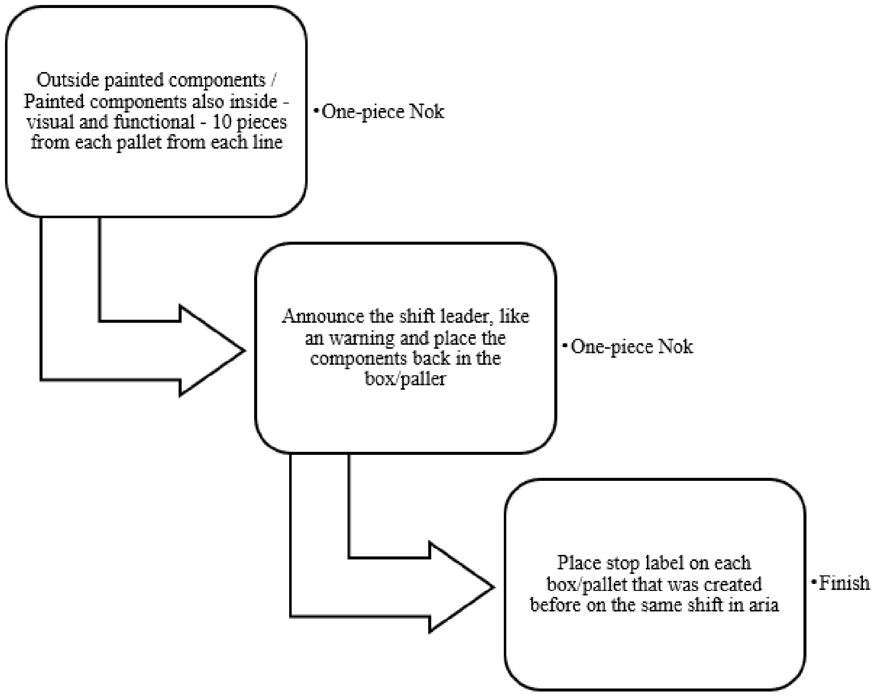


**Figure 1.** In-process quality inspection workflow for surface treatment.

**2.4.4 Quality in process for powder coating in surface treatment**
In surface treatment area for powder coating lines, the steps of verification are presented in Table 4.

**Table 4.** Quality in process for powder coating in surface treatment.

| Steps of verifications | Way of working |
|---|---|
| Hangers' verifications<br>For the hangers that are burned - check if operator first hits them on the ground | 5 hangers verified to have not much powder on it, so the electroplating can be done - 2 NOK - announce the shift leader |
| Blank components (from China or from metal workshop) - visual and functional | 5 pieces from each box/pallet – the verification will be done in order of priority of the powder lines<br>If 1 piece is defect, will verify 15 more pieces and if they will find 4 pieces or more, stop label will be placed on box/pallet<br>If less than 4 pieces of defects, quality inspector will announce the shift leader as a warning<br>If the defects are from China, the quality inspector from surface treatment need to announce incoming team |
| Verify the conformity of the hangers with the components (5 hanger with all the components that are on it) – visual | Conformity of the hangers, how the components are placed on them and the conformity of components<br>If quality inspector will found some deviation will announce the shift leade |
| Air gun use compliance for bent edge components (for 5 hangers with components) | If necessary to use the air gun and the operator doesn't use it - quality inspector will announce |
| Conformity of painted components on hangers when leave the oven (5 pcs of hangers with components) – visual | Painted components - visual and functional 20 pieces<br>If 4 pieces NOK from 20 will stop on everything that is produced before in the same shift<br>If less than 4 pcs of defects, will just announce on the group |

**2.4.5 Quality in process for assembly line for one lamp (each product has a different process for critique to quality)**
Quality controllers should check the compliance for different components:
- Cable
- Lamp holder cup assembled with plastic cap (turning by hand)
- Cord grip placement (EU version)
- Insulator placement and wire know creation before insertion of the wires (NA verion)
- Lamp holder and wires insertion compliance (pushing and pulling)

- Correct placement of the button (facing outwards) and the conformity of the cable (no cracks/pinches)
- Functionality and hi pot
- stability of the base and the conformity of the placement of the joint, washers, nut and plastic cover
- Checking the presence of joints on each tube
- Checking the number of tubes placed in the box (5 pieces)
- Check base assembly with pipes.
- Check perpendicularity
- Checking the uppermost tube thread and its placement in the box
- Checking compliance with information and symbols on the box
- Checking labels (Visually by comparing with the documentation in the file)

## 3. Results

By integrating quality controls directly into each production stage, defects are now detected and corrected at their source rather than at the final inspection. This proactive approach has led to a substantial reduction in scrap, rework, and non-conforming products, particularly in high-impact processes such as plastic injection and die casting, where early parameter deviations previously generated large volumes of defective parts.

In metal processing and surface treatment operations, in-process quality checks have improved process stability and consistency, resulting in better dimensional accuracy, improved surface finishes, and enhanced coating adhesion. These improvements have contributed to a measurable decrease in customer complaints related to functional and aesthetic issues.

Within the assembly area, the implementation of in-process inspections and standardized work instructions has reduced assembly errors and ensured better component compatibility. As a result, first-pass yield has increased, and final inspection times have been significantly reduced.

Overall, the shift to in-process quality has strengthened process ownership, increased operator awareness, and promoted a culture of continuous improvement. Quality is no longer verified only at the end of the line but is now built into every step of the manufacturing process, leading to improved product reliability, reduced costs, shorter lead times, and higher customer satisfaction.

The comparison of scrap data between May 2025 and June 2025 clearly demonstrates the financial impact of shifting quality control from end-of-line inspection to in-process quality management.

Following the implementation of in-process quality controls in key manufacturing areas (plastic injection, die casting, metal processing, surface treatment, and assembly), June 2025 recorded a significant reduction in total scrap costs compared to May 2025. This reduction reflects not only fewer rejected parts, but also lower losses related to material consumption, machine time, labor, energy, and secondary handling.

In May 2025, scrap was predominantly identified at the final inspection stage, where the full production cost had already been incurred. As a result, non-conforming parts represented a high direct financial loss. In contrast, in June 2025, deviations were detected earlier in the process, limiting the value added to non-conforming parts and significantly reducing the overall scrap cost per unit.

The month-over-month decrease in scrap value translates into a visible and measurable cost saving, confirming that in-process quality acts as a cost prevention mechanism rather than a cost detection activity. These savings contribute directly to improved manufacturing margin and allow resources to be redirected toward productivity improvements and process optimization.

Overall, the reduction in scrap costs from May to June 2025 provides tangible financial evidence that embedding quality into the process generates immediate economic benefits, not only technical improvements, as can be visible in Table 5.

**Table 5.** Comparative table for the differences between the scrap reduction from end-of-line quality control approach to an in-process quality management system.

| Area | May 2025 [euro] | June 2025 [euro] | Difference between May and June |
|---|---|---|---|
| Aluminum Assembly | 310 | 125 | 185 |
| Metal Assembly | 954 | 591 | 363 |
| Plastic Assembly | 476 | 378 | 98 |
| Surface treatment | 2385 | 1171 | 1214 |
| Die casting | 3626 | 1043 | 2583 |
| Plastic Injection | 808 | 398 | 410 |
| Total | 8367 | 3706 | 4661 |

## 4. Discussion

The results obtained after the transition from end-of-line quality control to in-process quality management indicate a clear improvement in scrap reduction and cost performance. However, beyond the numerical and financial outcomes, these results require a broader interpretation to fully understand their significance and sustainability.

One of the key discussion points is that the reduction in scrap observed between May and June 2025 cannot be attributed solely to increased inspection activities, but rather to a fundamental change in how quality is managed within the production process. By moving quality controls upstream, process deviations were identified earlier, allowing corrective actions to be taken before significant value was added to the product. This confirms that in-process quality primarily acts as a preventive mechanism, reducing the risk of high-cost non-conformities.

Another important aspect is the variability of impact across different manufacturing areas. Processes with higher technical complexity and higher material cost, such as plastic injection and die casting, showed a stronger financial response to early defect detection. In contrast, areas such as assembly benefited more from error prevention and standardization rather

than direct material savings. This indicates that the effectiveness of in-process quality depends on process characteristics and cost structure and therefore requires tailored implementation strategies.
The discussion must also consider the organizational and behavioral effects of this transition. In-process quality increased operator involvement and accountability, shifting responsibility for quality closer to the point of value creation. While this change contributed to faster problem identification, it also required additional training, clearer work instructions, and cultural adaptation. The long-term success of the system will depend on maintaining this level of engagement and avoiding a return to a purely inspection-driven mindset.
Finally, it is important to acknowledge the limitations of the current analysis. The comparison covers only a short time, and external factors such as production volume, product mix, or learning effects may have influenced the observed results. For this reason, continuous monitoring over a longer timeframe is necessary to confirm the stability of the improvements and to quantify their full financial impact.
In conclusion, the discussion supports the view that in-process quality is not only a technical improvement but a strategic shift in quality management. Its true value lies in its ability to prevent losses, support informed decision-making, and create a sustainable foundation for continuous improvement.
These results are reliable with recent research on in-process quality control and also for the predictive manufacturing.

**5. Conclusions**
This research starts to evaluate the influence of shifting from a rudimentary end-of-line quality control to an in-process quality approach in a lighting manufacturing company. The results clearly prove that incorporating quality control directly in the processes of production leads to measurable and immediate financial benefits, thus supporting the principal research aim of enhancing quality efficacy through early non-conformity detection.
The factual analysis, especially the comparison of scrap data between May and June 2025, delivers precise evidence that the application of quality in-process guides to prompt and measurable economic benefits. The observed diminution in scrap costs validates that identifying non-conforming products near to their origin minimizes the waste of the material, reduces rework, and decreases generally the cost of the production. These data confirm the study's fundamental assumption that proactive quality systems are better than traditional approaches.
Beyond cost reduction, the implementation of in-process quality has contributed to improving process stability and clearer ownership of quality at all production levels. The involvement of operators and the alignment of quality responsibilities with process execution have strengthened the foundation for sustainable quality performance and continuous improvement.
Although the current results are based on a limited evaluation period, they provide strong evidence that the strategic shift toward in-process quality represents a long-term improvement rather than a short-term correction. Continued monitoring, further process optimization, and expansion of in-process controls across all manufacturing areas are expected to amplify these benefits over time.
In conclusion, embedding quality within the process transforms quality from a final verification activity into a core operational capability. This shift supports higher product reliability, improved financial performance, and increased competitiveness in the lighting industry.
This study supplies a practical and capable structure for incorporating in-process quality control in lighting manufacturing systems. It provides the elevation of Quality 4.0 by proving how early identification can be implemented in real manufacturing conditions.

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The author(s) report no conflicts of interest.

**Data Availability Statement**
The data supporting the findings of this study are not publicly available due to confidentiality agreements with the company where the work was conducted. Access to the data may be granted upon reasonable request and with permission from the company.

**Institutional Review Board Statement**
Ethical review and approval were not required for this study, as it did not involve human participants or animals.

**CRediT Author Statement**
Author 1: Conceptualisation; Methodology; Data curation; Formal analysis; Investigation; Software; Validation; Visualization; Writing – original draft; Writing – review & editing.
Author 2 (Coordinator): Supervision; Project administration; Writing – review & editing.
All authors have read and approved the final manuscript.

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