Doctoral Dissertation
Doctoral Program in Management, Production and Design (37th Cycle)

Collaborative robots in quality control and management: applications and challenges

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1. Introduction

In recent decades, the manufacturing sector has undergone a significant transformation, moving from traditional mass production to a more flexible model of mass customisation. This evolution represents a move away from the production of uniform products in large quantities to the production of highly personalised items tailored to individual preferences and specifications. Mass production, characterised by its efficiency in high volume but low variety, contrasts sharply with mass customisation, which emphasises variety and individuality at the expense of speed of production and economies of scale (Alford *et al.*, 2000; Piller and Müller, 2004).

In mass customisation, product quality becomes even more important, as customer expectations are significantly higher due to the personalised nature of each product (Squire *et al.*, 2006). Quality assurance, which is critical in mass production to maintain standardisation, becomes even more complex as it must adapt to the diverse requirements of customised products. Defects or variations in product quality can be caused by many factors, including variability in raw materials, human error and inconsistencies in manufacturing processes.

In this context, collaborative robots (cobots) have emerged as essential tools. Cobots combine the precision and repeatability of traditional robotic systems with the adaptability and problem-solving skills of human workers, making them ideal for dynamic and flexible manufacturing environments (Torn and Vaneker, 2019). Indeed, setting up an automated production facility for customised production involves significant costs and requires highly specialised training for operators (Liker and Morgan, 2006).

Accordingly, this Doctoral Dissertation analyses quality inspections in collaborative robotics by addressing several key aspects. There are several important areas where this Dissertation provides an original contribution to the study of quality management in Human-Robot Collaboration (HRC). The following Research Questions (RQs) are specifically addressed throughout the Dissertation:

RQ1: How are collaborative robots used in quality control?

RQ2: Why is there a shift from manual to collaborative assembly processes?

RQ3: What parameters influence the quality of collaborative assembly processes? And what is the relationship between these parameters?

RQ4: What tools can be provided to monitor quality in collaborative assembly?

In order to systematically address the research questions posed, this dissertation is organised into six distinct chapters. A significant part of the analysis is devoted to present the growing importance of collaborative robots (cobots) in the manufacturing sector. In particular, it focuses on how cobots integrate human cognitive capabilities with robotic precision, thereby improving both the efficiency and quality of manufacturing processes. The Dissertation carefully reviews existing literature and various case studies to showcase the innovative use of cobots in quality control environments and to identify key areas where further research is needed.

Further research explores the operational and functional frameworks that govern cobots, providing a detailed classification of the current literature along with real case studies. This classification explores several dimensions, including industry types, process objectives and quality control paradigms, all of which contribute to a comprehensive examination of cobot applications in quality-focused environments. In addition, the study evaluates both the benefits and limitations of using cobots, considering variables such as inspection types, communication modalities, and the balance between human factors and robotic efficiency.

The research progresses to explore the impact of cobots on assembly lines, with a particular focus on end-of-line quality control processes. It argues for the strategic repositioning of quality control tasks at the beginning of the line to prevent the propagation of defects. A comparative analysis of collaborative systems versus traditional setups is undertaken to assess improvements in efficiency, safety and quality, thereby supporting a shift towards more collaborative methodologies.

The thesis also examines factors that affect collaborative assembly processes, particularly those that affect human operators, such as stress and general well-being. It presents advanced monitoring tools and techniques, such as the use of electrodermal activity to measure stress levels in cobot-assisted assembly processes. These methods are designed to provide real-time insights into both assembly quality and operator well-being, emphasising the symbiotic relationship between these factors.

Finally, the Dissertation presents advanced techniques for real-time quality monitoring in collaborative assembly processes. These methods include statistical process control techniques and the use of digital twin technology to simulate and prevent potential assembly errors. The discussion concludes with the presentation of a novel, non-invasive method for real-time quality control of electronic boards, highlighting the broad applicability of quality concepts and signalling potential innovations in collaborative manufacturing.

2. State of the art

Cobots have become a crucial aspect of Industry 4.0, and are evolving into Industry 5.0's vision of a human-centred manufacturing environment (Gervasi *et al.*, 2022). Unlike conventional robots, which require separation from humans, cobots work alongside human operators, enabling direct interaction (Hentout *et al.*, 2019). This synergy increases productivity and minimizes worker fatigue by combining the precision and consistency of robots with the adaptability and cognitive abilities of humans (Gladysz *et al.*, 2023). This collaborative model marks a significant shift toward integrating automation in a way that leverages the unique strengths of both humans and machines (Villani *et al.*, 2018).

The integration of cobots into production lines has had a revolutionary impact on assembly and quality control (Verna, Puttero, *et al.*, 2022). Despite their widespread use in manufacturing, cobots remain relatively underutilised in quality assurance (Verna *et al.*, 2023). Quality control remains a critical success factor for companies in competitive markets, preventing defective products from reaching customers and protecting the company's reputation (Montgomery *et al.*, 2010). Increasing consumer demand for high quality products has led academia and industry to explore innovative solutions, such as cobots, to improve quality control processes.

The emergence of Quality 4.0 represents a significant shift in quality management, integrating Industry 4.0 technologies to improve product quality and maintain competitiveness (Antony *et al.*, 2021; Sony *et al.*, 2020). This paradigm emphasises the role of cobots in ensuring defect-free products that meet customer expectations, a critical factor in consumer decision making (Küpper *et al.*, 2019). The adoption of Quality 4.0 practices, such as real-time monitoring and predictive maintenance through big data analytics, provides strategic advantages by preventing production problems and defective output. This evolution in quality management drives innovation and optimises business models through improved management of production processes (Antony *et al.*, 2021). Backed by scientific research and case studies, the integration of cobots into quality control processes has been shown to efficiently meet the increasing demand for high-quality products, thereby improving customer satisfaction.

However, despite the potential benefits, cobots are not yet widely used in quality control and are more commonly used in assembly processes. By analysing the scientific literature and real case studies, this dissertation provides an overview of the current state of the art in this area. The aim is to identify the factors limiting the adoption of cobots in quality control and to propose solutions to overcome these barriers. Key barriers include high initial costs, lack of technical expertise among workers, integration challenges with existing systems, data security concerns, and regulatory compliance issues. Overcoming these challenges could facilitate the wider adoption of cobots in quality control.

In examining the integration of cobots in industrial quality control, the study reveals a notable under-utilisation of cobots despite their promising benefits. These benefits include automated real-time monitoring capabilities that could significantly improve quality assurance processes. However, challenges such as the complexity of integrating these systems into existing production lines and the significant training requirements for operators have hindered widespread adoption. This forms the basis of the first research question (RQ1) investigated in the thesis.

The analysis also shows a contrast in the integration patterns of cobots, with more successful adoption in assembly than in quality control. This discrepancy is supported by a robust body of research favouring the use of cobots in assembly tasks, which facilitates their integration. Based on these findings, the thesis proposes a focused investigation of cobot integration into assembly operations as a proactive error prevention strategy. This approach is expected to not only streamline operations, but also improve cost efficiency and reduce material waste, in line with sustainable manufacturing objectives. The discussion highlights the potential of early stage cobot deployment to improve both the efficiency and sustainability of manufacturing practices.

3. Main results and discussion

As noted above, despite technological advances, the use of cobots for direct quality control in modern manufacturing environments remains limited. Cobots have the potential to significantly improve productivity and quality by shifting from a reactive to a preventive approach to quality management. This shift focuses on using cobots to proactively prevent defects during the assembly phase, thereby increasing the sustainability and effectiveness of quality control measures. This dissertation emphasises a paradigm shift in the use of cobots - from merely detecting defects to strategically enhancing upstream quality assurance within collaborative assembly processes. It reviews the current use of cobots, evaluates the quality parameters they influence, and highlights how these integrations improve production quality. The complexity of collaborative environments, coupled with dynamic product requirements and socio-economic changes, necessitates innovative approaches to human-robot collaboration (HRC), requiring intelligent job allocation and system adaptability in smart manufacturing environments.

3.1 Manual vs. collaborative assembly

Understanding assembly complexity is crucial for improving both operator performance and the assembly process itself. Recent studies have highlighted its impact on key performance indicators such as assembly time, quality defects, and production costs (Alkan *et al.*, 2018; Falck and Rosenqvist, 2012). Effective management of assembly complexity in HRC environments aims to optimize interactions by identifying and minimizing bottlenecks, ensuring more efficient and seamless operations of human-robot teams (Lv *et al.*, 2022).

In this analysis, the assembly complexity model based on Huckel's molecular theory is used to assess the assembly complexity (Hückel, 1932). This model can determine the assembly complexity of any network-based engineering system, taking into account three key factors: the complexity of the individual components (C_1); the pairwise interaction between the connected components (C_2); the overall topology of the system (C_3). By combining these three factors, it is possible to quantify the overall assembly complexity (denoted by C) with the following expression:

$$C = C_1 + C_2 \cdot C_3 \tag{1}$$

In order to analyse how assembly complexity affects productivity and quality in a collaborative assembly environment, the assembly of ARDUINO electronic boards was selected for this study. These boards are particularly suitable for such research because they emulate the assembly processes of printed circuit boards (PCBs), providing insights into the practical challenges and dynamics of real-world electronics manufacturing. An experimental campaign was carried out using the ARDUINO UNO Starter Kit (ARDUINO®) to assemble a product family consisting of six different variants of electronic boards. Figure 1 shows the six electronic boards assembled during the experiments. The primary objective of this experiment was to investigate the effect of assembly complexity on assembly time and the quality of the assembled products.

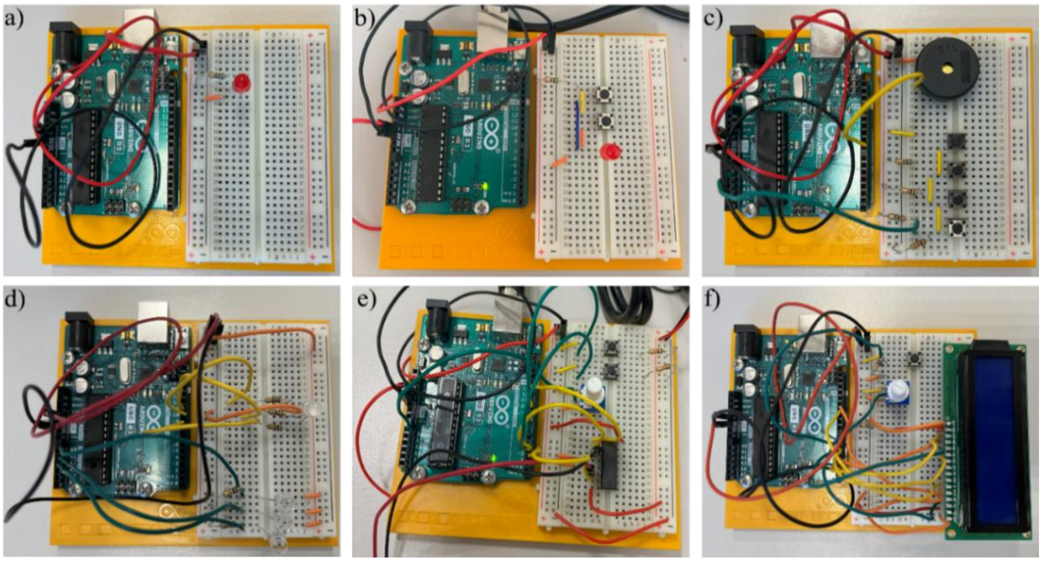

Figure 1. Example of the six assembled electronic boards a) Product 1 (P1); b) Product 2 (P2); c) Product 3 (P3); d) Product 4 (P4); e) Product 5 (P5); f) Product 6 (P6).

To analyse how assembly complexity affects productivity and quality, and to explore the impact of different assembly systems on these factors, three separate experimental studies of electronic board assembly were carried out. The first campaign (Manual) was a fully manual assembly of the boards, where the operator was responsible for the entire assembly process. In the other two campaigns, a cobot assisted the operator during the entire assembly process, based on their actual application in companies using cobots in assembly. In the first collaborative experiment (HRC), the cobot only had logistical functions to pick up the parts at predefined positions while in the second collaborative experiment (S-HRC), the cobot also recognized the parts to be picked up using a camera. During the experiments, information on assembly times and defects was collected. The aim was to investigate the relationship between time and defects and board assembly complexity, and whether these relationships were affected by the assembly system.

Each of the three experimental campaigns involved six expert operators, different for each experiment, for a total of 18 operators. Before the assembly trials, the operators were given preliminary training to ensure a consistent level of skill among the participants and reduce the impact of varying skill levels on the results. The training aimed to familiarise the operators with the assembly process and equipment. To avoid unwanted learning effects, the six operators assembled the six boards in a random order according to an experimental design.

The assembly process consisted of two distinct phases: an assembly phase and a quality control phase. In the assembly phase, each electronic board was assembled manually or with the cobot support, according to the selected assembly strategy. In this first phase, information on assembly time and in-process defects, i.e. defects occurring during the assembly process (Franceschini *et al.*, 2018), was collected. On the other hand, during the quality control phase, an operator experienced in performing quality control checked and detected any remaining defects in the electronic boards. The expert was the same for all three experimental campaigns. During the quality control phase, data on quality control time and offline defects, i.e. defects detected during the control phase (Franceschini *et al.*, 2018), were collected.

As mentioned above, data on productivity and quality of the process and product were collected during the three experimental campaigns. The main goal was to investigate the relationship between productivity and quality and the assembly complexity of the six electronic boards. Regarding process productivity, information on assembly time and quality control time was collected during each experimental campaign. However, quality control time was not further investigated in each assembly system after testing for non-significance at the 95% confidence level using a one-way ANOVA (p-value greater than the significance level of 0.05). Instead, the assembly time increased more than linearly with the assembly complexity. In particular, according to residual analysis, the most suitable model to represent this relationship was the power law model, as follows:

$$AT = \alpha \cdot C^{\beta} \tag{2}$$

where AT is the assembly time, C is the assembly complexity evaluated according to Eq. (1), and α and β are the nonlinear regression coefficients. This suggests that the cognitive effort and deliberation time required for assembly operations increases significantly as assembly complexity increases.

Concerning the defects, the process defectiveness was analysed in terms of total defects (i.e. the sum of in-process and offline defects). In particular, to study the relationship between total defects and assembly complexity, the Poisson regression model was used, as the total defects are count data (Cameron and Trivedi, 2013). The logarithm and square root link functions were considered, and different models were compared up to the third order of the predictor (i.e. assembly complexity C). The selection of the best model was made based on Akaike's Corrected Information Criterion (AICc) and Bayesian Information Criterion (BIC), goodness-of-fit tests (Deviance and Pearson tests), and deviance residual plots (Cameron and Trivedi, 2013; Myers *et al.*, 2012). The results showed that the most appropriate Poisson model was the one using the square root link function, represented as:

$$TD = \gamma \cdot C^2 \quad (3)$$

where TD is the total number of defects, C is assembly complexity evaluated according to Eq. (1), and γ is the regression coefficient.

According to the model in Eq. (2) and (3), it can be seen that the assembly complexity and the characteristics of a product within a product family affect the productivity and the quality of assembly processes. This finding is valid for all three assembly systems, both in terms of assembly times and total defects. In fact, according to Eq. (2), assembly times (associated to process productivity) increase following a power trend when increasing assembly complexity. This implies that an increase in assembly complexity leads to a more than proportional increase in assembly time. On the other hand, according to Eq. (3), the relationship between defects (associated to process quality) and assembly complexity is modelled using a Poisson model with square root link function. Thus, also total defects increase more than linearly with increasing assembly complexity.

To determine if there were significant differences between the different assembly systems, the curves shown in Figure 2 were plotted using the collected data. Figure 2 shows the regression curves of assembly time (Figure 2(a)) and total defects (Figure 2(b)) versus assembly complexity for the three assembly systems. Each curve is presented with its respective 95% confidence intervals, indicating that the regression lines closely follow the curvature of the points and that there are no systematic deviations from the fitted lines.

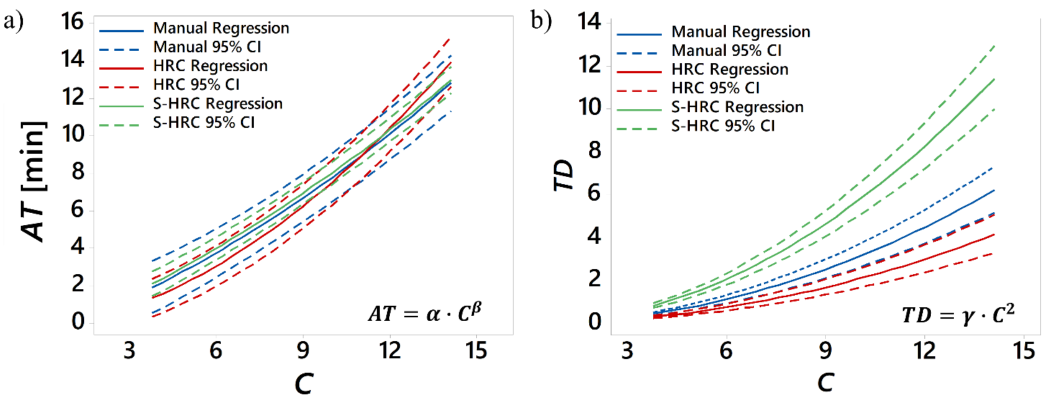

Figure 2. Comparison between Manual, HRC and S-HRC systems on (a) assembly time (*AT*) and (b) total defects (*TD*).

Regarding assembly time, it increases more than linearly with assembly complexity for all three systems. Figure 2(a) shows the three curves, one for each system, that describe this relationship between assembly time and assembly complexity. Since the 95% confidence intervals of the three regression curves overlap, no statistical differences between the three assembly systems in terms of assembly times at the 5% significance level are evidenced.

On the other hand, as far as total defects are concerned (see Figure 2(b)), in all three assembly systems the total assembly defects follow the same trend as a function of assembly complexity, i.e. the Poisson model with a square root link function, according to Eq. (3). As shown in Figure 2(b), the 95% confidence intervals of the three regression curves do not overlap. This implies that there is a difference in the estimated ranges of total defects produced by each of the three assembly systems (i.e. significant differences between Manual and HRC, Manual and S-HRC, HRC and S-HRC scenarios). Consequently, the lack of overlap between these intervals for the three systems indicates that the differences in mean total defects between the systems are statistically significant at the 5% significance level.

There is a statistically significant difference in the quality of the assembly process between different assembly systems when applied to different products within a product family. Conversely, there is no such difference in the productivity of the assembly process. This new finding, which has not been analysed in previous studies, is quite interesting. In fact, the results show that the way in which parts are selected and transported by or to the operator, whether in manual or cobot-assisted systems, does not significantly affect assembly times. As a result, the analysis indicates that there are no significant differences in the assembly times associated with the manual, HRC and S-HRC systems at the 5% significance level.

However, in terms of quality, the assembly system does influence the occurrence of total assembly defects. On closer inspection, and using a 5% significance level, the results show that the HRC system produces fewer defects than the Manual system, which in turn produces fewer defects than the S-HRC system. Therefore, in this specific case study, the HRC system performs better in terms of quality because it effectively eliminates part selection errors, a common problem in manual assembly. This provides an answer to the second research question (RQ2), which is why there is a shift towards more collaborative assembly.

3.2 Human well-being

As the use of cobots becomes more widespread in industry, their role goes beyond operational efficiency and touches on aspects of the human experience. This shift raises the question of how the complexity of assembly affects the well-being of human operators in collaborative environments. Answering this question (related to the third research question RQ3) is essential both for optimising operational parameters and for ensuring that technological advances contribute to favourable working conditions.

Recognising the critical role of operator well-being in collaborative operations, this section systematically integrates established methods for assessing human well-being with the experimental results presented above. Physiological measures can be used to assess the state of human well-being during production, providing an objective measure compared to self-report tools, which may suffer from retrospective post-task bias (Gervasi *et al.*, 2022). Electrodermal activity (EDA) data is used in this study as a measure of human well-being, as it is commonly used as an indicator of the human stress response (Zhao *et al.*, 2018). The Empatica E4 wristband (see Figure 2(a)), a non-invasive biosensor that records EDA information at 4 Hz, was used to collect the EDA data. In addition to EDA, the Empatica E4 also records information on pulsed blood volume (BVP), operator pulse motion (ACC), heart rate variability (HRV) and temperature (TMP). Figure 2(b) shows an example of the raw output provided by the Empatica E4.

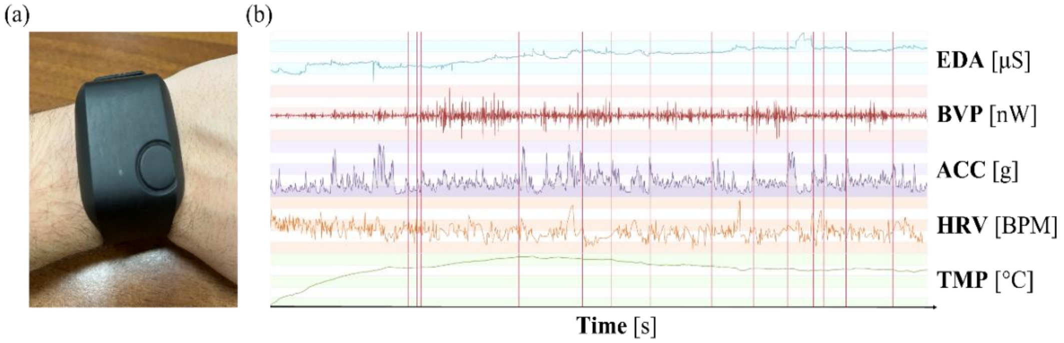

Figure 2. (a) Empatica E4 wristband (b) Empatica E4 outputs vs time.

For each test performed by the operators, this raw signal was recorded and then analysed using the EDA Explorer software (Taylor *et al.*, 2015). This software removes any external noise from the raw signal and decomposes the EDA signal into two types of signals: the tonic signal and the phasic signal. The tonic signal refers to the long-term fluctuations of the EDA signal that are not explicitly triggered by external stimuli. Changes in Skin Conductance Level (SCL) are the best indicator of tonic activity. On the other hand, phasic activity refers to transient changes in EDA that are triggered by typically perceived and externally delivered stimuli. It is best characterized by Skin Conductance Response (SCR) changes. Accordingly, the SCR can be defined as a change in the amplitude of the EDA signal from the SCL to a peak in the response (Zhao *et al.*, 2018).

According to its widespread use (Gervasi *et al.*, 2022; Zhao *et al.*, 2018), the average value of the SCR peak amplitude was used as a stress indicator for each assembly worker in this study. The peak amplitude values were then normalized in the formulation of the final stress indicator to remove individual differences between individuals. As a result, the human stress response (H_S) indicator for each operator can be defined as:

$$H_S = \left[\frac{\frac{\sum_{w=1}^{N_P} a_w}{N_P} - a_{min}}{a_{max} - a_{min}} \right] \cdot 100 \quad (4)$$

where a_w is the amplitude of the w-th SCR peak, N_P is the total number of SCR peaks during the assembly of a given product variant, a_{min} is the minimum amplitude of the SRC peaks and a_{max} is the maximum amplitude of the SRC peaks (both related to each operator).

To validate the analysis of operator wellbeing, electrodermal activity measurements from the collaborative assembly of electronic boards (HRC assembly) were used. In addition to quality and productivity metrics, data were collected on human stress responses during the 36 assembly processes, i.e. six assemblies of product variants performed by six operators. Specifically, the H_S value of each operator was related to the assembly complexity in order to model the function that captures their relationship. The "operator factor" was not considered in the analysis after checking its non-significance at 95% confidence level using a two-way ANOVA (p-value of 0.999). Figure 3(a) shows the two-term power curve fitting relating human stress response and assembly complexity, in the form:

$$H_S = k_2 \cdot C^{k_3} \tag{5}$$

where H_S is the human stress response, C is the assembly complexity evaluated according to Eq. (1), and k_2 and k_3 are the regression coefficients.

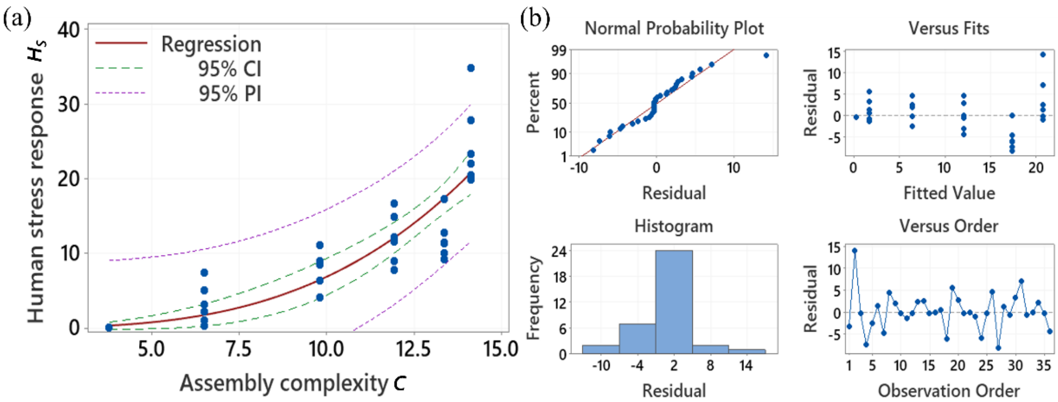

Figure 3. Human stress response (H_S) vs assembly complexity (C): (a) non-linear regression model, and (b) residual plots.

Having established correlations between total defects (TD) and assembly complexity (C), and between human stress response (H_S) and assembly complexity (C), it is possible to analyse the relationship between total defects and operator stress. In fact, it is well known from the literature that defects in a collaborative environment can also be caused by human parameters such as stress, and not only by process parameters such as assembly complexity. To facilitate this analysis, a tool called the Human-Robot Collaboration Quality and Well-Being Assessment Tool (HRC-QWAT) has been developed. This tool is designed to integrate previous assessments of quality and human well-being by directly correlating H_S and total defects TD, regardless of the complexity of the assembled product. The inclusion of TD and H_S in the HRC-QWAT framework is based on their significant influence in assessing the performance of the HRC system, which encompasses both product quality and human well-being.

Two typologies of HRC-QWAT are proposed. The first typology is intended for single variant production of highly customized products produced one by one in the HRC system, even if repeated over time. This type of production involves the manufacture of a single product variant at a time, typically in response to specific customer orders or market demand. In this scenario, the company is interested in monitoring the performance of each individual product variant assembly in terms of quality and human well-being. On the other hand, the second typology of HRC-QWAT is proposed to provide companies with a diagnostic method for products of the same variant manufactured in small batches, after each of such productions. This type of production involves the manufacture of small batches of the same product variant, typically in response to forecasted demand or market trends. The choice between single variant production and small-batch variant production generally depends on factors such as demand variability, lead time requirements, and production costs. Single variant production is best suited for highly customized products with low demand, while variant batch production is more efficient for producing a range of products with moderate to high demand.

The HRC-QWAT diagnostic tool (see Figure 4) uses the model as a reference for prediction and takes into account the associated uncertainty range. Specifically, the two prediction limits (Lower Prediction Limit LPL and Upper Prediction Limit UPL) serve as thresholds for identifying critical products and small batches, respectively. Products and small batches are classified as critical in terms of both defects and human stress response when a special source of variation i.e., a source not inherent to the process, occurs (Montgomery, 2019a).

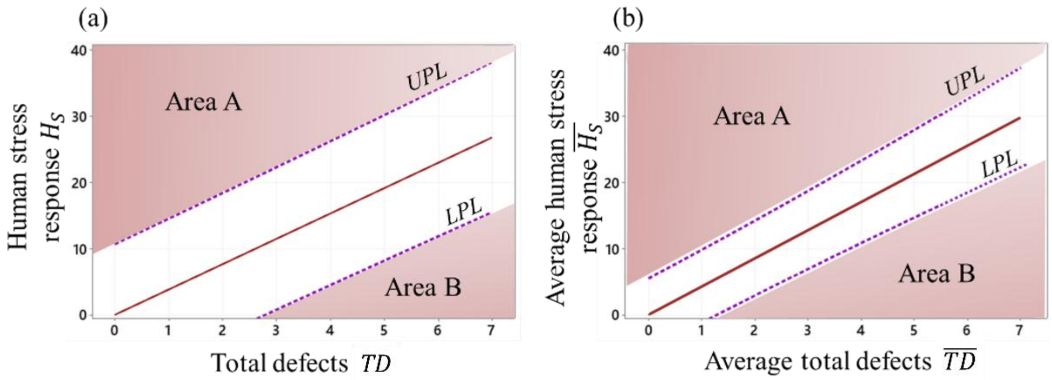

Figure 4. HRC-QWAT for (a) single variant production and (b) small-batch variant production.

The two prediction limits can be calculated as follows:

$$LPL = \widehat{H_S} - t_{1-\frac{\alpha}{2},\nu}\sqrt{[SE(Fit)]^2 + S^2}$$
$$UPL = \widehat{H_S} + t_{1-\frac{\alpha}{2},\nu}\sqrt{[SE(Fit)]^2 + S^2} \quad (6)$$

where $\widehat{H_S}$ is the predicted value of the regression curve, $t_{1-\frac{\alpha}{2},\nu}$ is the value of the Student's t distribution with ν degrees of freedom (i.e., number of observations minus 1) and significance level α, $SE(Fit)$ is the standard error of the fit, and S is the standard error of the regression (Montgomery, 2019a).

In the use phase, when new single products or small batches of products are produced, the observed values (TD, H_S) or $(\overline{TD}, \overline{H_S})$ are compared with the corresponding prediction limits from the HRC-QWAT for single variant or small-batch production, respectively. Accordingly:

a) If the observed (TD, H_S) or $(\overline{TD}, \overline{H_S})$ value falls within the prediction range (LPL, UPL), the product or batch is considered non-critical.

b) If the observed (TD, H_S) or $(\overline{TD}, \overline{H_S})$ value is higher than the upper prediction limit (UPL) (area A in Figure 4) or lower than the lower prediction limit (LPL) (area B in Figure 4), it indicates a mismatch between the human stress response and the total defects, and an abnormal situation exists, resulting in the product or batch being signalled as critical. Specifically, products or batches located in area A of Figure 4 are reported as critical due to the high level of stress response experienced by operators compared to the number of total defects detected. On the other hand, products or batches lying in area B are characterized by abnormal defectiveness compared to the level of human stress response.

The proposed diagnostic tool has been developed with a dual objective. Firstly, it aims to accurately position products or small batches on the HRC-QWAT, thereby providing a clear understanding of their relative position compared to other products. This information can be valuable in making informed quality control decisions and identifying areas for improvement. Secondly, the diagnostic tool is designed to detect unusual production scenarios and identify critical out-of-control situations. By continuously monitoring production processes, the tool can identify any deviations from established normal operating conditions, allowing corrective action to be taken in a timely manner. This feature of the diagnostic tool acts as an in-process control mechanism, ensuring that the quality of the overall system (product/process and human) remains consistently high throughout the production process.

3.3 Quality control tools in collaborative assembly

After establishing mathematical models for analysing quality in collaborative assembly and introducing a tool that relates this quality to operator perceived stress, this Section explores the progression towards the practical application of such methodologies for real-time quality control in collaborative assembly processes. In detail, two possible methodologies to exploit these relationships and improve process control are presented, in order to answer the last research question (RQ4).

The first proposed method of quality control for a collaborative assembly process is the use of Statistical Process Control (SPC). SPC is an analytical technique widely used in the manufacturing sector to ensure the quality and efficiency of processes using statistical methods. Among its various tools, control charts stand out for their ability to effectively monitor production processes. Previous studies have examined the use of SPC tools, such as control charts, to monitor various aspects of production processes (Bahria *et al.*, 2021; Verna, Genta, *et al.*, 2022). However, traditional SPC methods often focus solely on process-related variables, neglecting the importance of human-related factors in HRC systems (Coronado *et al.*, 2022; Damacharla *et al.*, 2018). Multivariate Control Charts (MCCs) are a more sophisticated form of SPC that can be used to monitor multiple variables simultaneously and detect any out-of-control situations (Hotelling, 1974; Montgomery, 2019b; Montgomery and Wadsworth, 1972). MCCs have been applied to various fields, including manufacturing, healthcare, and finance, among others (Ahsan *et al.*, 2018; Franceschini *et al.*, 2015; Harris *et al.*, 2016; Lowry and Montgomery, 1995; Rodrigues *et al.*, 2021; Suman and Prajapati, 2018).

Monitoring of human and process performance parameters refers to individual observations, with one value only for each parameter being obtained for each custom product. Indeed, products are typically not produced in batches but are often one-of-a-kind products manufactured in variable mix based on customer demand. Thus, specific values of the control limits for individual observations should be considered for the adopted charts. In detail, in Phase I, the Hotelling T^2 statistic can be approximated using a Beta distribution with parameters $\frac{p}{2}$ and $\frac{f-p-1}{2}$ (Tracy *et al.*, 1992):

$$T^2 \sim \frac{(m-1)^2}{m} \cdot Beta\left(\frac{p}{2}, \frac{f-p-1}{2}\right) \tag{7}$$

with:

$$f = \frac{2 \cdot (m-1)^2}{3 \cdot m - 4} \tag{8}$$

where p is the number of system variables and m is the number of samples used for chart construction in Phase I. Therefore, the lower control limit (LCL) and the upper control limit (UCL) are the values of T^2 statistics in Eq. (5.1) corresponding to a cumulative probability of 0.135% and 99.865% (corresponding to mean value -3 and +3 standard deviations for a normal distribution); however, LCL is typically set to zero since any shift in the mean results in an increase in T^2.

The use of the Beta distribution in Eq. (7) is valid only in Phase I. In Phase II, the Hotelling T^2 statistics can be approximated by a Fisher distribution with parameters p and $m-p$ (Tracy *et al.*, 1992):

$$T^2 \sim \frac{p \cdot (m+1) \cdot (m-1)}{m^2 - m \cdot p} \cdot F(p, m-p) \tag{9}$$

Therefore, UCL is now the value of T^2 statistics in Eq. (5.3) corresponding to a cumulative probability of 99.865% and LCL is set to zero.

In contrast, when using the Generalized Variance chart with individual observations, conventional formulas are not applicable and an ad-hoc procedure must be employed (Montgomery, 2019b; Sullivan and Woodall, 1996). All values should first be standardized using Sullivan and Woodall's special covariance matrix (Sullivan and Woodall, 1996):

$$S^* = \frac{1}{2 \cdot (m-1)} \sum_{i=1}^{m-1} e_i^2 \tag{10}$$

where e_i are the differences between successive observations:

$$e_i = x_{i+1} - x_i \qquad i = 1, \dots, m-1 \tag{11}$$

Then, an S chart can be used, in which each subgroup corresponds to each replication (Tracy *et al.*, 1992). Therefore, the General Variance control limits are:

$$LCL = s_m - 3 \cdot \frac{s_m}{c_4} \cdot \sqrt{1 - c_4^2} \quad UCL = s_m + 3 \cdot \frac{s_m}{c_4} \cdot \sqrt{1 - c_4^2} \tag{12}$$

where s_m is the average of the standard deviations of each subgroup and c_4 is the bias correction of the standard deviation estimate (Montgomery, 2019b). A central line corresponding to s_m is typically shown in the Generalized Variance chart. For the Generalized Variance charts, the calculation of control limits in Phase I and Phase II is the same.

To validate the proposed model, it was applied to the collaborative assembly of electronic boards (HRC assembly). However, there were some significant changings to the procedure: the first concerns the division into phases of the operators' tests for the construction of the board. The first five operators performed six assembly tests each, corresponding to one test for each product type classified as Phase I of chart construction. On the other hand, the sixth operator performed nine assembly tests, three more than before, and extended the tests to Phase II of surveillance, repeating the assembly of some boards. This adjustment was made to increase the robustness of the monitoring phase. A second change to the experimental design was the addition of a subsequent quality control step. In this revised design, an experienced operator inspected the assembled cards for residual defects after assembly. The purpose of this addition was to capture an additional variable quality control period.

Multivariate control charts were exploited to monitor the four human and process performance parameters related to each product variant assembly described above. The $p = 4$ system variables is an adequate number for the application of Hotelling T^2 and Generalized Variance control chart (Montgomery, 2019b).

The collected data were used to create a historical dataset and design the control charts in Phase I. As shown in Figure 5, no out-of-control data were detected in Phase I. Accordingly, the estimates of process mean vector and covariance matrix were used in Phase II to test whether the process remained in control under normal working conditions. In Phase II, the assembly of 9 additional custom electronic boards was performed by an additional operator in random order, and the related parameters were collected. The control limits of Hotelling T^2 and Generalized Variance charts of Phase II represented in Figure 5 were obtained from Eqs. (9) and (12), respectively. As shown in Figure 5, in such a phase, two out-of-control data were detected by Hotelling T^2 chart and four points were detected by Generalized Variance chart.

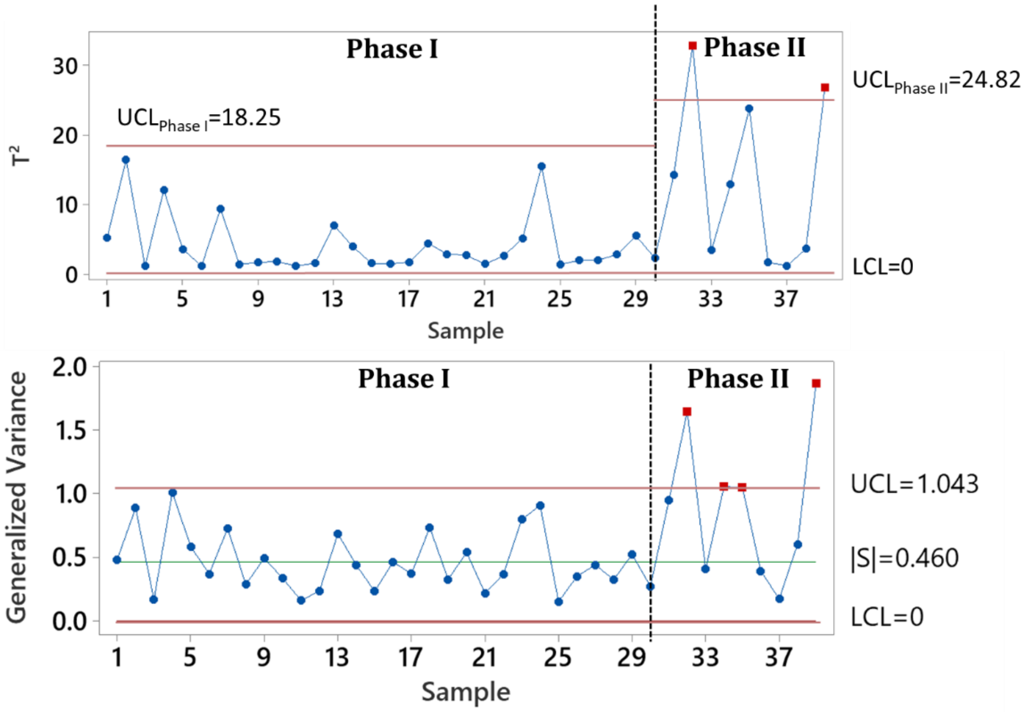

Figure 5. Hotelling T^2 and Generalized Variance charts for HRC assembly of custom electronic boards (Phase I calibration data and Phase II new data).

In detail, to interpret out-of-control points signalled by Hotelling T^2 chart of Figure 5 and test the significance of variables contribution to the composite value of each point, the T^2 statistic can be decomposed (Mason *et al.*, 1995). Accordingly, root causes can be promptly identified, and assignable causes of variations can be removed.

The second alternative proposed for quality control in a collaborative assembly is the use of a digital twin (DT) to exploit the patterns of defect generation found. DTs are virtual replicas of physical systems and enhance innovation by integrating the physical and virtual worlds. Introduced by Professor Grieves in 2002 and developed in subsequent studies, DTs consist of three core elements: the real world, the digital world, and bi-directional data links. These links, Physical-to-Virtual (P2V) and Virtual-to-Physical (V2P), allow seamless data flow between the two worlds, enabling real-time adaptation and continuous improvement of systems based on virtual simulations (Grieves, 2014; Grieves and Vickers, 2017).

Research continues to develop defect prediction models related to assembly complexity and defect rate, using designed experiments to analyse and model productivity and defect generation in assembly/disassembly processes. These models are critical for adapting assembly steps and predicting system performance based on product variant complexity. Such predictive capabilities are integrated into DTs for continuous quality management, enabling simulation of production scenarios, identification of failure-causing conditions, and rapid feedback mechanisms to the physical systems to improve overall product quality and system performance.

In the proposed study, the developed prediction models represent a virtual shadow of the physical process of assembly and disassembly process and can be integrated into a DT for in-process quality control. Figure 6 shows an example of a structure that integrates the defect generation models within the digital twin architecture.

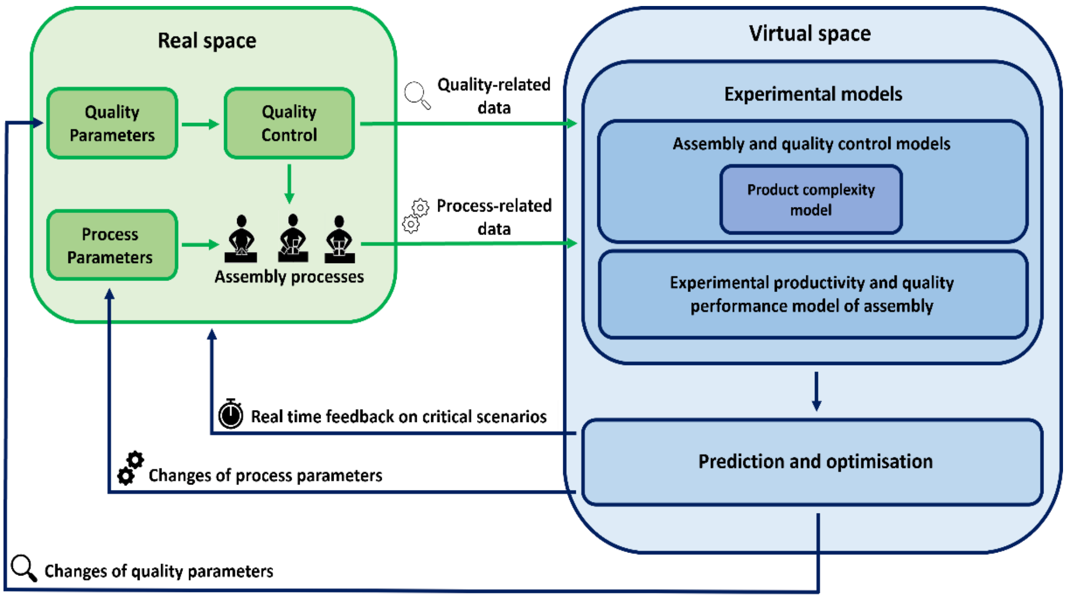

Figure 6. Structure of a digital twin for quality control in which the developed experimental models may be integrated.

However, the integration of defect generation models into the digital twin can be limited by inaccuracies in the data used to create the twin, which can lead to errors in the integration of the collected data. In addition, the digital twin may not fully capture the complexity and variability of real-world systems, making it difficult to calibrate and validate the predictive model. Accordingly, an initial calibration of the predictive models used is essential, in which data obtained from simulations are compared with data obtained in the real space (Yeratapally *et al.*, 2020). In this case study, some initial tests could be performed to observe how assembly times and defects vary with the complexity of the products assembled in the real and virtual environment. The data obtained from the simulations can then be compared with the data obtained from the real assembly, and the parameters of the prediction model can be corrected in case of discrepancies.

3.4 Automatic Component Recognition and Defect Detection in Electronic Board Inspection

The previous Section introduced two quality management approaches for collaborative assembly processes designed to minimise the occurrence of defects during assembly. Despite these methods, some defects may still remain at the end of the assembly process. Consequently, there is a need to implement an intelligent inspection system that is integrated into the automated assembly process. The following chapter proposes such a system based on a case study of electronic boards. This system is designed to detect defects quickly and non-invasively, offering an improvement over traditional board inspection technique.

The proposed intelligent inspection system incorporates a range of advanced technologies, including sophisticated machine learning (ML) algorithms and high-resolution imaging techniques, to significantly improve the efficiency and accuracy of defect detection during inspection processes. The aim is to develop a predictive method for identifying faulty components on generic electronic boards without the need for discrete component analysis. This system has been specifically developed as part of ongoing research aimed at minimising the generation of electronic waste, commonly referred to as Waste Electrical and Electronic Equipment (WEEE) or e-waste (Widmer *et al.*, 2005). This WEEE paradigm, introduced to address the escalating problem of electronic waste, focuses in particular on the widespread impact of printed circuit boards (PCBs), which have become ubiquitous in electronic devices.

The use of this system in collaborative board assembly lines is particularly significant. By integrating this technology, the inspection phase can be enhanced, thereby improving the quality of the output and reducing the likelihood of faulty boards reaching the end customer.

Figure 7 shows the proposed methodology schematically, highlighted in a red box. This methodology unfolds through three carefully designed steps, each of which is critical to improving the efficiency and effectiveness of e-waste management processes. The first step, component classification, involves the evaluation and categorisation of individual electronic components. This is followed by the second step, board classification, which focuses on assessing the overall condition of the board, integrating the results of the initial component classification. The third and final step, board testing, involves diagnostic testing of the classified board to further validate its condition and determine its suitability for reuse, repair or recycling.

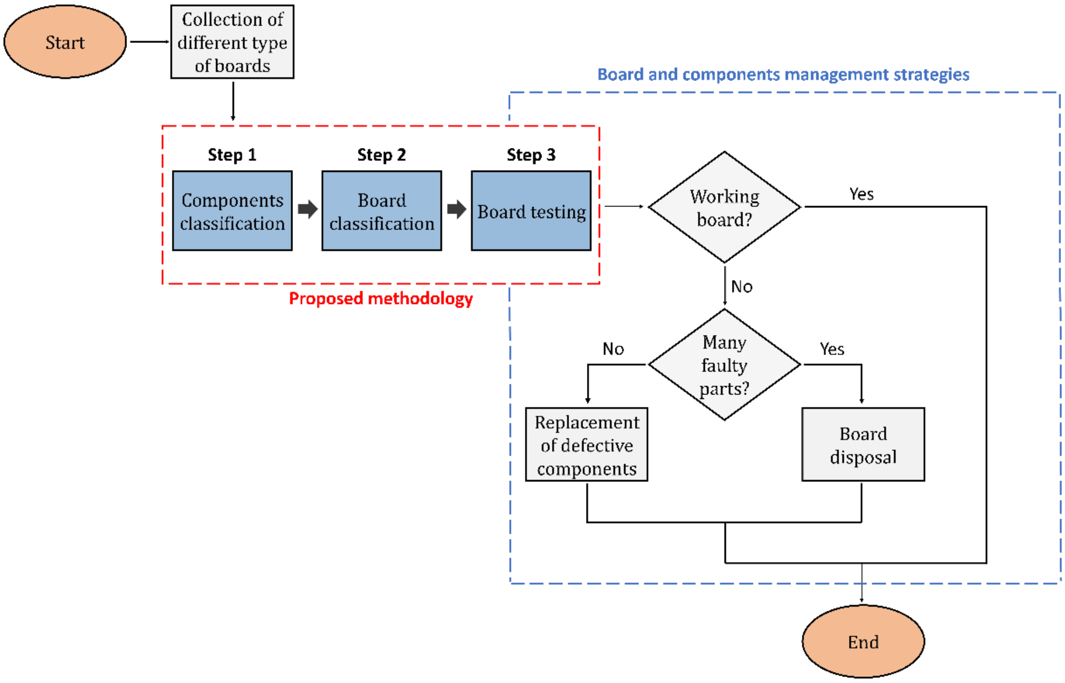

Figure 7. Schematic view of the proposed methodology to identify faulty electronic components.

More specifically, given the potential diversity and customisation of boards in a real production environment, it is assumed that different types of electronic boards arrive at the control station. Accordingly, the initial phase of the methodology (Step 1) consists in identifying the different electronic components that characterise each board. This initial classification can be achieved by using a CNN with high component recognition accuracy in real time, such as the YOLOv5 neural network (Alzubaidi *et al.*, 2021). YOLOv5's ability to detect and locate multiple objects makes it particularly suited to the complexities of WEEE management, where rapid and accurate identification of e-waste components is critical. Of the different versions of YOLOv5, YOLOv5s provides fast, real-time object recognition and high accuracy, making it ideal for the complexities of WEEE management (Adibhatla *et al.*, 2021).

Once the components have been identified, the data is used to create a system that classifies the electronic boards (Step 2). This classification is critical to associate each board with its corresponding circuit diagram, which provides information for the proper functioning of the board. The system evaluates the number and type of components on each board and compares them to a detailed database of various electronic board specifications. It methodically searches for a match in the number and type of components on the examined board by cross-referencing the identified components with the database records. Once classified, each board is automatically associated with its circuit diagram, along with a confidence level.

The final part of the methodology, referred to as Step 3, is critical in determining the health status of the electronic components within a circuit. This phase is closely linked to the analysis of the waveform outputs generated during the quality control checks, where the electronic board is subjected to electrical stimulation. These waveforms, defined by their amplitude, phase and frequency, reflect the nominal values and tolerances inherent in the electronic components. Such characteristics are critical in assessing the overall condition of the board, as highlighted by Naderi et al. (2013). The evaluation process begins with the compilation of a data set aimed at capturing the variances in waveform parameters that are affected by discrepancies in component values. Next, the advanced analytical technique known as Extreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) is used to decipher the intricate relationship between the waveform attributes and the component values. By analysing and associating waveform parameters with component tolerances, this methodology enables precise determination of whether component values are within acceptable limits. XGBoost thus plays a crucial role in predicting the electronic component values that describe the state of the board based on the various waveform characteristics. Specifically, the system is designed to classify components into three potential states: functioning, not functioning and to be tested. In scenarios where components are flagged as functioning or not functioning, decisions regarding retention or replacement are straightforward. Conversely, components flagged for further testing require individual assessment, introducing an additional layer of complexity and cost implications.

The proposed three-step methodology is valuable for multiple reasons. First, component classification ensures a thorough understanding of the individual components within the various electronic boards designated for testing and disassembly. Second, board classification involves categorising the various boards, which is essential for analysing the broader system architecture. Finally, the third step enables to test the board functionality and predict the status of each component. This step is crucial in supporting future maintenance decisions by indicating whether components are functional, non-functional, or require further analysis.

4. Conclusions

The findings of this dissertation represent a significant advance in the understanding of the role of collaborative robots (cobots) in mass customisation manufacturing and quality control. This research thoroughly examines how cobots are transforming quality control by increasing flexibility and integrating innovative human-robot collaboration (HRC) strategies to meet the increasingly personalised demands of today's markets.

As manufacturing paradigms shift from mass production to mass customisation, cobots have been identified as central to facilitating this transition. They are reorganising production processes to be more adaptable, efficient and customer focused. This study provides in-depth insights into how cobots are helping to improve quality in this evolving manufacturing landscape.

The research shows that cobots are significantly improving production processes, particularly in sectors geared towards mass customisation. They play a critical role in ensuring consistent accuracy and flexibility across multiple tasks, thereby improving quality and significantly reducing error rates. Cobots excel at performing complex tasks consistently and without fatigue, which is essential in environments where customisation and precision are paramount. Their adaptability allows them to respond quickly to changing product specifications while maintaining high quality through comprehensive real-time defect monitoring, in line with the Quality 4.0 paradigm.

However, despite their benefits, cobots are not yet widely used for direct quality control tasks. The study notes that while cobots are occasionally involved in quality control, their true value lies in assembly operations, where their integration is most effective. Cobots in assembly lines offer increased efficiency and flexibility, outperforming traditional manual processes. This integration combines human dexterity with robotic reliability, creating synergistic assembly lines that increase productivity without sacrificing quality or customisation.

The study also examined the critical factors that influence the quality of collaborative assembly processes. Assembly complexity was identified as a significant factor and its impact on assembly time and defect rates was thoroughly analysed. The study also considered human factors such as fatigue and stress, assessed through electrodermal activity, to provide a comprehensive view of how physiological responses affect the efficiency and quality of assembly processes.

Advanced monitoring tools and methods have been key to maintaining quality standards in collaborative assembly processes. Tools such as statistical process control (SPC) methods and digital twin (DT) technologies have been introduced. The integration of multivariate control charts and real-time data analysis facilitates the immediate detection and correction of anomalies, ensuring consistent product quality while improving operator comfort.

Finally, an innovative quality control method using electrical signal analysis was presented, offering a new perspective on real-time quality assessment. This method uses simulation tools and machine learning algorithms to efficiently detect potential defects, providing an alternative to traditional quality control methods. It highlights the contributions of the dissertation to broadening the understanding of quality in collaborative systems.

The findings of this Dissertation make a significant contribution to the academic literature on advanced manufacturing technologies, detailing the effective integration of cobots into complex production systems to improve product quality. While acknowledging certain limitations, such as the narrow scope of cobot applications studied, this analysis lays the groundwork for future research to explore more industries and investigate the long-term effects of cobot integration. Future studies could also explore the incorporation of advanced cognitive capabilities into cobots, enabling them to make autonomous decisions based on real-time production data, further enhancing their effectiveness in complex manufacturing environments.

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