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A novel quality map for monitoring human well-being and overall defectiveness in product variants manufacturing

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Abstract. Nowadays, companies are faced with demands for increasingly customised products, shifting from mass production to mass customisation. Thus, operators typically have to produce multiple product variants, often characterised by different complexity levels, while meeting quality standards. Companies, however, cannot only be concerned with production quality, but also with the quality and well-being of workers, as demanded by the human-centred paradigm of Industry 5.0. Therefore, this paper proposes a combined analysis of (i) production quality in terms of overall defects generated during product variants manufacturing and (ii) human well-being in terms of stress response. The combination of the two indicators results in a novel tool called "Quality Map", which enables the evaluation and monitoring of quality systems during the production of product variants from a broad standpoint. To demonstrate the viability of the method, a collaborative human-robot assembly is used as a case study.

Introduction

In recent years, the traditional approach to mass production is shifting towards mass customisation driven by technological advances, increased consumer demand for customisation and growing awareness of the environmental and social impact of mass production. However, this shift requires a flexible production system to adapt to product type and volume variations. Human-Robot Collaboration (HRC) seems to be an effective approach to achieve such mass customisation, combining the flexibility and versatility of operators with the precision of collaborative robots, i.e. cobots [1]. Interest in HRC has grown with the development of Industry 5.0, in which human well-being is placed at the centre of production systems to provide a more sustainable manufacturing sector that enables mass customisation [2].

However, many existing approaches to HRC prioritise task completion over realising its full potential. To achieve a more human-centred society and industry, HRC researchers need to broaden their focus [3,4]. To address this issue, the paper proposes the new "Quality Map" tool, which combines performance-centred and human-centred perspectives to assess the quality of HRC systems and enable more effective human-robot collaboration. The "Quality Map" evaluates and monitors the quality of a production system, combining two indicators, the process quality indicator, and the human operator stress indicator. The Quality Map provides a comprehensive view of the system's overall quality during the production of different product variants and allows for in-progress monitoring and diagnosis. The paper presents a real-life case study of the assembly of electronic board variants using an HRC system, showing the potential of the Quality Map for identifying critical production scenarios and implementing necessary corrective actions to maintain the desired quality level while considering the well-being of human operators.

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Case study

An experimental campaign is conducted to assemble six different customised variants of electronic boards (from variant A to variant F) using the ARDUINO UNO starter kit (ARDUINO®), as shown in Fig. 1(a). This starter kit consists of three main elements: (i) the components, i.e. the parts that are assembled to produce the different boards, which are listed in Table 1; (ii) the microcontroller, i.e. a small computer that allows the circuits to function; (iii) the Breadboard, i.e. a board on which the actual circuit can be built. Each electronic board has a different level of complexity and allows real-time verification of their proper functioning, i.e., the correct assembly of the products.

The experimental campaign to assemble the six selected electronic boards involved six skilled operators. The boards were assembled with the support of the UR3e cobot from Universal Robots™, equipped with an OnRobot RG6 gripper (OnRobot™), as shown in Fig. 1(b). The six operators assembled the electronic board variants randomly to avoid learning effects. The experimental campaign included an assembly phase and a quality control phase. In the former phase, the cobot passed the parts to the operator, who assembled the electronic boards following a strategy defined a priori according to the circuit theory [5]. The operator was in control of the process and activated the cobot through a pushbutton. In the quality control phase performed offline, an experienced external operator (different from assembly operators) checked the quality of the assembly, identifying any product defect which was left in the final assembly. Data about overall defectiveness and human stress response was collected during the trials.

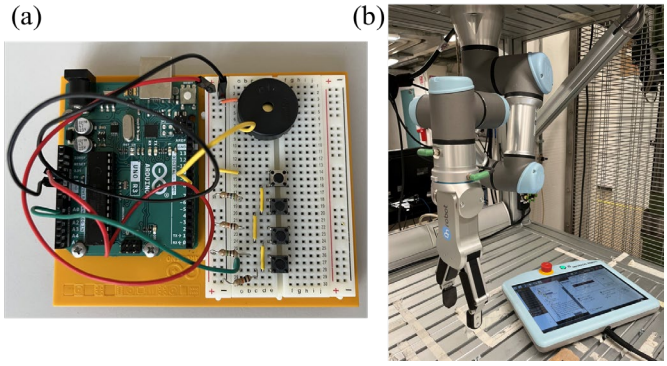

Fig. 1. (a) Example of an assembled electronic board (variant C) and (b) HRC workstation showing the single-armed UR3e cobot equipped with the OnRobot RG6 gripper.

Table 1. Components of the six electronic board variants (A-F).

	A	B	C	D	E	F
Long wires	-	1	2	8	9	13
Short wires	1	3	5	3	6	4
Resistors	1	1	4	6	2	2
Pushbuttons	-	2	4	-	2	1
LED	1	1	-	1	-	-
Phototransistor	-	-	-	3	-	-
Potentiometer	-	-	-	-	1	1
Piezo	-	-	1	-	-	-
LCD	-	-	-	-	-	1
Battery snap	-	-	-	-	1	-
DC Motor	-	-	-	-	1	-
H-bridge	-	-	-	-	1	-
Total parts number	3	8	16	21	23	22

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Complexity analysis

The scientific literature typically employs complexity as a metric to predict production performances, including production times and defects. In fact, a decrease in complexity is often found to correspond with a significant improvement in performance [6,7]. The structural complexity model, first introduced by Sinha et al. [8] and later adapted by Alkan and Harrison [9], and Verna et al. [7], is used in this study to assess the complexity of the assembly of selected ARDUINO products. This model defines the structural complexity of any network-based engineering system as a function of the complexity of individual parts (C_1), the pair-wise interaction between connected parts (C_2), and the effects of the system's overall topology (C_3). The structural complexity, represented as C, is a combination of these factors and can be expressed as:

$$C = C_1 + C_2 \cdot C_3. \quad (1)$$

In Eq. (1), C_1 represents the handling complexity of the product, i.e. the complexity of managing the individual components of a product when they are considered separately. One of the most accredited models to calculate a handling complexity index of individual parts is the Lucas method [9] based on Design For Assembly (DFA). C_2 is the complexity of connections and liaisons between parts, calculated as the sum of the complexities of pair-wise connections existing in the product structure. It may be estimated by the Lucas method [9], using the symmetrical binary adjacency matrix of the product. Each entry in the matrix denotes an assembly link between two components. Finally, C_3 represents the topological complexity related to the product's architectural pattern. It is calculated as the average of singular values of the adjacency matrix of the product [7]. It increases as the system topology shifts from centralised to more distributed architectures [8].

According to increasing total assembly complexity C, Table 2 lists the complexities C_1, C_2 and C_3 of the selected product variants. Notably, an increase in complexity does not always imply an increase in the number of parts (see Table 1 for comparison).

Table 2. Complexities of the six variants of electronic boards (A-F).

	A	B	C	D	E	F
C_1	1.39	2.87	5.10	6.35	7.25	6.72
C_2	2.98	5.44	13.84	14.58	21.79	26.02
C_3	0.94	0.90	0.90	0.93	0.83	0.84
C	4.20	7.77	17.51	19.95	25.35	28.61

HRC system quality analysis

During the manufacturing process, quality data on the overall defectiveness of product and process were collected to assess the quality of the HRC system. Experimental data were then statistically analysed to identify and exclude any possible outliers [10]. Then, the relationship between the total number of defects recorded by the 6 operators for each of the 6 variants of electronic boards and the complexity of assembly (calculated as described in the previous section) was analysed. 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 0.290). The Poisson regression model was adopted for the analysis, as total defects are count data [11]. The selection of the most appropriate Poisson model and link function (log, square root and identity link functions) 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 [11].

According to the results, the most appropriate Poisson model describing the relationship between defects and complexity was the one using the square root link function [11], defined as:

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$$D = (k_1 \cdot C)^2, \tag{2}$$

where D is the total number of defects, C is the assembly complexity evaluated according to Eq. (1), and k_1 is the regression coefficient. The results of the Poisson regression analysis, reported in Table 3 and Fig. 2(a), showed that the relationship between D and C was statistically significant. Additionally, the analysis of deviance residuals and the goodness-of-fit tests of Deviance and Pearson (in which p-values are higher than the significance level of 0.05) indicated that the model fit the data well. Furthermore, a very high value of the deviance R^2 was obtained. Results obtained for product and process quality show that the increase in assembly complexity of the variants leads to an increase in total defects following a nonlinear trend.

Table 3. Poisson regression output for total defects (D) vs assembly complexity (C). Model is in the form $\boldsymbol{D = (k_1 \cdot C)^2}$.

k_1	SE(k_1)	Coefficient p-value	Deviance R^2	Goodness-of-Fit Tests	
0.079	0.004	<0.0005	99.32%	Deviance Test p-value	0.619
				Pearson Test p-value	0.649

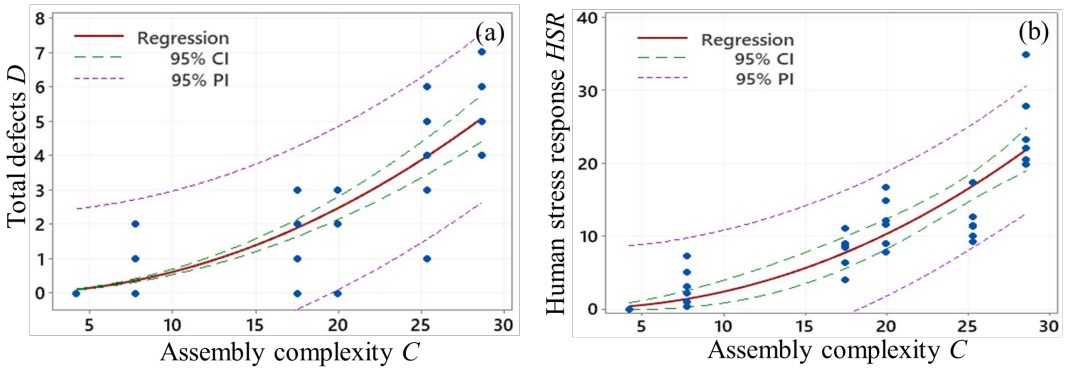

Fig. 2. (a) Poisson regression model of total defects vs assembly complexity, and (b) nonlinear regression model of human stress response vs assembly complexity.

On the other hand, physiological measures can be used to objectively assess the state of human well-being during production. Electrodermal activity (EDA) data are used in this study to measure human well-being, as they are commonly used as an indicator of human stress response [12]. The Empatica E4 wristband, a non-invasive biosensor that records EDA information at 4 Hz, was used to collect the EDA data.

For each test performed by the operators, the raw signal was recorded and then analysed using the EDA Explorer software, which removes external noise and separates the EDA signal into tonic signals related to Skin Conductance Level (SCL) and phasic signals related to Skin Conductance Response (SCR) [12,13]. According to its widespread use [12], this study used the average value of SCR peaks amplitude as a stress indicator for each assembly operator. The peak amplitude values were standardised to compute the final stress indicator to remove individual differences between individuals. As a result, for each operator, the human stress response (HSR) indicator results:

$$HSR = \left[\frac{\frac{\sum_{i=1}^{N_P} p_i}{N_P} - p_{min}}{p_{max} - p_{min}}\right] \cdot 100, \tag{3}$$

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Where $\boldsymbol{p_i}$ is the amplitude of the *i*-th SCR peak, $\boldsymbol{N_p}$ is the total number of SCR peaks during the assembly of a certain product variant, $\boldsymbol{p_{min}}$ is the minimum amplitude of SRC peaks and $\boldsymbol{p_{max}}$ is the maximum amplitude of SRC peaks (both referring to each operator).

Human stress response data obtained during the 36 assembly processes (i.e., the 6 product variants assembly performed by each of the 6 operators) are related to the assembly complexity. 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). Fig. 2(b) represents the two-term power curve fitting relating human stress response and product variants assembly complexity in the form:

$$HSR = k_2 \cdot C^{k_3}, \tag{4}$$

where HSR is the human stress response, C is assembly complexity evaluated according to Eq. (1), and k_2 and k_3 are the regression coefficients. This model was the best-fitting model compared to various linear and nonlinear models, considering the goodness-of-fit statistics and residual analysis [14]. The statistical significance of the parameter estimate is confirmed by verifying that the 95% confidence intervals for the parameters, calculated from the corresponding Standard Errors (SE) reported in Table 4, exclude the zero [14]. Note that nonlinear regression is preferable to linear quadratic regression, as using a logarithmic transformation can lead to bias in the predictions [15].

Table 4. Nonlinear regression output for human stress response (HSR) vs assembly complexity (C). Model is in the form $\boldsymbol{HSR = k_2 \cdot C^{k_3}}$.

k_2	SE(k_2)	95% CI for k_2	k_3	SE(k_3)	95% CI for k_3	S
0.019	0.020	(0.001, 0.158)	2.109	0.336	(1.444, 2.998)	4.067

This result, which is one of the first attempts at studying the relationship between assembly complexity and human stress response, shows that as the complexity of the product assembly increases, the assembly process becomes more challenging and requires a higher degree of cognitive effort, leading to an increase more than proportional in human stress response.

Quality Map

This section introduces the "Quality Map", a tool designed to synthesise previous HRC system quality analyses by directly relating *HSR* and *D*, regardless of the complexity of the product assembled. Two types of Quality Maps are proposed: one for single variant production, where each product is produced separately, even if it is produced several times in the HRC system, and the other for small-batch variant productions, where each variant is produced in small batches. Both types use the same tool in the use phase, but they differ in the realisation phase of the Quality Map.

To construct the Quality Map, the following operational steps should be followed. Firstly, a set of historical experimental data representative of production must be collected. In the case of the Quality Map for single variant production, a reasonable number of products (at least about thirty, for robust regression parameter estimates) should be produced, and quality and human stress responses should be measured (as described in previous sections). On the other hand, regarding the Quality Map for small-batch variant production, an adequate number of production units should be collected for each batch (at least about fifteen units for each product type, if possible [14]), and the average performance measures should be obtained for each batch. As mentioned above, it is advisable to perform a preliminary data analysis using traditional statistical techniques to detect and filter outliers [10].

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Secondly, the model relating the two performance measures should be developed, depicting the system's overall quality in terms of product/process quality and human well-being. In the case study, when considering single variant production, the combination of the models in Eq. (2) and (4) leads to a linear model, by considering the goodness-of-fit statistics and residual analysis [14]. Fig. 3(a) depicts the prediction model relating human stress response HSR with total defects D. On the other hand, when considering small batches of products from the same variant, average values of HSR and D should be obtained for each variant, and the prediction model using these averages should be derived. In the case study, six small batches are considered, one for each product variant, each consisting of six products. Fig. 3(b) illustrates the best fitting model, i.e. a linear regression model. Regression outputs are shown in Table 5.

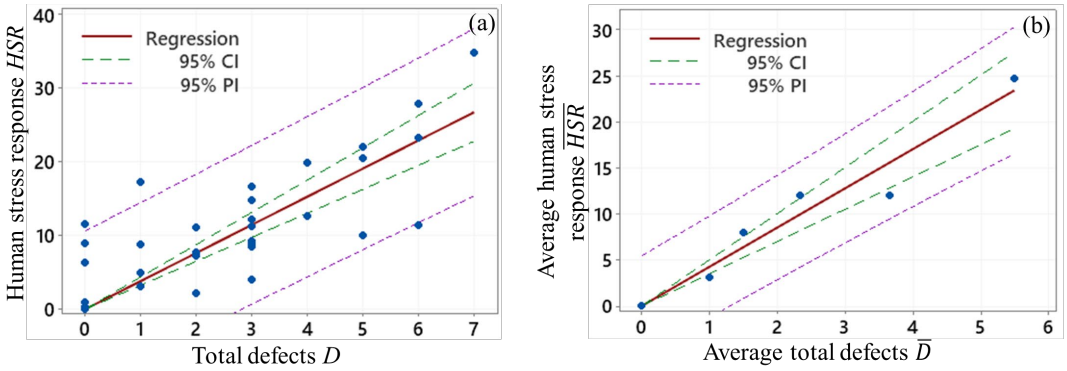

Fig. 3. Linear regression model of (a) human stress response (HSR) vs total defects (D) for single variant production, and (b) average human stress response ($\overline{\boldsymbol{HSR}}$) vs average total defects ($\overline{\boldsymbol{D}}$) for small-batch variant production.

Table 5. Linear regression output for human stress response (HSR) vs total defects (D). Model is in the form $\boldsymbol{HSR = a \cdot D}$.

	a	SE(a)	Coefficient p-value	R^2	R^2 pred.	S
Single variant production	3.821	0.278	<0.0005	84.38%	82.99%	5.243
Small-batch variant production	4.257	0.294	<0.0005	97.67%	95.64%	2.127

The diagnostic tool Quality Map (see Fig. 4) employs the model as a reference for prediction and considers the associated uncertainty range. Specifically, the two prediction limits (Lower Prediction Limit LPL and Upper Prediction Limit UPL) derived from the regression models, illustrated in Fig. 3, are used as thresholds for identifying critical products or small batches, respectively. Products and small batches are classified as critical if a special source of variation i.e., sources not inherent to the process, occurs [14]. It should be noted that negative values of LPL are set equal to zero being physically not possible. The two prediction limits can be calculated as follows:

$$LPL = \widehat{HSR} - t_{1-\frac{\alpha}{2},N-1}\sqrt{[SE(Fit)]^2 + S^2},\ UPL = \widehat{HSR} + t_{1-\frac{\alpha}{2},N-1}\sqrt{[SE(Fit)]^2 + S^2}, \quad (5)$$

where $\widehat{HSR}$ is the predicted value of the regression curve, $t_{1-\frac{\alpha}{2},N-1}$ is the point of Student's t distribution with level of significance α and $N-1$ degrees of freedom (where N is the total number of observations), $SE(Fit)$ is the standard error of the fit, and S is the standard error of the regression [14].

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During the utilisation phase, when new single products or batches are produced, the observed (*HSR, D*) value is compared with the corresponding prediction limits from the Quality Map for single variant or small-batch variant production, respectively. Accordingly, (i) if the observed (*HSR, D*) value falls within the prediction range (*LPL, UPL*), the product or batch is not deemed critical; (ii) if the observed (*HSR, D*) value is higher than *UPL* (region A in Fig. 4) or lower than *LPL* (region B in Fig. 4), it indicates a mismatch between *HSR* and *D* and an abnormal situation is present, resulting in the product or batch being signalled as critical.

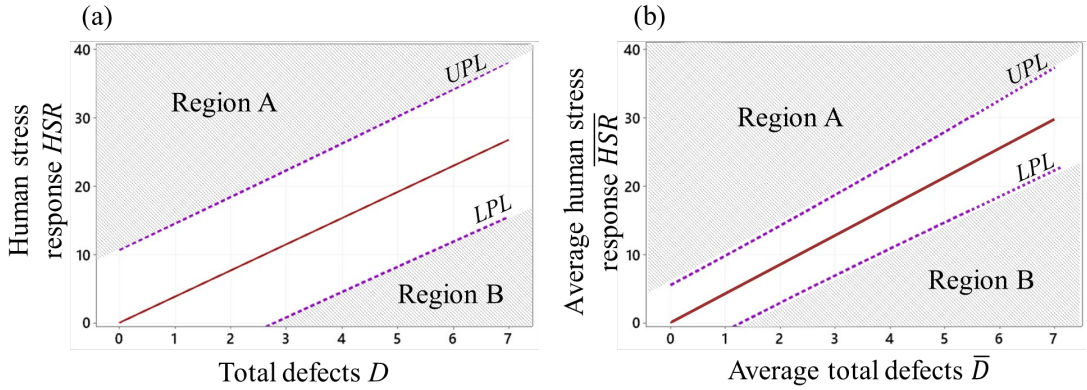

Fig. 4. Quality Map for (a) single variant production and (b) small-batch variant production.

The diagnostic tool has a dual purpose: to position products accurately in the Quality Map, aiding in quality control decisions and identifying areas for improvement, and to detect critical and out-of-control situations for prompt corrective action. This enables high-quality production and serves as an in-progress control approach. Overall, the diagnostic tool is a significant step forward in quality control and monitoring, providing real-time quality correction and consistent system quality.

Conclusions

This research aimed to propose a novel tool called the Quality Map, which combines two indicators to evaluate and monitor the quality of a production system: the overall defects generated during manufacturing product variants and the human stress response. The research was conducted using a collaborative human-robot system to assemble electronic boards as a case study to show the feasibility of the Quality Map approach. The Quality Map is implemented by collecting historical experimental data and developing a model relating the two performance measures that depict the system's overall quality. This tool can be utilised for both single variant production and small-batch variant production. It is worth noting that the proposed approach is general and can be applied to different case studies after refining and tailoring the model parameters used to build the Quality Map.

The study demonstrates that the Quality Map offers a comprehensive assessment of quality systems, encompassing both production/process quality and human well-being, in line with the human-centred approach of Industry 5.0. This highlights the significance of considering both technical and human factors in the quality assessment of production systems.

The proposed approach has some limitations, such as the use of a structural complexity model originally designed for manual and fully automated processes, and the comparison in the Quality Map being based only on two indicators. Future research efforts will be aimed at overcoming these limitations by refining the complexity model and performing a validation using different products and including other environmental/economic sustainability indicators.

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