Towards Zero Defect Manufacturing: probabilistic model for quality control effectiveness

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***Abstract* — Recent advances in the manufacturing industry have paved the way for a systematical deployment and implementation of systems, including Cyber-Physical Systems (CPS) and smart tools, aimed at reaching Zero Defect Manufacturing (ZDM). Nowadays, ZDM strategies are easier to be implemented due to the availability of the required amount of data coming from the distributed sensor network architectures of the production systems. Such a trend is transforming the manufacturing industry to the next generation, namely Industry 4.0. In this context, there is an urgent need to identify and adopt effective quality controls to be performed on the products. This paper proposes a probabilistic model that can be used to evaluate quality inspection effectiveness, i.e., the ability to identify product defects. This model, which integrates perfectly within the current modern manufacturing context, can act as a support tool for decision making and guide designers toward zero-defect strategies.**

Keywords—Quality control, probabilistic model, inspection effectiveness, zero defect manufacturing.

I. Introduction

In manufacturing, the concepts of Industry 4.0, Manufacturing 2.0, Smart Factory and Internet of Things (IoT) are increasingly recognized as enabling factors for a more flexible, customized, traceable, quality-oriented production [1]. At the same time, with the rapid development of IoT and the emerging Key Enabling Technologies - KETs, including in-line data gathering solutions, data storage and communication standards, data analytics tools and digital manufacturing technologies, more and more real-time data can be collected in situ from production processes, allowing to improve their quality and efficiency. Nowadays, the combination and integrated adoption of these technologies offer new opportunities for Zero Defect Manufacturing (ZDM) in modern complex production systems [2]. When these technologies are properly integrated with a cross-KETs approach, new Cyber-Physical Systems (CPSs) for supporting systemic ZDM solutions can be designed and implemented [3].

The strategy of ZDM, which was conceived in the late 1980s, has the goal to decrease and mitigate failures and defects in various manufacturing processes during production [4]. The main challenges associated with ZDM have been the integration of large amounts of data from many sources, the need to develop advanced technologies and methods, modeling of ZDM, and timely computation (online or real-time) [5], [6]. In light of this, CPSs contribute to achieving the goals of ZDM by integrating computation and physical actuation capabilities for improving manufacturing efficiency. In detail, networks and embedded computers are used to monitor and control physical processes, usually with feedback loops and, at the same time, physical processes affect computations, and vice versa [3]. Such CPSs are often used in the factory floor to support the implementation of efficient in-line and real-time quality-oriented production solutions [3]. To this aim, data-driven methods, including Machine Learning (ML) techniques, are typically combined with optimization algorithms and models for improving product and/or process quality in a framework of ZDM [7], [8].

In this context, the adoption of suitable inspection strategies able to achieve the goals of ZDM is of paramount importance. To this aim, this paper proposes a probabilistic model that can be integrated into CPSs to assess the effectiveness of quality inspections. The research question that is specifically addressed is the following: "*How to model quality control effectiveness in a CPS for supporting the achievement of ZDM goals?*". In order to answer this question, this study proposes a model that extends previous authors' research in the field of performance evaluation and planning of quality inspections [9], [10]. In detail, the proposed model considers possible interactions between process and inspection variables in terms of cause-and-effect relationships and potential inspection errors. Moreover, a synthetic indicator depicting the residual product defectiveness not detected by the quality control process is provided. Such a model, adequately integrated into CPSs, can act as a liaison between ML algorithms used to estimate the required model variables (both process and inspection related) and optimization algorithms to improve final products' quality.

The remainder of the paper is structured as follows. In Section II, the manufacturing process and the inspection process variables are described and integrated into an overall probabilistic model. Section III discusses the approach adopted for assessing inspection effectiveness, including possible variables interactions and inspection errors. A practical example to illustrate the proposed method are the subject of Section IV. Finally, Section V proposes closing remarks, research limitations, and future developments.

II. PRODUCT AND QUALITY INSPECTION MODELING

The proposed probabilistic model relies on modeling both product and related quality inspections, as detailed below. It has to be pointed out that this study refers to either final or semi-finished products that are produced by a manufacturing process not decomposable into steps (also called workstations), e.g. Additive Manufacturing (AM) processes.

The quality of each product, in nominal settings condition, can be examined through the inspection of n quality characteristics, i.e., output variables (as shown in Fig. 1) [10]. The output variables are denoted as Y_j, where j is in the range from 1 to n, being n the total number of output variables. Each j-th output variable of the product can be described by a probability p_{Y_j} of occurrence of a specific defect, i.e., the parameter of a Bernoulli distribution [11]. Moreover, each inspection of the j-th output variable may be affected by inspection errors. Hence, three probabilities can be associated to each j-th output variable: the first one related to the quality of the manufacturing process, while the latter two to the quality of the inspections. In detail, these are:

- p_{Y_j}: probability of occurrence of a defect related to output variable Y_j in nominal operating conditions (i.e., the parameter of the Bernoulli distribution);
- α_{Y_j}: probability of erroneously classifying the output variable Y_j as defective (i.e., type I inspection error);
- β_{Y_j}: probability of erroneously not classifying the output variable Y_j as defective (i.e., type II inspection error).

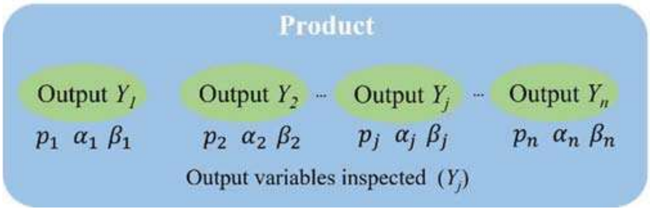

Fig. 1. Representation of product and quality inspection modeling.

The probability p_{Y_j} concerns the quality of the process and is strictly related to its propensity to generate defects. It should be remarked that this probability should be evaluated under nominal working conditions. It represents, therefore, the physiological defectiveness of the production process. On the other hand, the inspection errors α_{Y_j} and β_{Y_j} depend on the quality of the j-th output variable inspection activity. The latter includes the type of inspection performed, the technical skills and experience of the inspectors, the time allowed for inspection, the work environment, and other work- and inspection-related factors [12]–[15].

Referring to each output variable Y_j, the tree diagram illustrated in Fig. 2 shows the four different situations (represented by branches) that can occur during the inspection process. In detail, Y_j can be classified as defective when it is actually defective with a probability $p_{Y_j} \cdot (1 - \beta_{Y_j})$, or when it is conforming (false positive) with a probability $(1 - p_{Y_j}) \cdot \alpha_{Y_j}$. On the other hand, in the case no defect is detected, i.e., the output variable Y_j is classified as conforming, there can be an inspection error (false negative) with a probability $p_{Y_j} \cdot \beta_{Y_j}$, or there can be the real absence of any defect, with a probability $(1 - p_{Y_j}) \cdot (1 - \alpha_{Y_j})$.

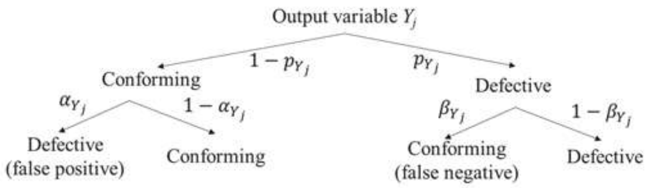

Fig. 2. Tree diagram of the inspection process of an output variable Y_j.

Referring to Fig. 2, n Bernoulli random variables (W_j) can be defined as follows:

- W_j =0, when either (i) the truly defective output variable Y_j is classified as such or (ii) the output variable Y_j is not defective;
- W_j =1, when the truly defective output variable Y_j is not classified as such (false negative).

Accordingly, the following probabilities arise:

$$P(W_j = 0) = p_{Y_j} \cdot (1 - \beta_{Y_j}) + (1 - p_{Y_j}) = 1 - p_{Y_j} \cdot \beta_{Y_j} \quad (1)$$

$$P(W_j = 1) = p_{Y_j} \cdot \beta_{Y_j} \quad (2)$$

III. QUALITY CONTROL EFFECTIVENESS

A. Model description

In most real situations, there may be interactions between defects and inspection errors of different output variables. In other words, different defective-output variables can occur jointly. Consequently, the corresponding output variables cannot be decoupled, and the related events cannot be considered disjoint events. The model proposed in this study takes into account the possible interactions between variables (defect probabilities and inspection errors). Such interactions have to be intended as cause-and-effect relationships between variables and not merely as correlations. Indeed, a correlation is a statistical measure of association between two or more variables that, however, does not provide information about the cause-and-effect relationship of the data [16]. Moreover, in the proposed model, both independence and dependence between events or variables are covered. It has to be remarked that two events are independent if the occurrence of one does not affect the probability of occurrence of the other. However, independence does not preclude interaction because this latter may arise when the effect of one causal variable on an outcome depends on the state of a second causal variable [17].

The following is a brief example to clarify the concepts described above. Consider the case of n=2 output variables, denoted by Y_1 and Y_2, inspected on the final product. In the case of interaction between defects and inspections errors of Y_1 and Y_2, there are 16 different possible configurations in such an inspection process, i.e., the tree diagram branches illustrated in Fig. 3. These include cases of misclassifications (due to inspection errors) and other of correct classifications.

As shown in Fig. 3, the dependence between the occurrence of defective-output variables is considered. In detail, the four possible combinations of defects that can occur are:

- Event (A): Y_1 defective and Y_2 defective;
- Event (B): Y_1 defective and Y_2 non-defective;
- Event (C): Y_1 non-defective and Y_2 defective;
- Event (D): Y_1 non-defective and Y_2 non-defective.

The probabilities associated with each event are reported in the tree diagram of Fig. 3. Specifically, the probability that the two defective-output variables occur jointly, $p_{Y_1 \cap Y_2}$, can be obtained by using the definition of conditional probability [18], as follows:

$$p_{Y_1 \cap Y_2} = \begin{cases} p_{Y_2} \cdot p_{Y_1} & \text{(a)} \\ p_{Y_2|Y_1} \cdot p_{Y_1} & \text{(b)} \\ p_{Y_1|Y_2} \cdot p_{Y_2} & \text{(c)} \end{cases} \quad (3)$$

where: (a) if the occurrence of Y_1 and that of Y_2 are independent, (b) if the occurrence of Y_1 and that of Y_2 are dependent (the occurrence of Y_1 is the conditioning event), (c) if the occurrence of Y_1 and that of Y_2 are dependent (the occurrence of Y_2 is the conditioning event). In light of this, according to the structure of the problem and the directionality of the cause-and-effect relationship between the output variables, in the graphical model depicted in Fig. 3, $p_{Y_1 \cap Y_2}$ should be replaced by the probabilities reported in (3).

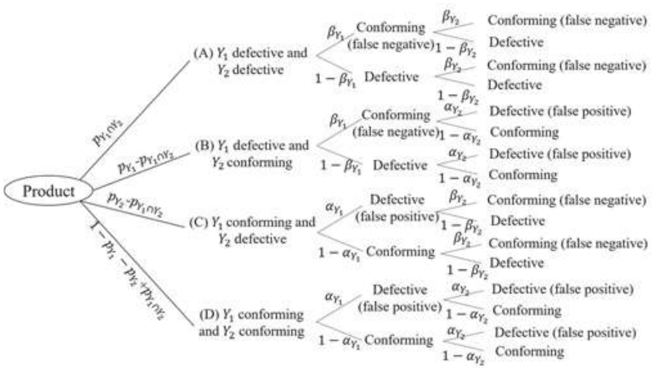

Fig. 3. Tree diagram of the inspection process of two output variables Y_1 and Y_2.

As far as inspection errors are concerned, their occurrences are considered independent in this study. Indeed, in practical applications, inspection errors are not mainly related to the part to be inspected and its defects. Instead, they depend closely on factors such as the measuring device and procedure, the inspector's abilities, and other work- and inspection-related factors [19], [20]. For that reason, as a first approximation, the model and the performance measure proposed in this study rely on the independence between inspection errors, and between inspection errors and the occurrence of defects, as depicted in Fig. 3. This situation is modeled by considering simple probabilities for the inspection errors. This assumption is necessary to model quality control effectiveness when *n* output variables are considered, as described in Section III.C.

More in general, when *n* output variables are inspected, the possible combinations in which the defects can occur are 2^n, each one associated with 2^n possible combinations of inspection errors, resulting in a total of 2^{2n} combinations, corresponding to all possible branches of the tree diagram.

B. Estimates of model variables

Both the defect probabilities and the inspection errors considered in the proposed model (p_{Y_j}, α_{Y_j} and β_{Y_j}) can be estimated using adequate prediction models or empirical methods (historical data, previous experience on similar processes, process knowledge, etc.) [10], [21]–[25].

In the modern industrial context, these estimates can be derived by exploiting emerging techniques described in Section I. In detail, the growing data sets coming from the distributed sensor network architectures integrated into CPSs can be used by data mining applications to acquire knowledge from historical data [7]. In particular, data-driven techniques from the machine learning and deep learning domains may be used to model defects (e.g., Artificial Neural Networks) [8], [26].

C. Modeling quality control effectiveness

According to the model proposed in the previous sections, a Bernoulli random variable related to the product (W_P) can be defined as follows:

- $W_P = 0$, when either (i) a truly defective output variable is classified as defective or (ii) an output variable is not defective;
- $W_P = 1$, a truly defective output variable is not classified as defective.

According to the graphical model of Fig. 3, $P(W_P = 0)$ can be obtained by multiplying the probabilities on the paths where conforming (both false positive and truly conforming) and truly defective output variables are encountered. On the other hand, $P(W_P = 1)$ can be derived by multiplying the probabilities on the paths where false negative output variables are encountered. As a result, given that the two probabilities are complementary, the following relationships may be obtained:

$$P(W_P = 0) = 1 - p_{Y_1} \cdot \beta_{Y_1} - p_{Y_2} \cdot \beta_{Y_2} + p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \quad (4)$$

$$P(W_P = 1) = p_{Y_1 \cap Y_2} \cdot \left[\beta_{Y_1} + \left(1 - \beta_{Y_1}\right) \cdot \beta_{Y_2}\right] + \left(p_{Y_1} - p_{Y_1 \cap Y_2}\right) \cdot \beta_{Y_1} + \left(p_{Y_2} - p_{Y_1 \cap Y_2}\right) \cdot \alpha_{Y_1} \cdot \beta_{Y_2} + \left(p_{Y_2} - p_{Y_1 \cap Y_2}\right) \cdot \left(1 - \alpha_{Y_1}\right) \cdot \beta_{Y_2} = p_{Y_1} \cdot \beta_{Y_1} + p_{Y_2} \cdot \beta_{Y_2} - p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \quad (5)$$

Therefore, according to (4) and (5), the mean total number of defective-output variables that are erroneously not detected in the inspection process for the two variables Y_1 and Y_2 can be defined as:

$$Insp\ eff = E(W_P) = p_{Y_1} \cdot \beta_{Y_1} + p_{Y_2} \cdot \beta_{Y_2} - p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \quad (6)$$

More in general, if there are *n* output variables to be inspected on the product, by exploiting the total probability theorem [18], the inspection effectiveness indicator becomes:

$$Insp\ eff = \sum_{j=1}^{n} \left(p_{Y_j} \cdot \beta_{Y_j}\right) - \sum_{j_1 < j_2} \left[\left(p_{Y_{j_1} \cap Y_{j_2}}\right) \cdot \left(\beta_{Y_{j_1}} \cdot \beta_{Y_{j_2}}\right)\right] + \cdots + (-1)^{t+1} \cdot \sum_{j_1 < j_2 < \cdots < j_t} \left[\left(p_{Y_{j_1} \cap Y_{j_2} \cap \ldots \cap Y_{j_t}}\right) \cdot \left(\beta_{Y_{j_1}} \cdot \beta_{Y_{j_2}} \cdot \ldots \cdot \beta_{Y_{j_t}}\right)\right] + \cdots + (-1)^{n+1} \cdot \left[\left(p_{Y_1 \cap Y_2 \cap \ldots \cap Y_n}\right) \cdot \left(\beta_{Y_1} \cdot \beta_{Y_2} \cdot \ldots \cdot \beta_{Y_n}\right)\right] = \quad (7)$$

$$\sum_{j=1}^{n}(-1)^{j+1}\cdot\sum_{1\le k_1<\cdots<k_j\le n}\left[\left(p_{\cap_{q=1}^{j}Y_{k_q}}\right)\cdot\left(\prod_{q=1}^{j}\beta_{Y_{k_q}}\right)\right]$$

where each sum $\sum_{j_1<j_2<\cdots<j_t}$ is calculated for all the $\binom{n}{t}$ possible subsets of t elements of the set $\{1,2,\ldots,n\}$. Thus, *Insp eff* is obtained by summing the probabilities of occurrence of defects multiplied by the related type II errors, minus the probabilities associated with defects appearing in even numbers, also multiplied by the related type II errors, and by summing again the probabilities associated with defects appearing in odd numbers, also multiplied by the related type II errors. Although (7) is formulated for the case of independence between inspection errors and the related defective-output variables, it can be considered a reasonable approximation of the inspection effectiveness when n defective-output variables can occur jointly.

For each output variable Y_j, a total cost related to the inspection, including costs for the inspection activity, defects removal and undetected defects, can also be considered, as described in [9]. However, a detailed cost analysis will be the object of future developments of this research.

The proposed model and related indicator can be implemented in a CPS within production systems for three different reasons: (i) to make assessments – in absolute terms – of the effectiveness of individual quality inspection procedures; (ii) to facilitate the comparison – in relative terms – between alternative inspection procedures; and (iii) to support the selection of the optimal inspection strategy that minimizes residual defectiveness. To this aim, the proposed model gets as input data the variables' estimates (see Section III.B) and returns as outputs the quantification of the inspection effectiveness indicators, *Insp eff*. Such outputs can be then embedded in a robust mathematical program performed in the CPS that, through optimization approaches, aims at reaching a local or global optimum for improving final product quality and achieving zero-defect goals.

IV. Practical Application

In this Section, an example taken from AM is proposed to show how the inspection effectiveness indicator can be calculated.

The aim of the application is to check the quality of a product made by a metal-based additive manufacturing process, immediately after the production (i.e., before any further post-processing treatments, such as surface finishing). Three output variables are inspected: porosity (*PO*), mechanical properties (*MP*), e.g., tensile strength, and dimensional accuracy (*DA*). Each output variable is inspected by using a specific inspection activity and test equipment.

TABLE I. Estimates of Model Variables Used in the Example

Output variable Y_j	Model variables		
	Defect probabilities	*Type II inspection error*	*Joint defect probabilities*
PO	$p_{PO}=2\%$	$\beta_{PO}=7\%$	$p_{MP\cap PO}=1.6\%$ $p_{DA\cap PO}=1.3\%$ $p_{DA\cap MP}=1.8\%$ $p_{MP\cap DA\cap PO}=0.06\%$
MP	$p_{MP}=2.98\%$	$\beta_{MP}=5\%$	
DA	$p_{DA}=3\%$	$\beta_{DA}=7\%$	

The probabilities of occurrence of defective-output variables, both single and joint probabilities, as well as the type II inspection errors, are provided in Table I. These values are obtained by a statistical analysis of historical data. Similar results can be obtained by using ML techniques.

According to (7), inspection effectiveness of the adopted quality inspections is the following:

$$Insp\ eff = p_{PO}\cdot\beta_{PO}+p_{MP}\cdot\beta_{MP}+p_{DA}\cdot\beta_{DA}-(p_{MP\cap PO}\cdot\beta_{MP}\cdot\beta_{PO})-(p_{DA\cap PO}\cdot\beta_{DA}\cdot\beta_{PO})-(p_{DA\cap MP}\cdot\beta_{DA}\cdot\beta_{MP})+(p_{MP\cap DA\cap PO}\cdot\beta_{MP}\cdot\beta_{DA}\cdot\beta_{PO})=4.38\cdot10^{-3} \quad (8)$$

As shown in (8), given a production of 1000 components, there will be nearly 5 defective-output variables that are erroneously not identified.

This indicator of inspection effectiveness can be useful to depict the quality of the inspection performed. Furthermore, it can enable to evaluate alternative inspection procedures to the one currently adopted.

V. Conclusions

In modern manufacturing industry, it is increasingly important to identify effective quality control procedures to achieve Zero Defect Manufacturing goals. To this aim, this paper presents a probabilistic model derived by combining probabilities of occurrence of defects in manufacturing products, related to selected output variables, and inspection errors. Such a model takes also into account potential cause-and-effect and dependence/independence relationships between variables. The model and the indicator of quality inspection effectiveness can be an effective decision support tool (i) to evaluate the effectiveness of alternative inspection strategies and (ii) to select the most appropriate according to manufacturer requirements.

The main critical aspect of this study concerns the empirical determination of process variable probabilities. These can be estimated using machine learning techniques applied to historical data and/or by using prior manufacturing experience. Further developments will be devoted to testing the proposed methodological approach within a real CPS by exploiting real-time data on defectiveness and inspection errors and performing optimization to improve the product's overall quality. Moreover, we are planning to extend this methodology to evaluate the overall inspection costs, including them within a broader performance assessment of a manufacturing process.

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