Doctoral Dissertation
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Inspection Strategies and Defect Prediction Models for quality control in low-volume productions

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I hereby declare that the contents and organisation of this Dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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Turin, December 12, 2020

Summary

This Doctoral Dissertation set out to plan quality inspection strategies by adopting suitable defects generation models and by assessing inspection performances in low-volume productions. The Dissertation offers some essential insights into the field of quality control for low-volume productions, where the limited historical data available and the difficulty of implementing traditional techniques and methodologies make the inspection process planning extremely challenging. The following Research Questions (RQs) are specifically addressed throughout the Dissertation:

RQ1: Can defects occurring in low-volume production processes be predicted using probabilistic models?

RQ2: How to evaluate the performances of quality inspections in low-volume productions?

RQ3: How to support designers in the early design phases of inspection process planning of low-volume productions?

In order to answer the aforementioned RQs, the Dissertation has been structured in six chapters, as described below.

A general introduction of the framework of the research and the importance of the topic is provided in Chapter 1, as well as the purpose statement and the research design and methods used in the current Dissertation.

Chapter 2 is concerned with an overview of the quality inspections in manufacturing processes. A considerable amount of literature has been published on inspection procedures in the manufacturing field. This chapter investigates the bibliography related to the inspection procedures from different perspectives. The specific aim is to review recent studies on inspection procedures and highlight research areas that are not adequately covered by the literature for identifying new challenges and research perspectives.

The identification of reliable and suitable prediction models of defects occurring in the final product is key to plan quality inspections, especially for low-volume production due to the scarcity of historical data. The different typology of inspection requires a different structure and conceptual paradigm of the models. With the purpose of

identifying reliable and suitable models of defect predictions and answering the first research question - RQ1, Chapter 3 begins by laying out a review of defect modeling in manufacturing in Section 3.1, and by proposing an overview of the current studies related to the application of machine learning for product quality control and improvement in Section 3.2. Then, a distinction between models to predict defects for in-process and offline inspections, respectively in Sections 3.3 and 3.4, is proposed. In detail, Section 3.3 introduces some defect prediction models designed for assembly processes, with a specific focus on the close relationship between assembly complexity and defect rates. In Section 3.4, a model specifically designed for offline inspections is proposed, using Additive Manufacturing as a case study.

The second research question - RQ2 - is addressed in Chapter 4, where the formulation of two useful indicators for assessing inspection strategy performance is proposed. In detail, to derive these indicators, the inspection strategy is modeled separately for in-process inspections and offline inspections, respectively, in Section 4.1 and 4.2. In such modeling, the defect prediction models proposed in Chapter 2 are combined with other inspection variables, including inspection errors and costs, with the purpose of assessing the performances of the two categories of inspection strategies through a pair of indicators. The first indicator provides an assessment of inspection effectiveness, evaluated based on undetected defects remaining in the final product. The second indicator is obtained by carrying out an overall economic evaluation of the strategy adopted. These indicators are formulated following a different architecture depending on their use for evaluating in-process or offline inspections. The probabilistic models formulated are strongly influenced by the cause-effect relationships between the process and inspection variables. In order to take this aspect into account, Section 4.2 extends previous studies in the field of in-process inspections, that are reviewed in Section 4.1, by including possible interactions between process and offline inspection variables, in terms of cause-and-effect relationships. The final section of Chapter 4 introduces a preliminary uncertainty evaluation of the two performance indicators.

Intending to support designers in the selection of the most suitable inspection strategy, Chapter 5 is conceived to answer the last research question - RQ3 – by proposing an operational tool, called Inspection Strategy Map (ISM). The ISM has the dual purpose of analyzing and guide the inspection planning process. The description of such a tool is provided in Section 5.1, while different applications of the proposed approach are finally described in Section 5.2. The case studies addressed belongs to different manufacturing sectors, specifically regarding assembly processes for in-process inspections and Additive Manufacturing technique for offline inspection.

The concluding chapter summarizes the original contributions of the Dissertation, focusing on the benefits, limitations and possible future developments.

Acknowledgment

First, I would like to thank my parents for all their support and endurance under stressful circumstances and my beloved sister Elena for being, sometimes, the necessary distraction. Without their love, trust and patience, it would have been difficult to reach the conclusion of the doctorate program. The last few months have often been difficult and discouraging, also linked to the epidemiological emergency of Covid-19. As never before, it is in these difficult moments that the family is found and rediscovered.

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To my beloved grandparents Piero and Remo, who would have been very proud of their granddaughter.

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Chapter 1 : Introduction

Manufacturing companies are increasingly focused on producing high-quality and fault-free products that meet customers' needs. Defects in the final product, particularly those generated during the production process, can significantly affect the product itself, both in terms of quality and cost. In this regard, designing effective and cost-efficient inspection strategies for the detection of defects and the reduction of quality-related costs has always been a great challenge and a crucial factor for achieving market competitiveness (Franceschini et al., 2018; Savio et al., 2016; Biffl and Halling, 2003; Tirkel and Rabinowitz, 2014; Verna et al., 2020e; Emmons and Rabinowitz, 2002).

A distinction between in-process and offline inspection strategies should be considered when designing inspections. In in-process inspections, units are inspected during the production process (Tzimerman and Herer, 2009; Tirkel et al., 2016; Azadeh et al., 2015; W. Wang, 2009), while in offline inspections, finished products are inspected after the production process is completed (Tzimerman and Herer, 2009; C. W. Kang et al., 2018). Although in-process inspections are considered more economical and effective than offline inspections, in some situations, they are impossible to perform, not adequate or not affordable (Tzimerman and Herer, 2009; Verna et al., 2020e).

Several methods have been adopted in literature to design quality-inspections in mass productions, including simulations (Neu et al., 2002, 2003; Münch et al., 2002), cost-benefit models (Savio, 2012), optimization and mathematical programming models (Hanne and Nickel, 2005; Shiau, 2003; Mohammadi et al., 2015). However, when dealing with low-volume productions, such techniques may not be appropriate (Trovato et al., 2010; Celano et al., 2011; Marques et al., 2015; Del Castillo et al., 1996; Pillet, 1996; Khoo and Quah, 2002). Although these productions are also constantly repeated over the years, the low production rate makes the application of traditional techniques difficult, partly because of the scarcity of historical data available.

This Doctoral Dissertation analyses quality inspections in low-volume production of manufacturing companies by addressing several key aspects. There are several important areas where this Dissertation provides an original contribution to the study of low volume production. The following Research Questions (RQs) are specifically addressed throughout the Dissertation:

RQ1: Can defects occurring in low-volume production processes be predicted using probabilistic models?

RQ2: How to evaluate the performances of quality inspections in low-volume productions?

RQ3: How to support designers in the early design phases of inspection process planning of low-volume productions?

In detail, this Dissertation includes four main chapters. After Chapter 2, which provides an overview of the research framework, the three research questions RQs are specifically addressed in the following three chapters, i.e., in Chapters 3, 4 and 5, as described below.

Chapter 2 is concerned with an overview of the quality inspections in manufacturing processes. Quality control activities include quality inspections, i.e., the activities of checking products (ISO 2859-1:1999). The main aim of quality inspections is to prevent non-compliant products from reaching end customers or end-users. These are carried out in various production contexts and by most companies, because defects remaining in the product can lead to a loss of market competitiveness (Franceschini et al., 2018; Savio et al., 2016; Biffl and Halling, 2003; Tirkel and Rabinowitz, 2014; Verna et al., 2020e; Emmons and Rabinowitz, 2002).

In scientific literature, inspection procedures have been addressed from several perspectives. An interesting classification was recently proposed by Genta et al. (2020) in their survey on inspection procedures. This classification is described in detail in Section 2.1. In particular, two classification categories for inspection procedures are considered: (A) general characteristics and (B) modeling structure. The first category, i.e., general characteristics, includes the type of inspection and the strategy adopted. On the other hand, the second category, i.e., modeling structure, entails different features describing an inspection procedure, including (a) errors, (b) costs, (c) human skills, (d) time, (e) defect modeling, (f) simulations and (g) low-volume production (Genta et al., 2020).

With the purpose of clarifying the classification of inspection procedures from the point of view of the type of inspection, Section 2.2 defines the two main inspection paradigms that have been addressed in the literature, i.e., in-process and offline inspection.

A brief review of key research contributions on inspection procedures since the 1960s and the emergence and differentiation of the two inspection paradigms is presented in Section 2.3. The first papers published on inspection procedures were within the framework of inspection allocation in multi-stage production systems (Beightler and Mitten, 1964; Lindsay and Bishop, 1964). On the contrary, the first study on offline inspections dates back to the early 1980s.

Among the papers published in the last 20 years, both addressing in-process and offline inspections, it is possible to identify some common research lines, including similar research approaches, research objectives and application fields. In detail, according to Genta et al. (2020), these can be grouped in five main clusters: (i) multi-stage production systems, (ii) systems with multi-characteristic components, (iii) multi-objective optimization models, (iv) Economic Order Quantity (EOQ), (v) low-volume productions and defect generation models. An overview of the main studies carried out in each cluster is provided in Section 2.4.

Several inspection models have been developed in the scientific literature, considering one or more features. In Section 2.5, the models with a complete structure are reviewed for both in-process inspections and offline inspections.

With the aim of highlighting the gaps in the literature on inspection procedures, Section 2.6 provides an overview of the main research areas covered by the most recent papers and, finally, Section 2.7 offers some insight into the future research perspectives that are sought to be addressed in the following chapters of this Dissertation.

In low-volume productions, the lack of historical data available and, often, the non-applicability of traditional statistical techniques, makes it difficult to predict the defects that might occur in the finished product or the semi-finished products (Koons and Luner, 1991; Montgomery, 2012). However, defects occurring during the manufacturing process represent a huge issue even for low-volume productions owing to the dramatic impact they can cause, both in terms of quality and costs. Accordingly, the development and identification of appropriate models of defects predictions have long been a question of great interest. In the literature, extensive research has been carried out on the prediction of product defects (Antani, 2014; Su et al., 2010; Shibata, 2002; Psarommatis et al., 2020), as described in Section 3.1. Besides, with the increased digitalization, lots of data can now be generated in the overall production process that can be used by machine learning approaches for several purposes, including product quality improvement, as discussed in Section 3.2. However, such approaches have been mostly restricted to mass productions, involving millions of parts and operations. To date, defect prediction models suitable for low-volume manufacturing processes are still lacking. In this regard, to answer the first research question - RQ1, two novel paradigms of defect generation models are developed and discussed in Chapter 3. In detail, a novel prediction model suitable for in-process inspections is presented in Section 3.3, while a different methodology to estimate defects investigation using offline inspections is proposed in Section 3.4. The specific content of these two chapters is proposed below.

After having discussed the main defect prediction models existing in the literature for in-process inspections, a specific focus is dedicated to those models relating assembly defects to complexity. The latter is a crucial factor in assembly processes that should be managed appropriately in order to avoid compromising the final quality of the finished products. Different approaches are adopted to assess assembly complexity, based on the product to be assembled or the process sequence for the assembly (Alkan et al., 2017). A general overview of these approaches is proposed in Section 3.3. Furthermore, one of the most accredited models developed in the literature that relies on the process- and design-based complexities defined by Shibata (2002) and Su et al. (2010) is reviewed. The structure of this model is resumed to develop a novel prediction model based on another complexity paradigm, i.e., the structural complexity paradigm (Sinha et al., 2012; Alkan, 2019). Complexity is evaluated considering structural properties associated with handling and insertion of assembly parts and their architectural structure (Alkan, 2019). This approach, depending solely on physical design information, can be considered more practical from the design point of view, especially in the early design stages. A low-volume production of wrapping machines is considered as a case study.

Regarding the defect models developed for offline inspections, a scant number has been proposed in the literature. To fill this gap, Section 3.4 develops a novel probabilistic model suitable to predict defects occurring in low-volume manufacturing processes in case of offline inspections. The methodology proposed includes the definition of input and output variables, the determination of the mathematical relationship among these variables, the identification of all the uncertainty contributions and the estimation of probabilities of occurrence of defective-output variables. The approach is then applied to an Additive Manufacturing (AM) production in the automotive industry. Indeed, quality inspections performed on AM products are mainly restricted to offline controls, i.e., carried out at the end of the production process, owing to the difficulty implement corrective or adaptive actions once a defect has been detected during the process (Tapia and Elwany, 2014; Everton et al., 2016; Rao et al., 2015; Grasso and Colosimo, 2017; Colosimo, 2018; Tsung et al., 2018; Galetto, Genta, et al., 2020).

Both models for in-process and offline inspections are conceived to predict defects using the ‘a priori knowledge’ of the product and process, without any additional experimental test. These predictions are useful to the designers for designing effective and affordable inspection procedures, as is then discussed in the following Chapters 4 and 5.

The Inspection Process Planning (IPP), that defines which quality characteristics of a product should be inspected, where and when, represents a key factor within organizations for achieving these objectives (Zhao et al., 2009; Pfeifer, 2015; Mohammadi et al., 2015). There are several aspects that inspection designers have to consider during the IPP, including (i) the typology of production to be inspected, and (ii) the kind of quality control to be performed. Despite the fact that this topic is attracting increasing interest from researchers and practitioners, there remains a paucity of guidance and methodological approaches that can be used by manufacturing companies to support the inspection design process of low-volume productions. In this regard, Chapter 4 attempts to answer the second research question - RQ2 - by extending the studies proposed by Franceschini et al. (2018) and Genta et al. (2018) and adapting the two practical performance measures conceived for in-process inspections to offline inspections.

In particular, Section 4.1 reviews the methodology proposed by Franceschini et al. (2018) and Genta et al. (2018) to assess inspection effectiveness and cost in the case of in-process inspection strategies. They proposed to decompose the manufacturing process into a certain number of steps, i.e., specific operations providing an added value to the end product. Next, they developed a probabilistic model with the aim to define two performance indicators for inspection strategies, related to inspection effectiveness and affordability.

The probabilistic model and the two performance measures described in Section 4.1 are then adapted to the case of offline inspections in the next Section 4.2. After having modeled the inspection strategy and defined the two practical performance indicators specific for offline inspections, the method is improved by including possible interaction between model variables and costs occurring during the inspection process. An excerpt from the application of the method to a real case study in the field of Additive Manufacturing processes is proposed.

In Section 4.3, an approach to evaluate the uncertainty of the performance measures, both in the case of in-process and offline inspections, is finally provided.

Chapter 5 is conceived to address the third research question - RQ3 - and therefore try to fill the gap in the literature regarding the scarcity of tools to support the designers in the early design phases of inspection process planning. The models of defect prediction developed in Chapter 3 and the methods to assess the performance of inspection strategies proposed in Chapter 4 are combined in a practical tool allowing for the assessment of the adequacy of alternative inspection strategies. In the first section of Chapter 5 (Section 5.1), a general framework to assess the effectiveness and cost of inspection strategies is developed through the definition of a novel tool, named Inspection Strategy Map (ISM). Two are the main purposes of ISM: (i) analyzing the positioning of different inspection strategies on the map, in terms of effectiveness and cost, allowing the designer to compare more alternatives (analysis tool); and (ii) supporting the designer in determining the conditions of effectiveness and cost to allow an *a priori* inspection strategy positioning. The framework tool proposed in this chapter is applied in Section 5.2 to (i) the low-volume assembly of wrapping machines, regarding in-process inspections, and (ii) the additive manufacturing process of SLM, as regards offline inspections. With this tool, engineers are driven to identify alternative inspection procedures in order to make the inspection strategy more effective and cost-efficient.

The concluding chapter summarizes the original contributions of the Dissertation, focusing on the benefits, limitations and possible future developments.

Chapter 2 : Quality inspections in manufacturing processes

Quality control activities include quality inspections, i.e., the activities of checking products (ISO 2859-1:1999, 1999). According to the standard ISO 2859-1:1999, an "inspection" is defined as an *"activity such as measuring, examining, testing or gauging one or more characteristics of a product or service, and comparing the results with specified requirements in order to establish whether conformity is achieved for each characteristic"* (ISO 9000:2015, 2015). The main aim of quality inspections is to prevent non-compliant products from reaching end customers or end-users. These are carried out in various production contexts and by most companies, because defects remaining in the product can lead to a loss of market competitiveness (Franceschini et al., 2018; Savio et al., 2016; Biffl and Halling, 2003; Tirkel and Rabinowitz, 2014; Verna et al., 2020e; Emmons and Rabinowitz, 2002). A variety of products can be inspected, ranging from parts used in production to semi-finished or finished products before shipment to the customer (Genta et al., 2020). Depending on the characteristics of the parts to be inspected, inspections can be performed manually, using automatic detection devices or a combination of both (H. Y. Wang and Wang, 2020; Aydin et al., 2017).

Quality inspections are typically performed according to specific inspection procedures, depending on the production process. For instance, in multi-stage production systems, quality inspections may be carried out after some or all production steps (Raz, 1986; Eger et al., 2018). However, to be effective, strict consideration must be given to where performing an inspection, often after particular processing activities (Raz, 1986). Cost and constraint factors, as well as operational alternatives, interact intricately and make the solution far from trivial (Mandroli et al., 2006; Genta et al., 2020). In this respect, deciding when, where and how performing an inspection is a truly strategic decision in the inspection planning process (Zhao et al., 2009; Pfeifer, 2015; Mohammadi et al., 2015).

A considerable amount of literature has been published on the formulation and application of inspection procedures in the manufacturing field.

This chapter investigates the bibliography related to the inspection procedures from different perspectives. The specific aim is to review recent studies on inspection procedures and highlight research areas that are not adequately covered by the literature for identifying new challenges and research perspectives. In detail, the rest of Chapter 2 has been organized as follows:

- Section 2.1 proposes a classification of inspection procedures, adapted from the recent survey by Genta et al. (2020).
- Section 2.2 deals with the description of the two inspection paradigms that can be identified from the inspection type perspective: in-process and offline inspections.
- Section 2.3 presents a brief review of key research contributions on inspection procedures since the 1960s, and the emergence and differentiation of the two inspection paradigms are presented.
- Section 2.4 highlights the main research lines that can be distinguished among the papers published in the last 20 years, both addressing in-process and offline inspections.
- Section 2.5 reviews the prominent reference models identified in the literature for both in-process inspections and offline inspections.
- Section 2.6 provides an overview of the main research areas covered by the literature on inspection procedures and identifies the major literature gaps.
- Section 2.7 finally offers some insight into future research perspectives.

2.1 Classification of inspection procedures

In scientific literature, inspection procedures have been addressed from several perspectives. An interesting classification was recently proposed by Genta et al. (2020) in their survey on inspection procedures. In detail, two classification categories for inspection procedures are considered: (A) general characteristics and (B) modeling structure (see Figure 2.1). The first category, i.e., general characteristics, includes (Genta et al., 2020):

(i) The type of inspection, i.e., in-process and offline inspection. This classification is specifically addressed in Section 2.2.

(ii) The strategy, i.e., sampling and/or 100% inspection. The strategy to be adopted, ranging from 100% inspection, acceptance sampling or a mixture of both, is a central element of statistical quality control. In order to prevent defects from reaching customers or end-users, companies should inspect productions with a 100% inspection strategy. However, in some circumstances, 100% inspection may be inefficient and impractical, especially in the case of destructive tests or expensive inspections (Schilling and Neubauer, 2017; Kahraman et al., 2016).

On the other hand, the second category, i.e., modeling structure, entails different features describing an inspection procedure, including (a) errors, (b) costs, (c) human skills, (d) time, (e) defect modeling, (f) simulations and (g) low-volume production (Genta et al., 2020). A brief description of each feature is given below:

(a) *Error* – Two types of inspection errors can occur during an inspection activity: (i) type-I error, i.e., the wrong rejection of a conforming unit, and (ii) type-II error, i.e., the erroneous acceptance of a nonconforming unit (Mandroli et al., 2006; C. W. Kang et al., 2018). In some papers, inspection errors are also regarded as the absence of inspection capability (Mandroli et al., 2006; Shetwan et al., 2011).

(b) *Cost* – Implementing an inspection-oriented quality-assurance strategy entails a detailed economic assessment, aiming at allocating an appropriate level of inspection activity according to a cost-benefit logic. In particular, in order to achieve this aim, a trade-off must be sought between the various cost components associated with inspection. These include repair/rejection costs and replacement costs due to a quality defect, the costs of undetected defects, e.g., warranty penalty, incurred when a non-compliant product reaches customers (Emmons and Rabinowitz, 2002; Franceschini et al., 2018). Accordingly, an inspection-oriented strategy points to cost-effective production and tolerates a non-zero level of defective production (Mandroli et al., 2006; C. W. Kang et al., 2018).

(c) *Human skill* – In various production systems, most of the quality inspections still rely on human labor (C. W. Kang et al., 2018; Mehmood Khan et al., 2014), although there is an increasing trend to use sophisticated automatic quality monitoring devices and techniques to avoid human errors. Thus, the quality and performance of the inspection process may depend on the skill of the inspectors.

(d) *Time* – The inspection time is closely related to the type of product and its complexity. By switching from a low complexity product to a high complexity product, the number of operations to be performed, the number and variety of components, their size and product design increase (Sardar and Lee, 2015). As a result, the inspector has to check more quality features that increase the inspection time. The inspection time also affects the performance of the individual inspector as well as the overall inspection station (W. Wang, 2009; C. W. Kang et al., 2018). It also contributes significantly to the total production costs (Shetwan et al., 2011).

(e) *Defect modeling* – The defect modeling in a production process can be considered as the modeling of defects probability in the overall production process or in the several stages in which it can be decomposed. This concept of defect modeling is the one adopted in this Dissertation. Other authors consider the defectiveness in the inspections by considering the defect rate, defined as the proportion of defective items among all items manufactured by a process at a stage. In some studies, the defect rate is assumed as known and constant for all operations, whereas in others is a random defect rate. In the papers in which a random defect rate is considered, in some cases, a probability of occurrence of defects is considered for specific ranges of defect rates, while in other cases, the defect rate is explicitly treated as a random variable (Genta et al., 2020). To summarize, in the survey of Mandroli et al. (2006) four possible combinations of defect rates are considered:

- ✓ Single type constant defect rate.
- ✓ Single type random defect rate.
- ✓ Multiple type constant defect rate.
- ✓ Multiple type random defect rate.

(f) *Simulation* – In the field of inspection procedures, most of the research problems are formulated using an analytical model. This analytical formulation of the problem can be solved through analytical and/or simulative approaches. Although the first approach is preferable, simulative approaches typically provide additional information or result in highly complex production processes (Genta et al., 2020).

(g) *Low-volume production* – The performances of inspection procedures of a manufacturing process are tightly related to the production volume. Statistical Process Control (SPC) techniques are straightforwardly applied (Montgomery, 2012) in the case of mass production. On the contrary, when dealing with low production volumes, most of the SPC techniques are often unsuitable (Marques et al., 2015). Section 2.4.5 is specifically concerned with low-volume productions.

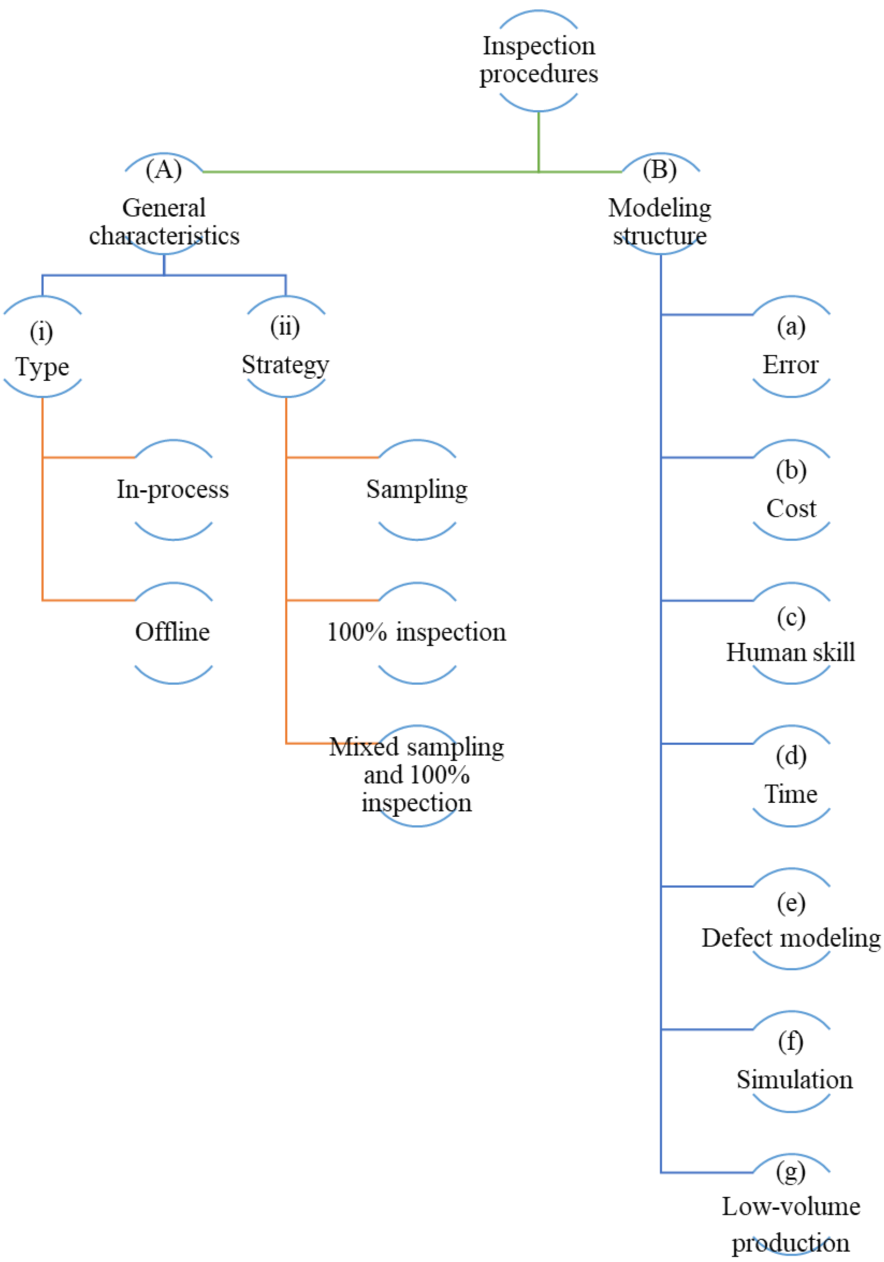


Figure 2.1 - Classification of inspection procedures. Adapted from Genta et al. (2020).

2.2 In-process and offline inspection paradigms

In scientific literature, two general inspection paradigms can be identified: in-process inspection and offline inspection.

In-process inspections are often referred to in the literature as “online” inspections (Mandroli et al., 2006). However, in the manufacturing field, it is preferable to use the term “in-process” or “on-machine” instead of “online” because this latter is mainly employed in web-based contexts. In in-process inspection, the production units are inspected during the manufacturing process (Tzimerman and Herer, 2009; Tirkel et al., 2016; Azadeh et al., 2015; W. Wang, 2009). On the contrary, in offline inspection, the units are inspected after the manufacturing process is completed (Tzimerman and Herer, 2009; C. W. Kang et al., 2018). In-process inspection regimes are typically more economical and effective than corresponding offline inspection ones (Tzimerman and Herer, 2009). However, there are situations in which in-process inspections are not adequate, impossible to perform or not economically convenient due to operation type and time (Raz et al., 2000). In these cases, an effective approach is to perform offline inspection after preserving the order in which the product is processed (Genta et al., 2020).

Offline inspections can be performed on the finished product at the end of the production line or on the semi-finished product at different stages of the manufacturing process (Tzimerman and Herer, 2009; Ramzan and Kang, 2016).

A considerable amount of literature has been published around the topic of in-process and offline inspection. Generally, papers in this research field are concerned with only one of the inspection paradigms. As far as the in-process inspection paradigm is concerned, an extensive collection and analysis of the most prominent research papers have been provided in the survey of Mandroli et al. (2006). This survey reviews more than 100 papers produced from the 1960s to the early 2000s, extending the previous survey of Raz (1986) published in the 1980s. Regarding offline inspection regimes, the paper of Kang et al. (2018) can be considered, so far, the reference survey for researchers and practitioners. It classifies more than 30 papers drawn up in the last 15 years, reorganizing the previous survey of Ramzan et al. (2016). In the recent study of Genta et al. (2020), the surveys of Kang et al. (2018) and Mandroli et al. (2006) were extended by recent papers concerning in-process and offline inspections, for a total of almost 70 papers examined.

2.3 Key research contributions

A brief review of key research contributions on inspection procedures since the 1960s and the emergence and differentiation of the two inspection paradigms is presented. The first studies within the framework of inspection allocation in multi-stage production systems are the papers of Beightler and Mitten (1964) and Lindsay and Bishop (1964). In the first study, a detailed description of the interacting effects which exist between quality control stations associated with the various stages of manufacture of a product was provided, as well as the influences that these interactions have on the optimal choice of sampling plan for a given station. They described and demonstrated the applicability of the mathematical theory of dynamic programming to the design of an optimal sequence of such interrelated plans. In the research, a digital computer program solving a simplified version of the above design problem was given in order to illustrate the dynamic programming solution procedure (Beightler and Mitten, 1964). Lindsay and Bishop (1964) proposed a general screening inspection program in which inspection levels and locations of inspection points were treated as variables. The model, assuming complete inspection of the production run rather than sampling, is designed to minimize the sum of the unit inspection cost and the cost of lost production due to improper processing. They showed that the function representing the total of inspection and scrap costs was minimized by an extreme-point solution, allowing the minimum-cost inspection program to lie in a relatively restricted subset of all possible allocations. The application of a computational procedure based on dynamic-programming enabled the minimum-cost program to be readily determined for cases in which the requirement for inspection is the maintenance of a specified quality level or when a linear cost may be associated with outgoing defective material (Lindsay and Bishop, 1964).

In the early seventies, the first author addressing non-serial production systems was Britney (1972). In his model, a perfect inspection and immediate repair of nonconforming units were considered. The total expected cost includes components for unit inspection and repair, fixed repair costs and shipment of nonconforming units. The optimization problem was solved with a branch and bound method (Britney, 1972). The following year, Hurst (1973) introduced for the first time a model including possible inspection errors. These are the type-I inspection error, i.e., the risk of rejection of conforming units and the type-II inspection error, i.e., the risk of acceptance of nonconforming units. In the model, the production system was assumed to be serial with only one inspection operation possible after each processing step, with the units perceived as non-conforming removed from the production flow. The model proposed by Hurst (1973) was only descriptive without providing a method to optimize system performance. In the early 1980s, the research strand introduced by Hurst was carried on by Ballou and Pazer (1982), whose investigations included a "what-if" simulation analysis of n-stage linear production systems with inspection errors. The input parameters of the simulation were the number of phases, the value-added in each phase, the unit inspection costs, and the cost of the penalty for accepting a non-compliant unit. Cost per good unit accepted by the customer is used as the optimizing criterion. The cost-quality response surface was explored through a sequential sensitivity analysis. The results indicated that, under certain conditions, the level of predictable inspector fallibility significantly impacts the number and placement of inspection stations as well as cost per good unit produced. The modeled systems, however, were relatively insensitive to the variability of inspectors' performance (Ballou and Pazer, 1982).

Until 1982, studies carried out within the framework of inspection procedures had focused on inspections carried out during the production process, i.e., in-process inspections. The first study that dealt with offline inspections was published two years later by Hassin (1984), who thus launched the new inspection paradigm, although he actually used the term "dichotomous search". He proposed a search strategy aimed at minimizing the expected number of inspections needed to locate the exact transition time for a process with a constant failure rate, where that last unit is known to be non-conforming. Applications of the strategy cover the areas of quality control and maintenance of communication and supply lines (Hassin, 1984). The first paper that discusses offline inspection policies directed towards an economic optimization rather than an identification of the transition unit of the process was published by Raz et al. (2000). In their research, the problem of determining the optimal inspection/disposition policy for a finite batch of items produced by a machine that is subject to random breakdowns was addressed. In detail, they identified which units should be inspected and in which order to minimize the sum of inspection costs and penalties (Raz et al., 2000). Henceforth, the two inspection paradigms, in-process and offline, have been definitively established.

2.4 Recent common research lines

Among the papers published in the last 20 years, both addressing in-process and offline inspections, it is possible to identify some common research lines, including similar research approaches, research objectives and application fields. In detail, according to Genta et al. (2020), these can be grouped in five main clusters: (i) multi-stage production systems, (ii) systems with multi-characteristic components, (iii) multi-objective optimization models, (iv) Economic Order Quantity (EOQ), (v) low-volume productions and defect generation models. An overview of the main studies carried out in each cluster is provided below.

2.4.1 Multi-stage production systems

Multi-stage production systems are the first main cluster that is investigated within the research framework of in-process inspections. A large number of studies were published in recent years that have enriched and deepened the preliminary studies on the topic discussed in Section 2.3. In a multi-stage production system, each manufacturing stage may include three possible kinds of stations, i.e. (i) manufacturing station, (ii) inspection station, and (iii) rework or replacement station, as shown in Figure 2.2.

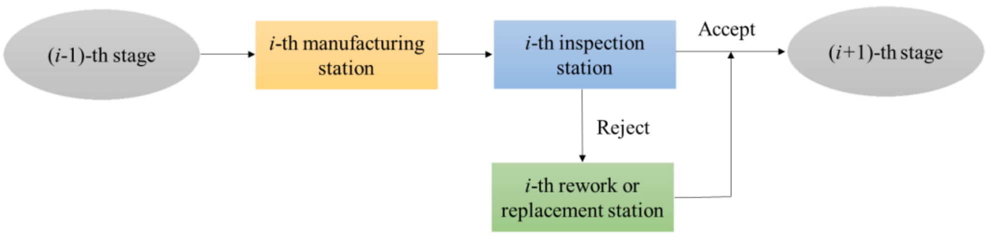


Figure 2.2 – Schematic of a complete manufacturing stage (*i*-th stage) in a multi-stage production system. Adapted from Genta et al. (2020).

The methodologies proposed in the scientific literature regarding quality control and improvement of multi-stage production systems typically entail quantitative modeling of the system, which can be (i) analytical, i.e., based on physical laws, or (ii) data-driven, i.e., based on process experimental data (Shi, 2006; Shi and Zhou, 2009).

The most prominent method belonging to the first category, i.e. analytical modeling of the system, is the “state space model”, proposed for the first time by Jin and Shi (1999) in the dimensional control field. In the state space modeling approach, for each manufacturing stage, the key quality characteristics of the product (e.g., the dimensional quality), represented by a “state vector”, are put in relationship with the process error sources (e.g., tooling locating errors, part accumulative errors, re-orientation errors). Such a model is used to model variation propagation through different multi-stage manufacturing processes, including machining and assembly (Loose et al., 2010; Yang et al., 2017; Xin Li et al., 2017).

With reference to the second category that includes studies based on data-driven models, the focus is moved to the investigation of patterns in the extensive historical quality database, without a comprehensive *a priori* knowledge of the production process. The purposes of these data-driven techniques are manifold. These include statistical inference of direct interactions among the different stages of the production process (Zeng and Zhou, 2007; Liu et al., 2019; Eger et al., 2018), as well as design optimization, focusing on quality improvement, reduction of inspection costs and optimal allocation of inspection resources (Rezaei-Malek, Mohammadi, et al., 2019; Vaghefi and Sarhangian, 2009; Rezaei-Malek, Siadat, et al., 2019).

Among the most recent studies carried out in the design of quality inspection procedures, Van Volsem et al. (2007) proposed a modeling to the problem of determining the optimal inspection strategy for a given multi-stage production process as a joint optimization of inspection location, type and inspection limits. This results in identifying the inspection strategy leading to the lowest total inspection cost, while still assuring a required output quality. They assumed a constant production and inspection rate, perfect inspection, and perfect rework. They proposed a fusion between a discrete event simulation to model the multi-stage process subject to inspection and to calculate the resulting inspection costs, and an Evolutionary Algorithm (EA) to optimize the inspection strategies (Van Volsem et al., 2007). Azadeh and Sangari (2010) developed a solution algorithm based on simulated annealing.

The optimization of inspection plans for multi-stage manufacturing systems with possible misclassification errors was the core topic of the research conducted by Vaghefi and Sarhangian (2009). They proposed a new mathematical model that minimizes total inspection costs while still assuring a required output quality. The complexity of the model required a simulation algorithm to model the multi-stage manufacturing system subject to inspection and to estimate the corresponding inspection costs (Vaghefi and Sarhangian, 2009). Two years later, Korytkowski (2011) proposed an approach to identify the optimal location of inspection stations in a multiproduct multistage production system. A multiproduct setting where part types compete with each other for common production resources was considered, as well as factors such as throughput time variability and the corresponding queuing aspects were included in the model. The optimal allocation was determined by using a genetic algorithm with tournament selection, one–point crossover and uniform mutation. Since the codes used in the chromosome reflect inspection allocation policies, the genetic approach proved to be suitable for modeling the problem of inspection allocation (Korytkowski, 2011).

In a later study, Azadeh et al. (2012) proposed a particle swarm optimization (PSO) algorithm to determine the optimal inspection policy in serial multi-stage processes. The policy consisted of three decision parameters to be optimized, i.e., the stages in which inspection occurs, tolerance of inspection, and size of sample to inspect. The performance measure of the algorithm was the total inspection cost.

They showed that PSO provided better results in comparison with other previous algorithms proposed in the scientific literature (Azadeh et al., 2012). A few years later, the same authors addressed the problem of finding optimal inspection policies in serial multistage production processes to minimize total inspection cost where the cost components are described by the use of fuzzy numbers. In fact, in practical applications, cost values are generally imprecise and not known exactly and, therefore, fuzzy sets, i.e. specific ranges of values, are suitable to describe them (Dubois and Prade, 1980; Klir and Yuan, 1996). The decision variables considered were the type of inspection in each stage, the acceptance limits, and the size of sample to inspect. They also considered the case in which the inspectors were not error-free. A solution algorithm was proposed based on particle swarm optimization, and a simulation was used to provide better insight into the optimal solution (Azadeh et al., 2015).

A mixed-integer linear mathematical programming model for the integrated planning problem of the part quality inspection and preventive maintenance activities in serial multi-stage manufacturing system was developed by Rezaei-Malek et al. (2018). The model concurrently determined the right time and place for performing the inspection activities while the objective is to minimize the total cost, including the production, maintenance, inspection, scrap, replacement, and the penalty of shipped defective items to customers. It was assumed that each production stage was deteriorating in time, and consequently, the probability that a conforming item acquired a defect in each stage increased. The results showed that the determination of inspection locations along a manufacturing line in different periods of time regarding the impact of preventive maintenance activities on defective production probability resulted in a more efficient manufacturing system (Rezaei-Malek et al., 2018).

Rezaei-Malek et al. (2019) published an extensive survey on the existing researches on the optimization of the part quality inspection in multi-stage manufacturing systems. They examined the studies from the viewpoint of the considered production system characteristics, the applied modeling approaches, and solution methodologies. This survey remarked that almost all the authors have ignored manufacturing constraints and have not taken the uncertainty of the system into account. The survey remarked that although numerous works have already been done on the part quality inspection planning (PQIP), the development of multi-objective optimization frameworks considering real production constraints under parameter uncertainty was still lacking. Besides, the creation of integrated models aiming to plan the inspection, maintenance and production activities simultaneously identified as an important potential future research direction (Rezaei-Malek, Mohammadi, et al., 2019). Accordingly, a multi-objective mathematical model involving real production constraints and uncertainty of production system to plan part quality inspection and preventive maintenance activities concurrently was proposed by the same authors (Rezaei-Malek, Siadat, et al., 2019).

2.4.2 Systems with multi-characteristic components

A second common research line that can be identified within the papers regarding inspection procedures, especially those referring to offline inspections, deals with systems with multi-characteristic critical components (Genta et al., 2020). Such multi-characteristic critical components exist in different systems and include, e.g., aircraft engines, space shuttles, gas ignition systems. Duffuaa and Khan (2005) proposed an inspection plan in which different inspectors examine different characteristics of each component. In detail, for each characteristic, the components can be classified as (i) meeting specifications, (ii) scrap or (iii) rework. All the accepted components and those that meet the specifications at the rework station go to the next inspector, who inspects the next characteristic. This chain of inspection continues until all the characteristics have been inspected once, completing one cycle of inspection. If needed, all accepted components go to the next cycle of inspection, and this process is repeated a total of n times before the components are finally accepted. Therefore, the accepted components will be those that are accepted in the n-th cycle, and the total scrapped components will be the sum of those scrapped in the first, second, ... , n-th cycle. Figure 2.3 depicts the inspection plan for the generic j-th cycle concerning a generic characteristic (Duffuaa and Khan, 2005). This inspection plan considers several types of classification errors made by the inspector. In the study, the performance measures for this plan were defined, and the statistical and economic impact of the several types of inspection errors on these measures were investigated. The impact of the errors was studied by conducting a sensitivity analysis on the errors utilizing computer software by implementing an algorithm that determines the optimal parameters of the model of the plan. The behavior of the performance measures upon variation in the levels of errors was also investigated. They assumed characteristic failures of the components to be statistically independent. The results indicated that these errors had a considerable effect on the performance measures of the inspection plan.

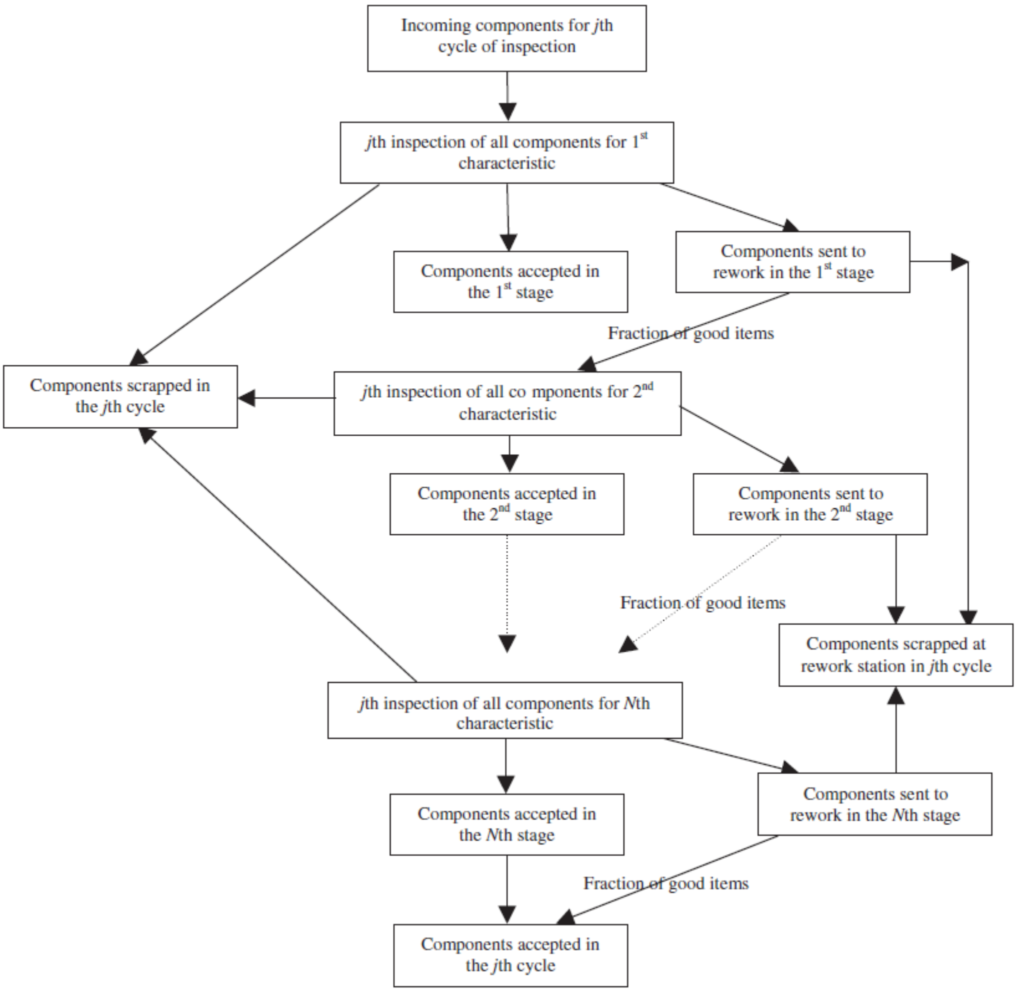


Figure 2.3 – Inspection plan for the generic *j*-th cycle in systems with multi-characteristic critical components, *j* = 1, …, *n* (Duffuaa and Khan, 2005).

Later, the two authors developed a novel inspection plan considering statistical dependence of characteristics' failures of critical components (Duffuaa and Khan, 2008). The advantage of the new model over the previous one was illustrated in the case of dependency. The model resulted in an average of 32.4% reduction in cost compared to the situation where the dependency case is solved, assuming statistical independence (Duffuaa and Khan, 2008). In a further study on the field, Elshafei et al. (2006) proposed a dynamic programming approach to the problem of determination of the inspection sequence of multi-characteristic critical components and the number of repeat inspections for each characteristic. Even in this model, an inspector can classify a product as non-defective, to be reworked, or to be scrapped, with respect to a certain characteristic. The model accounts as well for possible misclassification by the inspector. The dynamic programming algorithm searches for a solution that minimizes the total cost of inspection per accepted component. The total cost includes the cost of false rejection of good items, the cost due to false acceptance of an item which is either reworkable or to be scrapped, the cost of inspection, and the cost of rework (Elshafei et al., 2006).

2.4.3 Multi-objective optimization models

Again, with regard to offline inspections, multi-objective optimization models for process targeting have been recently studied in the literature. In the past, process targeting problems were usually modeled using a single objective optimization model. In the second decade of the 2000s, Duffuaa and El-Ga'aly (2013b) introduced multi-objective optimization in the process targeting research field. In the model, the quality characteristic under consideration Y is normally distributed with unknown mean and known standard deviation and has two market specification limits, namely SL_1 and SL_2. 100% inspection was used as the mean of product quality control. Products that satisfy the first specification limit SL_1 are sold in a primary market at a regular price, while products failing the first specification limit SL_1 and satisfying the second one SL_2 are sold in a secondary market at a reduced price. On the other hand, the product is reworked if it does not satisfy both specification limits. Figure 2.4 shows a schematic flowchart of the production process. The developed multi-objective optimization model consisted of three objective functions, i.e., the maximization of (i) profit, (ii) income and (iii) product uniformity, using Taguchi quadratic function as a surrogate for product uniformity. They proposed an algorithm to obtain and rank the set of Pareto optimal points. Sensitivity analysis was conducted and showed that the results of the model are sensitive to changes in process variance. Besides, they showed that the optimal objectives of the profit function and product uniformity were more sensitive to changes in model parameters than the income function (Duffuaa and El-Ga'aly, 2013b). The same authors expanded the research by considering the case in which the quality of the product is controlled using lot-by-lot acceptance sampling (Duffuaa and El-Ga'aly, 2013a). Moreover, they also assessed the impact of the inspection errors on the optimal parameters and objectives functions values of multi-objectives optimization model for process targeting in inspection sampling plan (Duffuaa and El-Ga'Aly, 2015), and further in 100 % inspection (Duffuaa and El Gaaly, 2017).

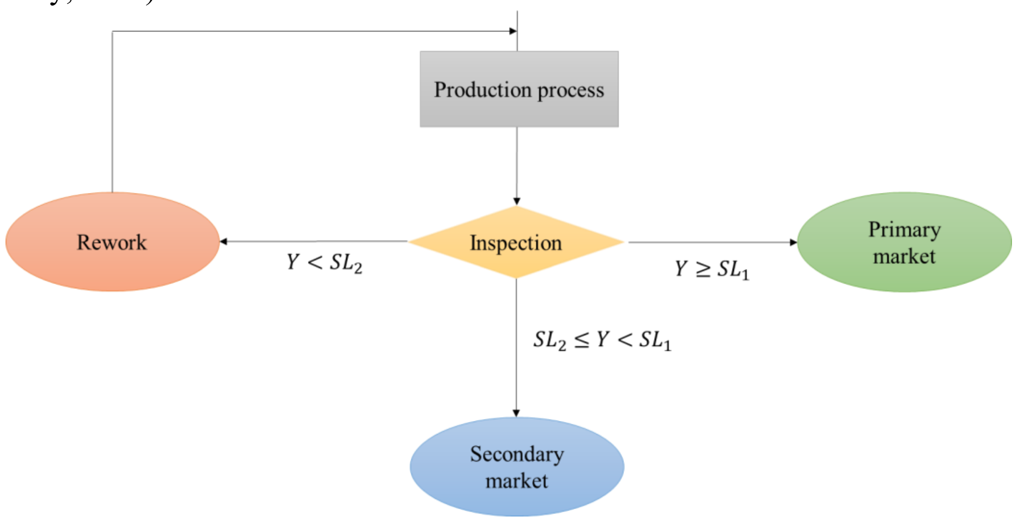


Figure 2.4 - Schematic of a production process in a multi-objective optimization framework. Adapted from Duffuaa and El-Ga'aly (2013b).

2.4.4 Economic Order Quantity

In the offline inspection framework, the inventory model of the Economic Order Quantity (EOQ) is often adopted (Harris, 1913). EOQ is defined as the order quantity that minimizes the total holding costs and ordering costs. According to Salameh and Jaber (2000), the assumptions necessary to justify the use of EOQ models are rarely met. Accordingly, they extended the traditional EOQ model to provide mathematical models that more closely conform to actual inventories and respond to the factors that contribute to inventory costs. In detail, received or produced items with imperfect quality were considered in the model. They assumed that 100% inspections were carried out with an error-free screening. The behavior of inventory level (i.e., actual lot size) with respect to time is illustrated in Figure 2.5. It is considered a lot of initial size y being delivered to the buyer in a cycle time T. An inspector identifies the defective items over an inspection period of duration t. Therefore, according to Figure 2.5, py is the number of defective items withdrawn from the inventory. The model showed that the economic lot size quantity tends to increase as the average percentage of imperfect quality items increase. This result is in contrast with the finding of Rosenblatt and Lee (1986) of reducing the lot size quantity as the average percentage of imperfect quality items increase. The reasonable explanation found by Salameh and Jaber was that Rosenblat and Lee assumed that defective items are reworked instantaneously and kept in stock. This resulted in an increase in the holding cost per unit per unit time that, as a consequence, produces smaller lot sizes. On the contrary, in Salameh and Jaber's model, items of imperfect quality are withdrawn from stock resulting in lower holding cost per unit per unit time and larger lot sizes.

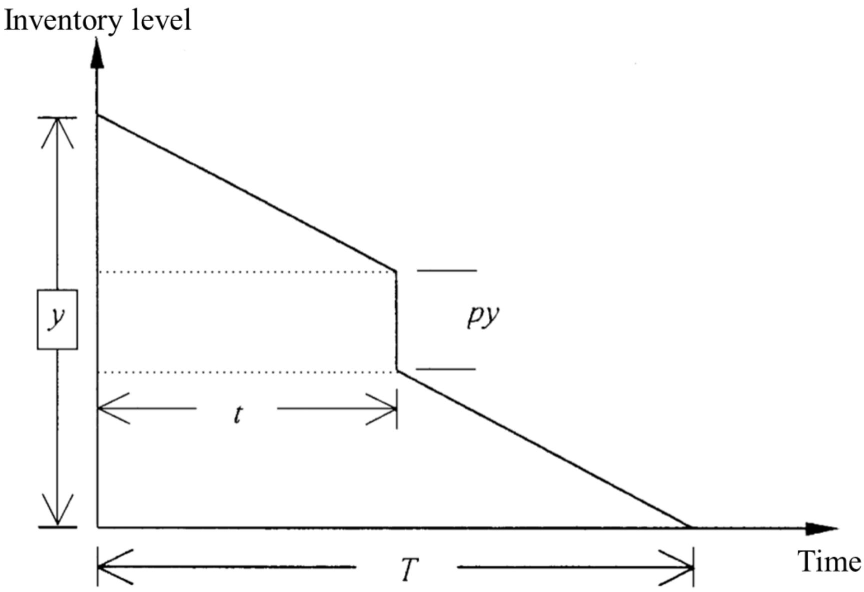


Figure 2.5 - Behavior of the inventory level over time. Adapted from Salameh and Jaber (2000).

Ten years later, Khan et al. (2010) further extended this model by considering the presence of learning in the inspection. The model proposed considered situations of lost sales and backorders. Mathematical models were developed with numerical examples provided and results discussed for the cases of (i) partial transfer of learning, (ii) total transfer of learning, and (iii) no transfer of learning. Later, they extended Salameh and Jaber's model by proposing an optimal production/order quantity taking care of imperfect processes. Therefore, in addition to the items classified as defective by the inspection process, the items returned as defective from the market are also considered. Such an inspection process involves three costs: (i) cost of inspection, (ii) cost of type-I errors, and (iii) cost of type-II errors.

Finally, variations of Salameh and Jaber's model were applied to the supply chain context (Yao and Askin, 2019; M Khan et al., 2012; Mehmood Khan et al., 2014).

2.4.5 Low-volume productions and defect generation models

In the literature, several techniques such as cost-benefit models (Savio, 2012), simulation (Neu et al., 2002, 2003; Münch et al., 2002), optimization models (Hanne and Nickel, 2005; Shiau, 2003) and mathematical programming models (Mohammadi et al., 2015) have been proposed to design inspection processes. However, although these techniques are highly applicable to mass production, they may not be suitable for low-volume productions.

The effectiveness of possible inspection strategies is, indeed, strictly related to the production typology and volume (Genta et al., 2018; Franceschini et al., 2018). In the case of mass production, traditional statistical approaches, including, e.g., Statistical Process Control (SPC) techniques, are straightforwardly applied (Montgomery, 2012). SPC consists of methods for understanding, monitoring, and improving process performance over time, with the aim to make the process stable or predictable, by distinguishing common variation from special or sporadic variation (Montgomery, 2012; Aivaliotis et al., 2017; Mourtzis et al., 2018; Woodall, 2000). SPC techniques have been extensively used to monitor process performance and detect anomalous situations in multiple industrial contexts. However, traditional SPC approaches are usually not appropriate for single-unit or low-volume productions, and for situations where a wide variety of mixed products exist (Koons and Luner, 1991; Del Castillo et al., 1996; Does, 1997; Trovato et al., 2010; Marques et al., 2015). The category of low-volume productions certainly includes low-volume assembly manufacturing processes, often characterized by a high level of customization and complexity. Therefore, owing to the limited historical data available and the difficulty in applying traditional techniques, the design of inspection procedures and quality control for such productions represents a challenging issue in the manufacturing field (Trovato et al., 2010; Celano et al., 2011; Marques et al., 2015; Del Castillo et al., 1996; Pillet, 1996; Khoo and Quah, 2002).

In the past decades, different approaches inherent to quality control and specific for low-volume productions have been proposed in the literature, and each of these has its advantages, shortcoming, and is more suitable for certain production scenarios than for others (Koons and Luner, 1991; Del Castillo et al., 1996; Does, 1997; Trovato et al., 2010; Marques et al., 2015). In recent studies proposed by Genta et al. (2018) and Franceschini et al. (2018), innovative methodologies were developed within the framework of inspection procedures for low-volume productions by defining novel probabilistic models of the production process, with the related inspection procedures. In detail, in case of in-process inspections, Genta et al. (2018) decomposed a generic manufacturing process into a certain number of steps, i.e. specific operations providing an added value to the end product. The probabilistic model relied on the following simplifying assumptions: (i) a single type of defect for each step, and (ii) the absence of correlation between the parameters related to the different steps. Furthermore, two performance indicators for inspection procedures related to inspection effectiveness and affordability were developed (Franceschini et al., 2018). The first is the expected value of the total number of true defects not detected by the inspection procedure. In contrast, the second concerns the total cost of the inspection, including the costs of specific inspection activities, necessary repairs, unnecessary repairs and undetected defects. Next, defect generation models were included in the probabilistic model with the aim to estimate the probability of occurrence of defects in the different stages of the production process (Genta et al., 2018). According to the investigations carried out by Hinckley (1994), Shibata (2002) and Su et al. (2010) on assembly processes, the *a priori* knowledge of the elementary operations and the design parameters may enable to predict, without any supplementary experimental test, the number of defects which can be generated in each process step, and then the probabilities of occurrence of defects. These predictions are useful to the inspection designers to design effective and economically viable inspection procedures (Franceschini et al., 2018). Figure 2.6 graphically represents the overall methodology proposed by Genta et al. (2018) and Franceschini et al. (2018) in the case of in-process inspections for low-volume assembly manufacturing processes.

The research conducted by these authors is the starting point for the models and approaches that will be discussed in the following chapters of this Doctoral Dissertation.

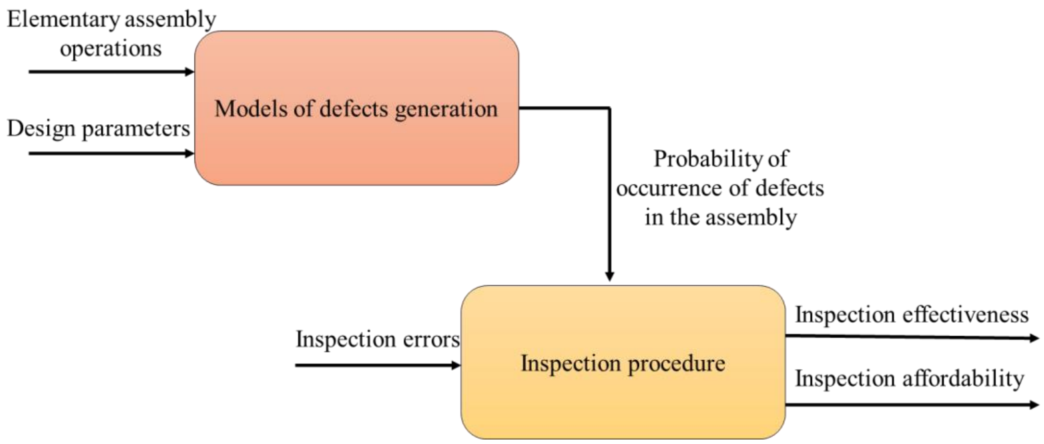


Figure 2.6 - Schematic of overall methodology for low-volume assembly manufacturing processes (Genta et al., 2018; Franceschini et al., 2018)

2.5 Prominent inspection models

Several inspection models have been developed in the scientific literature, taking into account one or more features described in the introductory part of this chapter and shown in Figure 2.1. In this section, the models with a more complete structure are reviewed. The great descriptive capabilities and the multiple modeling features addressed, including errors, costs, and defect modeling makes them reference models in the inspection procedures field. According to Genta et al. (2020d), these models are scientifically robust, being experimentally and/or numerically validated in the corresponding papers, and widely accepted by the scientific community, as evidenced by the high citation rate. The prominent reference models for both in-process inspections and offline inspections are described below.

2.5.1 In-process inspection models

As regards in-process inspections, three main models can be identified in the recent scientific literature (Genta et al., 2020). The first model, identified as a reference model, was developed by Yu and Yu (2007). The other two models have already been mentioned in Section 2.4.1. and were proposed in two papers on multi-stage production systems (Vaghefi and Sarhangian, 2009; Azadeh et al., 2015). The three models are briefly described below, following the chronological order of publication.

The first reference was designed to determine the optimal mixed policy of inspection and burn-in (Yu and Yu, 2007). Inspection and burn-in are two techniques extensively used by vendors to screen out defective items in a production lot in order that an outgoing batch satisfies the purchaser's quality requirements (Yu and Yu, 2007). Due to two types of inspection errors and high cost of burn-in, making a trade-off between them is a challenging task for vendors. To address this issue, Yu and Yu (2007) adopted the average outgoing quality (AOQ) as a measure of inspection and burn-in success. Being AOQ defined as the ratio between the number of undetected defective items and the total number of accepted items, it must be lower or equal to a threshold value agreed between producer and vendor. More specifically, under the constraint that the outgoing batch meets an AOQ requirement, the following issues are determined to maximize the expected profit that the vendor makes in a certain period (P_v):

- The total number of produced parts (Q);
- The number of inspected parts (Q_s);
- The number of parts put into burn-in (Q_b);
- The optimal burn-in time if the burn-in test is needed (t_b).

Accordingly, the expected profit may be expressed as:

$$P_v = P_v(Q, Q_s, Q_b, t_b) \tag{2.1}$$

In the study of Vaghefi and Sarhangian (2009), with the aim of optimizing inspection plans, a mathematical model that minimizes the total inspection cost (*TIC*) was developed:

$$TIC = \sum_{i=1}^{r} a_i \cdot [n_i + (1 - P_{ai}) \cdot (N_i - n_i)] \tag{2.2}$$

where:

- r is the number of inspection stages;
- a_i is inspection cost per item at stage i;
- n_i is the number of items to be inspected (sample size) at stage i;
- N_i is the lot size at stage i;
- P_{ai} is the acceptance probability of a lot at stage i.

The third reference model was proposed by Azadeh et al. (2015), who addressed the problem of finding the optimal inspection policy when the cost components are described by fuzzy numbers. The exact values of cost components are rarely achieved in practical situations as they can be vague and imprecise. Those values are well described by fuzzy sets, which include a specific range of values that allow the decision-maker to have some flexibility in defining parameters and to deal with the uncertainties related to real situations (Hu et al., 2011). In their study, the objective function was the expected value of the total inspection cost, defined as follows:

$$TIC = IC + RC + PC = \sum_{i=1}^{n} (IC_i + RC_i) + PC \tag{2.3}$$

where:

- n is the number of production stages;
- IC_i is the fuzzy inspection cost at stage i;
- RC_i is the fuzzy rework cost at stage i;
- IC is the fuzzy total inspection cost;
- RC is the fuzzy total rework cost.
- PC is the fuzzy total penalty cost due to delivering defective products to the customer.

As highlighted in the survey of Genta et al. (2020), each in-process inspection model has its own strengths and weaknesses, which have been summarized in Table 2.1.

Table 2.1. Strengths and weaknesses of main in-process inspection models proposed in the scientific literature (Genta et al., 2020).

Model's authors and publication year	Equation Ref.	Strengths	Weaknesses
Yu and Yu (2007)	2.1	Definition of an optimal mixed inspection and burn-in policy (the latter is poorly considered).	Disregard for the peculiarities of long-term contracts between producer and vendor, e.g., possible discounts.
Vaghefi and Sarhangian (2009)	2.2	Development of a comprehensive mathematical model to minimize total inspection costs in multi-stage production systems.	Need for specific simulation optimization methods to solve the multi-stage inspection problems.
Azadeh et al. (2015)	2.3	Identification of an optimal inspection policy in a multi-stage production system when the quality characteristic of the final product depends on all previous production stages.	Simplified idealistic framework, with unlimited inspection facilities, without cost constraints, etc.

2.5.2 Offline inspection models

With regard to offline inspections, four reference models developed in the recent literature are identified (Genta et al., 2020). In the same way as in-process inspections, offline inspection models are briefly described below, following the chronological order of publication.

The first reference model is the one developed by Duffuaa and Khan (2005), already mentioned in Section 2.4.2. with reference to systems with multi-characteristic critical components. The purpose of the model was the identification of the number of inspection cycles n that minimizes the expected total cost per accepted component tc. This is defined as the ratio between the expected total cost (TC) and the total number of accepted components (TA), as follows:

$$tc = \frac{TC}{TA} = \frac{TCFR + TCFA + TCI}{TA} \tag{2.4}$$

where:

- $TCFR$ is the total cost of false rejection;
- $TCFA$ is the total cost of false acceptance;
- TCI is the total cost of the inspection.

Each of these cost components can be expressed as follows:

$$TCFR = \sum_{j=1}^{n} CFR_j \tag{2.5}$$

$$TCFA = CFA_n \tag{2.6}$$

$$TCI = \sum_{j=1}^{n} \left(CI_{1,j} + CI_{2,j} \right) \tag{2.7}$$

where:

- CFR_j is the cost of false rejection in the j-th cycle;
- CFA_n is the cost of false acceptance for all the n cycles;
- $CI_{1,j}$ is the cost of the inspection in the j-th cycle at regular inspection stages;
- $CI_{2,j}$ is the cost of the inspection in the j-th cycle at inspection stages in rework stations.

This model has been re-examined and developed by the authors themselves in subsequent studies (Elshafei et al., 2006; Duffuaa and Khan, 2008).

The second reference model was proposed by Yu et al. (2009). The identification of a mixed policy between precise inspection and continuous sampling plan CSP-1 (Dodge, 1943) was proposed in this model. The optimal policy is the one that maximizes the unit net profit (*NP*), which can be expressed as:

$$NP = \frac{R - TC}{Q} \tag{2.8}$$

where:

- R is the expected overall revenue;
- TC is the expected total cost;
- Q is the expected production quantity.

These three variables are related to seven parameters:

a) type-I error;
b) type-II error;
c) the selling price of an item;
d) the unit repair cost;
e) the unit return cost;
f) the unit precise inspection cost;
g) the process defective fraction.

In the third reference model (Sarkar and Saren, 2016), a deteriorating production process, which randomly shifts to an out-of-control state from an in-control state, is described. Sarkar and Saren (2016) proposed a product inspection policy with a warranty period aimed at obtaining reduced inspection costs. The model is formulated to minimize the expected total cost per item $C(t,u)$, where t is the production-run length, and u is the non-inspected fraction in the batch, which is defined as:

$$C(t,u) = LC + HC(t) + SC(t) + PcIC(t) + RC(t) + PdIC(u) + DCWC(t,u) \quad (2.9)$$

where:

- LC is the labor cost;
- $HC(t)$ is the holding cost;
- $SC(t)$ is the setup cost;
- $PcIC(t)$ is the process inspection cost;
- $RC(t)$ is the restoration cost;
- $PdIC(u)$ is the product inspection cost;
- $DCWC(t,u)$ is defective cost and warranty cost.

The last reference model, defined by Ramzan and Kang (2016), aims at reducing inspection cost by determining the optimum number of quality inspectors with respect to their skill levels. The total inspection cost per quality inspector (*tic*) can be expressed as:

$$tic = \frac{[L \cdot IQ_l + M \cdot IQ_m + H \cdot IQ_h] \cdot I_r}{L + M + H} \quad (2.10)$$

where:

- L, M and H are, respectively, the number of inspectors having low, medium and high skills;
- IQ_l, IQ_m and IQ_h are, respectively, the inspected quantity by inspectors having low, medium and high skills;
- I_r is the inspection rate.

The results showed that the inspection cost might be reduced by optimizing the skill level of the quality inspector.

Table 2.2 summarizes the strengths and weaknesses of the four reference offline inspection models.

Table 2.2. Strengths and weaknesses of main offline inspection models proposed in the scientific literature (Genta et al., 2020).

Model's authors and publication year	Equation Ref.	Strengths	Weaknesses
Duffuaa and Khan (2005)	2.4	Assessment of statistical and economic impact of classification errors on the performance of a general inspection plan.	The model is not robust when there is a lack of high confidence estimates of its parameters.
Yu et al. (2009)	2.8	Definition of a mixed policy between precise inspection and continuous sampling plan CSP-1 which maximizes the net profit.	Hypothesis of production control, i.e., non-consideration of possible process deteriorations.
Sarkar and Saren (2016)	2.9	Definition of an economic production quantity model where the process deteriorated based on production of defective products.	Hypothesis of negligible product inspection times.
Ramzan and Kang (2016)	2.10	Development of a multi-objective optimization model aims at minimizing the inspection cost which considers human factors.	Non-consideration of variability over time of inspectors' skill level and inspection targets.

2.6 Research areas covered by the literature

The survey published by Genta et al. (2020) proposed an exhaustive classification of almost 70 recent papers concerning inspection procedures, basing on the two classification categories previously mentioned and illustrated in Figure 2.1, i.e. "General characteristics" and "Modeling structure". In addition, the classification included possible applications considered in the examined papers. Main highlights that emerged from the bibliographic analysis performed by the authors of the survey are described below.

With regard to the general characteristics of inspection procedures, a broader bibliography on offline inspection procedures has emerged from the literature review. In addition, most of the documents examined only consider acceptance sampling as an inspection strategy, being generally more efficient and practical than 100% inspection (Genta et al., 2020).

Regarding the modeling structure of inspection procedures, it was found that most papers included in the research approach the inspection errors and costs, while about one-half of the papers considered the modeling of defects. Conversely, only about one-third of the examined papers involved the inspection time in the analysis. Although time may significantly affect the inspection performances, it is generally challenging to evaluate and standardize and, thus, few authors considered it as a model variable.

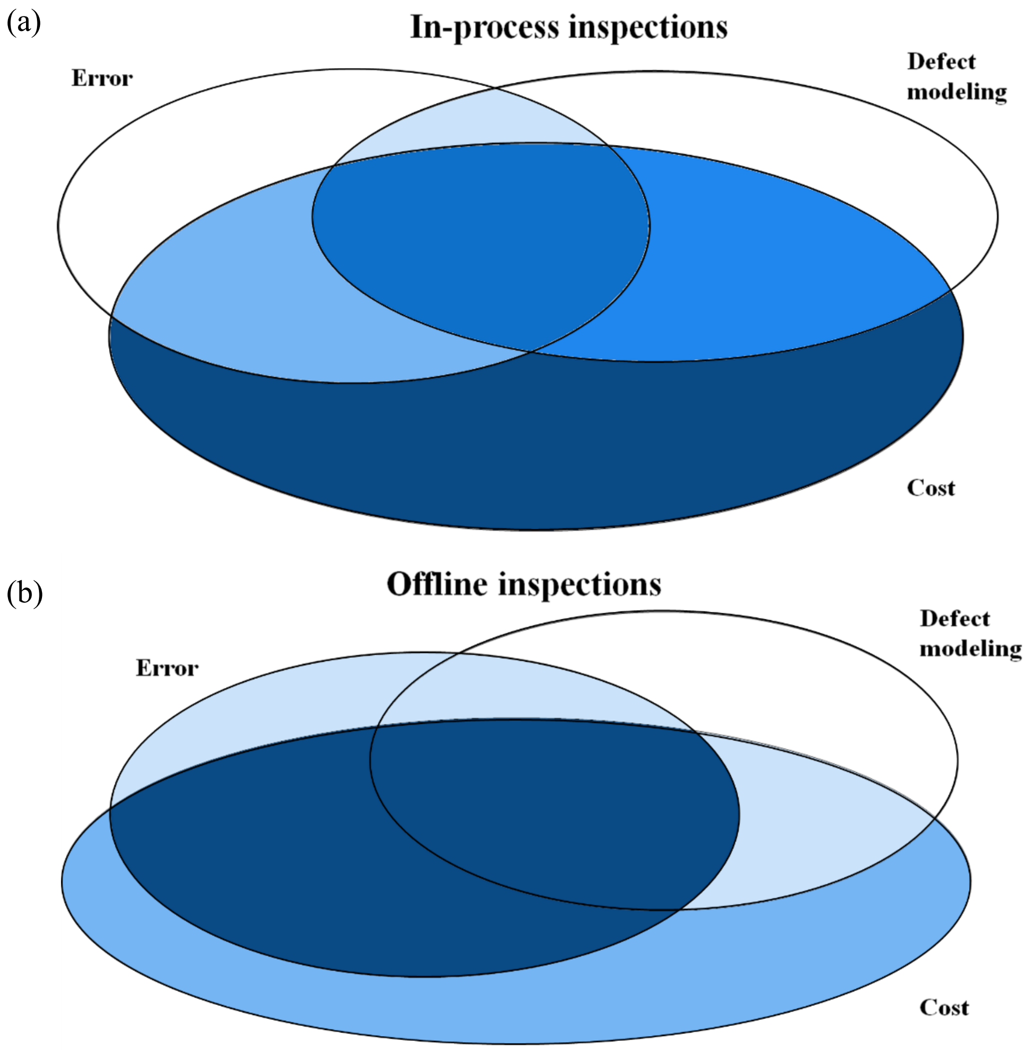
Besides, features seldom covered by the literature are the human skills of the inspectors and the low-volume productions. In many cases, the inspection process is controlled through human labor. However, only a few industrial sectors, e.g., the garment industry (Ramzan and Kang, 2016; C. W. Kang et al., 2018; Ramzan et al., 2019) allow investigating in detail the effect of human factors on process improvement activities. Secondly, the close relationship between the performance of inspection procedures and the production volume is not adequately addressed in the literature. Only a limited number of documents have been published within the framework of inspection procedures for low-volume productions (Trovato et al., 2010; Franceschini et al., 2018; Genta et al., 2018).

Lastly, about half of the papers adopt a simulative approach in their methodology, because sometimes it is the most suitable solution due to the complexity of analytical models.

As far as the possible applications of inspection procedures are concerned, only about half of the examined papers apply their approaches to real production processes. The main manufacturing sectors investigated are the semiconductor and automotive fields (see, e.g., the papers of Avinadav and Perlman (2013), Yu and Yu (2007), Rezaei-Malek et al. (2018)). The remaining documents examined are purely methodological without practical examples.

Figure 2.7 illustrates by Venn diagrams the different areas covered by the recent papers examined in the survey of Genta et al. (2020) on inspection procedures. In particular, separately for in-process and offline inspections, the diagram classifies the papers into "Error", "Cost" and "Defect modeling", i.e., the more considered modeling features of inspection procedures (Genta et al., 2020). A color scale with six levels is used to visually represent the intensity of coverage of examined literature on inspection procedures. As highlighted by Figure 2.7, only a limited proportion of the examined papers consider at the same time "Error", "Cost" and "Defect modeling". This diagram clearly shows the research areas which are not adequately covered by the literature. In detail, about one-fourth of the papers for in-process procedures and one third for offline procedures cover the three modeling features. In order to provide a complete overview of the current state of the art of the literature on inspection procedures, a summary coverage map showing the different research areas is reported in Table 2.3. It is evident from the table that “Human skill” and “Low-volume production” appear to be the less studied modeling features of inspection procedures.

For the detailed classification of recent papers concerning inspection procedures, refer to the survey of Genta et al. (2020).



Color scale level	Proportion of examined literature
	Not covered
	Lower than 1/10, but nonzero
	Between 1/10 and 1/6
	About 1/5
	About 1/4
	About 1/3

Figure 2.7 - Classification of recent papers on inspection procedures by Venn diagrams considering the features "Error", "Cost" and "Defect modeling" for (a) in-process inspections and (b) offline inspections. Adapted from Genta et al. (2020).

Table 2.3. Coverage map of recent literature on inspection procedures, with reference to the classification illustrated in Figure 2.1. Adapted from Genta et al. (2020).

		General characteristics of inspection procedures				
		Type		*Strategy*		
		In-process	**Offline**	**Sampling**	**100% inspection**	**Mixed sampling and 100% inspection**
Modeling structure of inspection procedures	**Error**					
	Cost					
	Human skill					
	Time					
	Defect modeling					
	Simulation					
	Low-volume production					

Color scale level	*Proportion of examined literature*
	Lower than 1/3
	Between 1/3 and 2/3
	Greater than 2/3

2.7 Research perspectives

The results provided in Figure 2.7 and Table 2.3 highlight the need for accurate defect modeling, as well as the need for greater attention to human skill of inspectors and low-volume productions. To fill some of these gaps encountered in the literature, this Doctoral Dissertation focuses in particular on the development of defect generation models specific for low volume production and on the design of effective and economically sustainable inspection strategies for this type of production.

The research areas addressed in this Dissertation are particularly relevant in the current framework of Industry 4.0. In the modern manufacturing processes, increasingly innovative inspection strategies are needed to cope with the growing presence of cyber-physical systems (Schmitt and Voigtmann, 2018; Tao and Qi, 2017). The application of modern information technologies in the so-called “smart manufacturing" leads to the development of new "smart inspection strategies" (Genta et al., 2020). The drastic evolution of technology and digitalization in manufacturing is also requiring more efficient manufacturing system design. Manufacturing systems simulation has proven to be a powerful tool for designing and evaluating a manufacturing system due to its low cost and risk, and quick analysis. Simulation comprises an indispensable set of Information Technology (IT) tools and methods for the successful implementation of digital manufacturing. It allows experimentation and validation of product, process, and system design and configuration (Mourtzis, 2020). In this context, technological developments are rapidly expanding the number of devices connected to the Internet of Things (IoT) (Ahmed et al., 2017). In most IoT applications, the focus is not only on monitoring discrete events, but also on mining the information collected by IoT objects. Several flexible and cost-effective IoT solutions are based on the use of sensors in production to perform online inspections with real-time data. In order to collect product quality data, sensors are embedded into production equipment and real-time data are used to determine which equipment requires service, repair or replacement (Genta et al., 2020). Thus, IoT is one of the biggest sources of big data, which are rendered useless without analytics power. IoT interacts with big data when voluminous amounts of data are needed to be processed, transformed, and analyzed in high frequency. In this context, big data analytics support the overall quality monitoring, early warning of quality defects, and rapid identification of root causes (Ahmed et al., 2017).

According to these considerations, the aforementioned "smart inspection strategies" will be of fundamental importance in the framework of the Industry 4.0 future. In particular, two different scenarios could be envisaged (Genta et al., 2020). In the first scenario, a continuous quality monitoring is assumed, obtained with 100% inspections integrated into the production process and carried out automatically, without requiring massive human intervention. On the other hand, the second scenario involves acceptance sampling, required only in case of technological constraints, as it lacks the efficiency and reduced cost advantages typical of a 100% inspection performed with IoT sensors. Although data-driven models used in modern production processes to monitor and control products are more accurate and reliable, they are becoming increasingly complex. In fact, the complexity of production processes requires the control of an increasing number of process parameters and disturbance variables (Schmitt and Voigtmann, 2018). The acquisition and reporting of these parameters during the process is a major challenge that both researchers and practitioners are facing.

Chapter 3 : Defect modeling

In low-volume productions, the lack of historical data available and, often, the non-applicability of traditional statistical techniques, makes it difficult to predict the defects that might occur in the finished or the semi-finished products (Koons and Luner, 1991; Montgomery, 2012). However, these defects represent a huge issue even for low-volume productions owing to the dramatic impact they can cause, both in terms of quality and costs. Accordingly, the development and identification of appropriate models of defects predictions have long been a question of great interest. In the literature, extensive research has been carried out on the prediction of product defects (Antani, 2014; Su et al., 2010; Shibata, 2002; Psarommatis et al., 2020). Currently, a growing body of literature is focusing on the use of machine learning (ML) approaches for predicting defects and, in general, improving product quality. However, these methods have been mostly restricted to mass productions, involving millions of parts and operations. To date, only a limited number of studies is directed to the investigation of defects occurring in low-volume manufacturing processes. In order to fill this research void, two novel paradigms of defect generation models are developed and discussed in this chapter. The former is specifically designed for those processes decomposable in steps and inspected by in-process inspections, such as the assembly, whilst the latter for finished product that may be inspected using offline inspections. Both models are conceived to predict defects using the 'a priori knowledge' of the product and process, without any supplementary experimental test. These predictions are useful to the designers for designing effective and affordable inspection procedures, as will be discussed in the following Chapters 4 and 5. In detail, Chapter 3 has been organized as follows:

- Section 3.1 reviews the main defects generation models and the related modeling in the manufacturing field.

- Section 3.2 proposes an overview of the current studies related to the application of machine learning in manufacturing, especially for product quality control and improvement.
- Section 3.3 addressed the defect prediction models suitable for in-process inspections. After examining the literature on this subject, a novel model is developed and compare with one of the most accredited in the electromechanical field.
- Section 3.4 covers the modeling of defects in those processes inspected by offline inspection by proposing a new methodology for estimating the probability of occurrence of defects in the finished product.

3.1 Defects generation in manufacturing and related modeling

Much research has been conducted in recent years focusing on the problem of defect generation in manufacturing because of the relevance of the topic from an engineering and economic point of view. The sources of these defects may be extremely different, according to the product typology and the production context. Many studies have focused on the identification of the factors that may cause defects, considering, e.g., Ishikawa diagrams, in which the sources of defects can be classified into several categories: machines, methods, materials, people, measurements and environment (Ishikawa, 1976). The use of these cause-and-effect diagrams may help to improve the product design and prevent the occurrence of defects.

Different typologies of defects in production processes can be recognized. Kaempf (1995) proposed a classification of defects in semiconductor manufacturing. In detail, he subdivided defects into three environments:

- Type-A: random defects, evenly distributed with a stable mean density. The yield of the process has a binomial distribution: In particular, a Poisson model can be considered.
- Type-B: systematic and repeatable defects.
- Type-C defects: combined systematic and random defects.

Figure 3.1 shows a small set of six 44-dice wafers manufactured in Type-A and Type-B environment.

(a) (b)

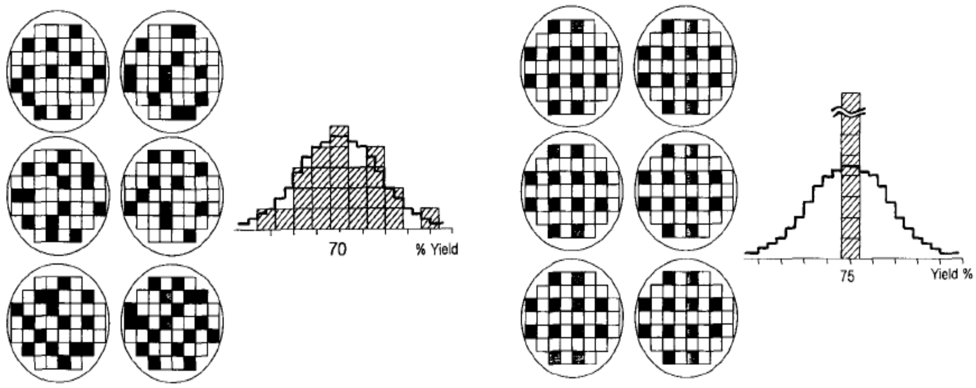


Figure 3.1 – (a) Type-A defects with random, even distribution and good binomial fit. (b) Type-B defects with systematic, reticle induction: distinct narrowing of yield distribution (Kaempf, 1995).

The yield of the process is the percentage of elements (dice) of the wafer without any defects. This can be described through a Poisson model for the Type-A defects, as follows:

$$Y = \exp(-A \cdot D) \tag{3.1}$$

where D is the defect density per cm^2, and A is the critical area sensitive to the considered defects, modeled in the paper of Ferris-Prabhu (1985).

Again in semiconductor manufacturing, Nigh and Gattiker (2004) and Shankar and Zhong (2005) proposed to segment the product and mapped the related defects by means of Direct Drain Quiescent Current (IDDQ) signature analysis and a template-based vision system, respectively.

A further case study of defects and their modeling in production processes was carried out by Baker et al. (1954) in the textile yarn manufacturing. By analyzing the results of a specially planned set of observations, the authors showed that a partially subjective test of yarn quality provided reliable results. In detail, with visual analysis, two different quality measures can be derived:

- D: the average number of defects per unit length;
- p: the proportion of defect-free unit lengths present. This corresponds to the yield of the process. If the yarn is assumed to be homogeneous, p follows a binomial distribution (Andersons et al., 2009).

They proposed an index of yarn quality through the definition of the variable Φ, which can be approximated by a normal distribution:

$$\Phi = \frac{2}{\pi} \cdot \sin^{-1}\left(\sqrt{p}\right) \tag{3.2}$$

When defect types exhibit clustering or very high variability, Pareto analysis can give very misleading results. Engineers and managers making decisions based on Pareto charts or part per million defect rates risk concentrating manpower and funds on off-line quality control projects which may not significantly improve yield. Albin and Friedman (1992) proposed two measurements in the assembly of electronic components, yield loss and conditional yield loss, with the aim to reveal the defect types having the greatest impact on yield. They compared these ranking measures under the assumptions of different defect distributions: (i) Poisson distribution; (ii) Neyman distribution; (iii) negative binomial distribution (see also Koren et al. (1994)); (iv) combination of Poisson and negative binomial distribution (see also Koren et al. (1994)). These measurements produced conclusions identical to the Pareto chart in ranking defect types if defects are Poisson distributed. However, if clustering or high variability of some types of defect is present, the proposed measurements show the type of defect that causes the greatest loss of performance.

The importance of the identification of defects has already been assessed in other research, mainly in the field of assembly manufacturing processes. Assembly, which is one of the activities constituting the manufacturing of complex products, together with the acquisition of raw materials, processing, functional testing, etc., is crucial for the cost and quality performance (Vandebroek et al., 2016; Xiaoqing et al., 2010). Recently, a growing body of literature has recognized the importance of the role of quality control in the assembly production context, since the product life cycle requires a faster response and a lower defect rate. As a result, assembly quality control is considered to be one of the most crucial issues in modern manufacturing environments (Zhong et al., 2010; Ferrer, 2007). Assembly defects have been classified into four categories: improper design, defective part, variance in the assembly system (induced by the changes in the plan/schedule/arrangement of a machine, fixture, tooling, etc.), and operator mistakes (Su et al., 2010). In recent years, much research has focused on the first three categories, and some useful assembly quality control technologies and management approaches have been developed (Zhang and Luk, 2007; Gearbox et al., 2015; Zheng, 2000; Ping et al., 2008; He and Kusiak, 1997; Evans et al., 1997; Vandevelde et al., 2018; Qin et al., 2015; Chiang and Su, 2003). As far as the fourth category is concerned, there is a large volume of published studies that have described the significant impact of human errors on the performance of assembly systems, which is sometimes higher than that of technological errors (D. Shin et al., 2006; C. W. Kang et al., 2018; Le et al., 2012; Báez et al., 2014; Saptari et al., 2015; Su et al., 2010; Shibata, 2002; Kolus et al., 2018; Krugh et al., 2016b; Genta et al., 2018; Xiaoqing et al., 2010; Falck et al., 2017b; Caputo et al., 2017). Research in the field of semiconductor products has shown that 25% of the total assembly errors are induced by human mistakes (Shibata, 2002). Another study has demonstrated that operator errors account for 20% of the total defects in copier assembly (Su et al., 2010). These high percentages suggest that more attention should be paid to operator-induced assembly defects, and that reducing the number of operator mistakes is a central problem for assembly manufacturing processes. For instance, Caputo et al. (2017) developed a quantitative model to assess the probability of errors and the correction costs of errors in part feeding systems for assembly lines, in order to compare alternative part feeding policies and identify corrective measures.

In the assembly field, a research line has focused on the close relationship between assembly complexity and human mistakes (Hinckley, 1994; Shibata, 2002; Su et al., 2010; Antani, 2014; Krugh et al., 2016a; Falck et al., 2017b; Galetto, Verna, and Genta, 2020; Le et al., 2012; Verna et al., 2020c). According to Alkan (2019), Krugh et al. (2016a) and Falck et al. (2017a), if assembly complexity is not managed adequately at the early stages of process planning, it can lead to increased assembly time and errors and reduce assembly quality. Therefore, understanding and assessing complexity and its root causes are core for increasing the efficiency of manual assembly operations (Falck et al., 2016). Accredited models developed in the literature include those in the electromechanical field. Shibata (2002) proposed a power-law defect-rate prediction model based on two factors, i.e., process and design based complexity factors. Su et al. (2010) developed a new defect model to match the characteristics of copier assembly. Besides, Antani (2014) successfully tested that manufacturing complexity can be used to predict product quality reliably. By focusing on mixed-model automotive assembly, manufacturing complexity was estimated to incorporate variables driven by design, process and human factors (Antani, 2014). In later studies, Krugh et al. (2016b, 2016a) adapted the approach proposed by Antani to be implemented with automotive electromechanical connections in a large complex system. Falck et al. (Falck et al., 2017b) designed a tool to predict and control operator-induced quality errors by developing a method for predictive assessment of the complexity of manual assembly.

3.2 Machine learning for product quality control and improvement

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 (Riel et al., 2017). At the same time, with the rapid development of IoT, cloud computing, and Artificial Intelligence (AI) technologies, more and more real-time data is collected in situ from production processes, allowing to improve its quality and efficiency. In such a framework, multi-source data, e.g. inspection measurements, optical images, text and other structured/unstructured sources of process and product data, are becoming indispensable resources for quality improvement (Liu et al., 2019).

These growing data sets coming from the ongoing process of digitalization in industry can be used by AI and especially Machine Learning (ML) applications to acquire knowledge from historical events. In particular, ML techniques have proven to be very effective in the domain of manufacturing in analyzing complex systems and solving problems (Z. Kang et al., 2020). As described in the recent review by Fahle et al. (2020), in the last 5 years ML techniques shifted from research-only solutions to applications in the industrial environment. The main problems addressed by ML techniques belong to different manufacturing fields, including manufacturing process planning, quality control, predictive maintenance, logistics, robotics, assistance and learning systems, ML-training concepts in learning factories and process control and optimization (Fahle et al., 2020).

3.2.1 An overview of machine learning approaches

ML allows computer programs and applications to perform complex tasks, including prediction, diagnosis, recognition and planning, by learning from historical data. Both data and algorithms strictly affect the performance of machine learning models (Z. Kang et al., 2020). Regarding data, the accuracy of machine learning models can be improved by the high quality and large sizes of data. Besides, as far as the algorithms are concerned, it is essential to apply the correct algorithms to solve different problems, including different types of data sets.

ML can be divided into four types: (i) supervised learning, (ii) unsupervised learning, (iii) semi-supervised learning and (iv) reinforcement learning. Besides, ML techniques are applied in numerous areas to solve different kinds of tasks. These include (a) regression, (b) classification, (c) clustering, (d) data reduction, and (e) anomaly detection (Z. Kang et al., 2020).

The four ML types are summarized below.

(i) Supervised Learning (SL).
In SL, computer programs derive an inferred function between inputs and outputs from labeled training data consisting of a set of training examples, that are provided by humans. In SL, each example is a pair consisting of an input object, typically a vector, and a desired output value. An optimal scenario will allow for the algorithm to correctly determine the class labels for unseen instances (Russell and Norvig, 2002; Mohri et al., 2012). Thus, SL requires heavy human intervention, especially in the labeling of the output for the training set, as well as in the selection of input variables (also called features), algorithms, and control parameters of algorithms based on their assumptions. Generally, SL is used for those problems in which humans have specific knowledge and expertise. A drawback may be that SL requires massive data processing for feature selection and expects parameter optimization for a better configuration of the algorithm (Z. Kang et al., 2020).

(ii) Unsupervised Learning (UL).
Differently from SL, UL looks for previously undetected patterns in a data set with no pre-existing labels and with a minimum of human supervision. Typically, UL is adopted when the relationships between input variables are unknown. Besides, the output of UL algorithms is not a value of the output like in the case of SL. On the contrary, UL allows for modeling of probability densities over input variables and mostly presents different clusters obtained on the base of the input data (Hinton et al., 1999).

(iii) Semi-Supervised Learning (SSL).

SSL is an approach that combines a small amount of labeled data with a large amount of unlabeled data during training. Unlabeled data, when used in conjunction with a small amount of labeled data, can produce a considerable improvement in learning accuracy with respect to UL approaches. Besides, the acquisition of less labeled data for learning problem allows to dramatically reduce the cost of the labeling process compared to SL approaches (Zhu, 2005; Zhu and Goldberg, 2009).

(iv) Reinforcement Learning (RL).

In RL, software agents observe the environment, perform some actions, and get some rewards (negative/positive) based on the selected action, and then the model is updated accordingly. RL uses a feedback mechanism to reward positive action and punish the negative action. Reinforcement learning differs from SL in not needing labelled data, and in not needing sub-optimal actions to be explicitly corrected. Instead, the focus is on finding a balance between exploration of uncharted territory and exploitation of current knowledge (Kaelbling et al., 1996). This approach is used, for instance, in self-driving cars and online games such as backgammon (Sutton and Barto, 2018).

Machine learning approaches are applied in several areas to solve different tasks. Five common tasks are explained as follows (Z. Kang et al., 2020):

(a) Regression.

Regression is used to estimate a relationship between independent and dependent variables. Output variables are continuous numerical variables (both integers and floating-point numbers). Machine learning algorithms are used to optimize the coefficients of each independent variable to achieve a minimum error in the prediction.

(b) Classification.

Classification maps input features to one of the discrete output variables. The output variable represents a class for the underlying problem. For binary classification, the output variable can only be one or zero. For multi-class classification, the output variable can consist of several classes.

(c) Clustering.

Clustering is the task of dividing a set of data points into relevant groups (or clusters). This grouping is based on the similarity pattern between data points.

(d) Data Reduction.

Data reduction or dimensionality reduction is the transformation of data from a high-dimensional space into a low-dimensional space. Both the number of input variables (features) or the rows (i.e., data points) can be removed, due to the noisy data instances or repetitive data points. To create faster models, some of the features that are highly correlated or not very relevant may be removed from the data set. Generally, data reduction is combined with other tasks, especially regression and classification.

(e) Anomaly Detection.
Anomaly detection is the identification of rare items, events or observations that significantly differ from the majority of the data. Anomaly detection task is primarily handled with unsupervised learning methods. Similar to the clustering, anomaly detection algorithms group the samples, and the anomalies (or outliers) are identified in the dataset by anomaly detection algorithms.

An overview of the types of machine learning and the tasks that can be addressed with machine learning algorithms is depicted in Figure 3.2.

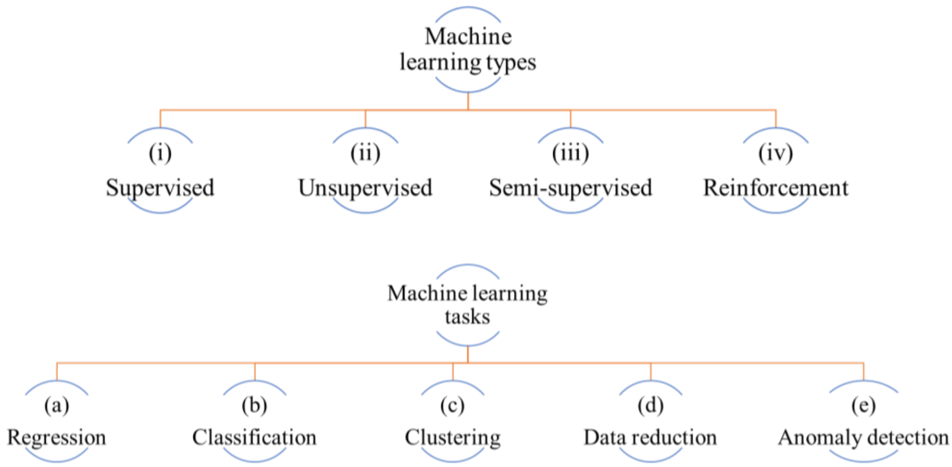


Figure 3.2 - Schematic of machine learning types and tasks (adapted from Kang et al. (2020)).

3.2.2 Main topics addressed

ML approaches are widely used in the manufacturing industry for addressing several issues, including product quality and/or process improvement. Generally, the object of the improvement can be product- or process-specific quantities. Product-specific quantities can be, for instance, surface roughness or shrinkage, while waste reduction or yield improvement of a production line can be examples of the process characteristics (Weichert et al., 2019; Z. Kang et al., 2020). Typical industrial applications for quality improvement based on ML can be found in production such as plastic injection molding and semiconductor manufacturing (Khakifirooz et al., 2018; Chien et al., 2017; Kashyap and Datta, 2015), due to high amount of data points and the short cycle times.

Several reviews and surveys on data mining and ML applications focusing on the issue of quality in the manufacturing have been published in the literature, see e.g., Weichert et al. (2019), Cadavid et al. (2020), Dalzochio et al. (2020), Fahle et al. (2020), Kang et al. (2020).

In this section, a general overview of the main topics addressed by ML in the area of product/process quality improvement is provided. Figure 3.3 summarizes the adopted taxonomy. In detail, three are the major topic addressed:

- Root cause analysis;
- Quality prediction: virtual metrology and early prediction;
- Systems diagnostics.

3.2.2.1 Root cause analysis

Root cause analysis is the analysis of existing data records to extract relevant features and feature combinations for high or low product quality. It may be performed by means of feature selection at preliminary stages of learning a model or as specific root cause analysis (Weichert et al., 2019). Supervised learning is the dominant ML type adopted for root cause analysis and regression/classification and clustering are the main tasks. Different algorithms have been used in the literature, including Principal Component Analysis (PCA), Decision Trees (DT), Random Forests (RF), feature selection, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Multivariate Adaptive Regression Splines (MARS).

3.2.2.2 Quality prediction: virtual metrology and early prediction

Differently from physical detection of defects, virtual detection, also called virtual metrology or quality prediction in the literature, refers to a set of algorithms that are fed with sensor and production data from the manufacturing of the product and are analyzed in order to find a defect without measuring the actual part. Those techniques for predicting product output are useful in cases where the physical measurements are not possible or too expensive, as in the semiconductor manufacturing (Psarommatis et al., 2020; S. Kang and Kang, 2017).

Furthermore, some authors moved further, trying to make a reliable prediction of the final quality at early stages of the process and to identify relations between process steps. Hence, correcting actions before finishing the whole production process may be undertaken. These may include ejecting products from the production line before critical steps, i.e., expensive in terms of time or price, or performing additional corrective manufacturing actions. In the literature, different approaches were adopted for quality prediction, including ANN, self-organizing maps (SOM), that are a type of ANN, k-Nearest-Neighbor (kNN), decision trees, gradient boosting and bagging (Weiss et al., 2016; H. Chen and Boning, 2017; Lieber et al., 2013).

3.2.2.3 System diagnostic

Diagnostic systems within the production line may monitor both the product itself (part diagnosis) and/or the machines (equipment diagnosis). Both approaches signal a part/machine condition that is abnormal or becoming abnormal, requiring corrective action to be taken.

Regarding part diagnosis, several studies focus on automatic visual inspections and diagnosis of part assemblies. Methods for visual inspection often use images data sources for identifying possible defects. They include PCA, learning based approaches like SVM, Hidden Markov Models (HMM), convolutional neural networks (CNN) for regression classification (S. H. Chen and Perng, 2011; Valavanis and Kosmopoulos, 2010; Weimer et al., 2016). Regarding diagnosis of assembled parts, recently authors try to cover not only one specific processing stage but multi-stage processes as well (Z. Kang et al., 2020). To this aim, different methods that use data sources different from images are generally adopted, e.g., SVM or piecewise least squares approach for use in a state-space model (Ceglarek and Prakash, 2012; Luo et al., 2014).

Diagnosis of production plants or machines can be realized by anomaly detection methods, which are mostly used for failure detection (H. J. Shin et al., 2005). Closely related to anomaly detection methods is the field of maintenance methods which aim to prevent machine failures due to deterioration of the machine. A distinction is made between time-based and condition-based maintenance, called preventive and predictive maintenance (Dalzochio et al., 2020; Mobley, 2002; Ahmad and Kamaruddin, 2012). Preventive maintenance tries to extract the mean useful life of a machine and/or its parts to schedule maintenance activities before breakdown. On the other hand, predictive maintenance tries to extend the maintenance intervals by monitoring the condition of the machine, avoiding costs for time-based and unnecessary scheduled maintenance activities. In this field, several ML approaches are used, e.g., ANN, kNN, and SVM (Dalzochio et al., 2020).

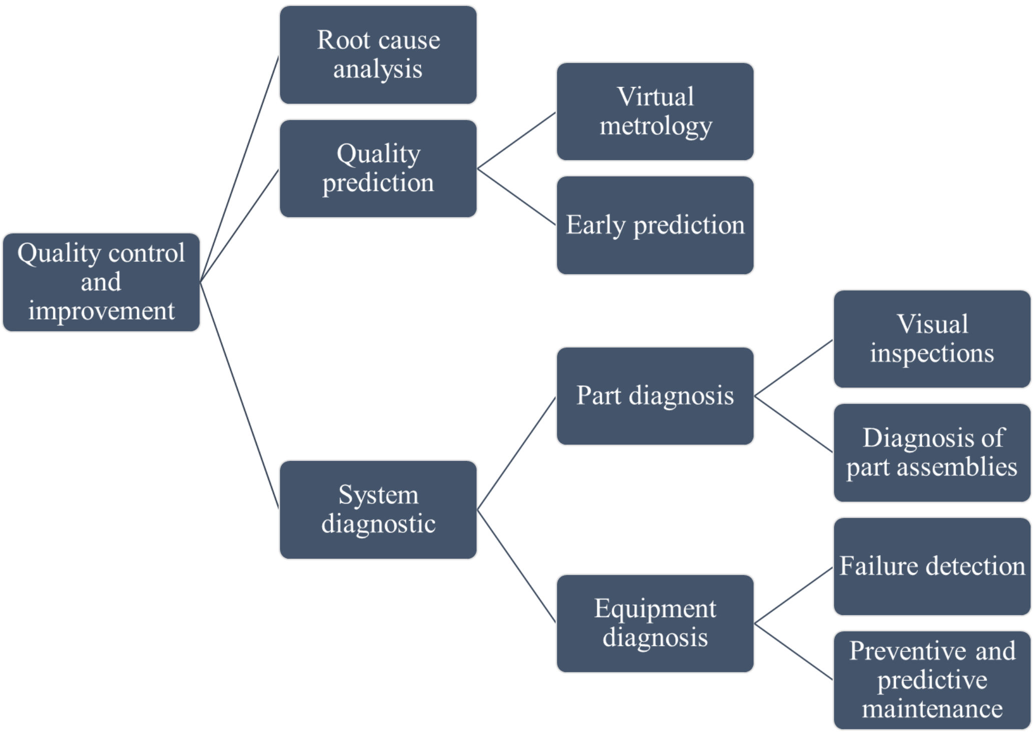


Figure 3.3 - Taxonomy of the main topics addressed by ML in the area of product/process quality improvement.

The majority of methods used in the manufacturing quality control and improvement fields are supervised methods, as also reported in previous surveys (Z. Kang et al., 2020; Weichert et al., 2019; Fahle et al., 2020). However, some studies used both supervised and unsupervised learning methods. Referring to the ML classification provided in Figure 3.2, the main tasks addressed is regression, followed by classification and data reduction (i.e., dimension reduction) algorithms for data processing. For instance, Principal Component Analysis (PCA) is widely used to reduce the number of parameters for regression and classification problems (Z. Kang et al., 2020).

The most widely used ML algorithms in this area are the artificial neural network algorithms (ANN), Decision Trees (DT), Support Vector Machines (SVM), and Random Forests (RF). Other algorithms applied for manufacturing quality improvement are kNN (K-nearest neighbours), GBDT (gradient boosted decision tree) and CNN (convolutional neural network) (Z. Kang et al., 2020; Weichert et al., 2019; Fahle et al., 2020). Further descriptions of the mentioned models and algorithms are not in the scope of this Dissertation and can therefore be found in current literature, for example Goodfellow et al. (2016) or Russell and Norvig (2002).

3.2.3 Machine learning for low volume productions

Several interesting insights can be derived from this general overview of ML techniques applied in the field of manufacturing quality control and improvement. First of all, the results of the study indicate that ML techniques have been widely used to solve several manufacturing quality-related problems, including root cause analysis, quality prediction and system diagnostic. These are the three major research directions in recent years, and ML approaches have been proved to be effective in such areas. However, some problems are still not fully addressed. First of all, the lack of relevant data or difficulties in getting access to the machine's control systems that may compromise the performance of ML methods. For this reason, ML is mostly applied in highly complex processes, where a huge amount of data is generated from the production, especially in the domain of metal production and semiconductor industry. Such a problem might be overcome, at least partially, with time passing to gain expertise, fill storages, and break down obstacles by hardware and software.

The lack of relevant data is one of the main obstacles to the adoption of ML approaches in manufacturing contexts such as low-volume production systems. In a low-volume production framework, the cycle time is relatively long as a result of high flexibility and diversity of products. Moreover, typically, many human interventions and limited automation exist during the production process. As a consequence, the scarcity of process data makes the adoption of ML methods extremely difficult.

Although the numerous advantages of adopting ML methods in high-volume manufacturing are recognized, in this Dissertation, since low-volume productions are investigated in detail, specific models based on statistical methods will be developed in the next Sections 3.3 and 3.4. Future research will be addressed to investigate the implementation of appropriate ML methods also in low volume systems.

3.3 Defect prediction models for in-process inspections[1]

As mentioned in Section 3.1, a growing number of studies adopted the assembly complexity to predict the occurrence of defects in the final product (Hinckley, 1994; Shibata, 2002; Su et al., 2010; Antani, 2014; Krugh et al., 2016a; Falck et al., 2017b; Galetto, Verna, and Genta, 2020; Le et al., 2012; Verna et al., 2020c). Although these predictions models play a crucial role in improving the quality of product and production process of companies in various industrial contexts, most of them are highly dependent on the method used to evaluate assembly complexity, which is designed for the specific industrial application and/or is obtained from subjective evaluations of operators (see Section 3.3.1). To overcome this, Section 3.3.4 aims to investigate the relationship between product defects and assembly complexity by proposing a novel prediction model in the electromechanical manufacturing field. Defect rates in the model are predicted by using the recent conceptual paradigm of complexity proposed by Alkan (2019) and Sinha (2014) (see Section 3.3.3) that considers only structural properties associated with handling and insertion of assembly parts and their architectural structure. This novel approach is compared with one of the most accredited in the literature, i.e., the Shibata-Su model, described in Section 3.3.2. Although the assembly of wrapping machines is used as a case study for developing and testing the novel prediction model, the overall methodology proposed can be used in other similar industrial contexts to predict defects in low-volume productions. Adopting this novel approach can effectively help designers to quantitatively estimate defects of newly developed products and support decisions for assembly quality-oriented design and optimization, especially in early design phases.

3.3.1 Assembly complexity paradigms in the literature

The scientific literature proposes different approaches to assess assembly complexity, based on the product to be assembled or the process sequence for the assembly (Alkan et al., 2017). Several methods are built upon the concept of easy of assembly, e.g., Design for Assembly and Manufacture (DFMA) (Boothroyd and Alting, 1992; Miyakawa, 1986). Such approaches aim at enhancing the product

[1] Part of the research addressed in this section is also present in the following papers:

- Verna E., Genta G., Galetto M., and Franceschini F. (2020a). "Product assembly and defect prediction: a novel model based on the structural complexity paradigm" Submitted to *Journal of Intelligent Manufacturing*.
- Verna E., Genta G., Galetto M., and Franceschini F. (2020b). "Defect prediction model for wrapping machines assembly" Submitted to 4th International Conference on Quality Engineering and Management ICQEM 2020.

design by reducing part numbers, optimizing part handling and insertion attributes, penalizing inefficient design (Alkan et al., 2017).

Moreover, a growing body of literature provides an assessment of assembly complexity by using different design complexity criteria and time estimation methodologies (Su et al., 2010; Shibata, 2002; Hinckley, 1994; Alkan et al., 2017). Hinckley (1994) defined an assembly complexity factor based on the Westinghouse DFA worksheet suggesting a theoretical time required to assemble a product. Shibata (2002) proposed to evaluate process complexity based on the method of Sony Standard Time (SST) and design complexity through the design for assembly/disassembly Cost-effectiveness (DAC) method. Although these approaches provide a robust assessment of assembly complexity, the methodologies used are designed for specific assembly products. For instance, Hinckley (1994) based his study on the Westinghouse Database, specifically designed for semiconductor products. Moreover, the DAC method used by Shibata as a measure of design assemblability is a Sony's methodology specific for audio equipment. Therefore, in order to extend the methodologies proposed by these authors to other contexts, it is necessary to adapt them to the specific case study, either by slightly modifying them or by identifying more suitable approaches.

Further approaches consider physical and cognitive elements to calculate the relative effort of each manufacturing task to define an "*operational complexity index*" (ElMaraghy and Urbanic, 2004). Such an index is designed as a function of the quantity and diversity of both product and process elements and the relative complexity coefficient. In a later study, Samy and ElMaraghy (2010) extended the approach mentioned above by adding DFA criteria to evaluate the assembly complexity of individual product parts. Besides, Richardson et al. (2006) proposed a practical model to predict the difficulty of assembly of an object based on its physical attributes. However, this approach is dependent on the specific application it is developed for, and, therefore, requires further efforts to produce a more general model.

Extensive research has shown that complexity may have a subjective nature and depend on the specific context and operator who perceives it (Lee, 2003). Accordingly, survey-based methods are often adopted to assess the perceived level of complexity arising from human–system interactions and manufacturing systems (Falck et al., 2017b, 2012; Mattsson, 2013).

Recent studies tried to overcome the above restrictions (specific industrial domain and applications, subjective elements, etc.) proposing a method based on structural complexity that allows supporting early design phases of assembly products (Sinha et al., 2012; Sinha, 2014; Alkan et al., 2017; Alkan, 2019).

3.3.2 Process- and design-based complexity model (Shibata-Su model)

One of the most accredited models developed in the literature is the Shibata-Su model that combines the approaches proposed by Shibata (2002) and Su et al. (2010). This model has also been successfully implemented in recent studies by the authors (Genta et al., 2018; Verna et al., 2020c; Galetto, Verna, and Genta, 2020; Galetto, Verna, Genta, et al., 2020).

According to Shibata (2002), the product assembly process can be decomposed into a series of process steps, or workstations, defined through sheets of operation standards. In each workstation, a certain number of job elements, i.e., elementary operations, is performed (Aft, 2000; Shibata, 2002). The job elements are the minimum components of a specific task. These should have easily identifiable starting and stopping points and be repeatable on a regular basis throughout the workday. To predict the process complexity, Shibata defined a process-based complexity factor for each workstation, as follows:

$$Cf_{P,i} = \sum_{j=1}^{N_{a,i}} SST_{ij} - t_0 \cdot N_{a,i} = TAT_i - t_0 \cdot N_{a,i} \tag{3.3}$$

where the index i refers to the generic i-th workstation (i=1,…,m); $N_{a,i}$ is the number of job elements in the workstation i; SST_{ij} is the Sony Standard Time spent on the job element j in the workstation i; TAT_i is the total assembly time related to the workstation i; t_0 is the threshold assembly time, i.e., the time required to perform the simplest assembly operation, below which neither assembly operations nor assembly defects should exist (Shibata, 2002). It should be remarked that in Shibata's study, the assembly times SST_{ij} are derived from Sony Standard Time (*SST*), a commonly used time estimation tool for electronic products. Accordingly, they are the standard times in which the operators should complete each job element and not the actual assembly times.

As evidenced by Shibata (2002), the time-related measures, and therefore the $Cf_{P,i}$, may not capture all the sources of defects. For this reason, he introduced a second predictor, a design-based assembly complexity factor (Shibata, 2002). It was defined as the ratio between a calibration coefficient and the ease of assembly (EOA) coefficient of the corresponding workstation estimated through the assembly/disassembly cost-effectiveness (DAC) method developed in Sony Corporation (Yamagiwa, 1988). In a later study, Su et al. (2010) remarked that the DAC method, which was developed specifically for Sony electronic products, may not be directly suitable for other types of products, such as electromechanical products. To cope with this issue, he proposed a different method to evaluate the design complexity (Su et al., 2010).

Su's methodology is based on the approach developed by Ben-Arieh for evaluating the degree of difficulty of assembly operations (Ben-Arieh, 1994). According to Ben-Arieh (1994), assembly operations can be specified by parameters related to the parts' geometry (geometry-based parameters) and to the type of contact between components (non-geometrical parameters), see Table 3.1.

Depending on the characteristics of the products to be assembled, a number l of parameters should be selected as criteria for evaluating the design-based complexity. Then, to obtain an integrated index, the weights w_q of the l parameters are allocated using the Analytic Hierarchy Process (AHP) approach (Ben-Arieh, 1994; Wei et al., 2005; Saaty, 1980), according to Eq. (3.4):

$$w_q = \frac{\left(\prod_{r=1}^{l} a_{qr}\right)^{\frac{1}{l}}}{\sum_{q=1}^{l}\left(\prod_{r=1}^{l} a_{qr}\right)^{\frac{1}{l}}} \qquad (q = 1, \ldots, l) \qquad (3.4)$$

where:

- a_{qr} is the relative importance of parameter q over parameter r ($r = 1, \ldots, l$);
- l is the number of parameters;
- w_q is the weight of parameter q.

Table 3.1- Parameters of assembly operations (introduced by Ben-Arieh (1994)).

Geometry-based parameters		Non-geometrical parameters	
(A)	Shape	(N)	Position contact
(B)	Force required	(O)	Snap contact
(C)	Mating direction	(P)	Spring contact
(D)	Alignment of components	(Q)	Gear contact
(E)	Mating component's length	(R)	Clamp fit
(F)	Length of components intersection	(S)	Belt contact
(G)	Ratio of length to width (diameter) of the mating component		
(H)	Ratio of the mating component's weight to the mated one		
(I)	Stability of the resultant assembly		
(L)	Amount of support required for the assembly operation		
(M)	Interference (reachability) to the assembled component		

Then, a number e of experts is asked to express an evaluation on the degree of difficulty of each parameter in each workstation. In particular, the degree of difficulty D_{kqi} is the evaluation of the parameter q in the workstation i estimated by the expert k. The values D_{kqi} are rated by scores between 0 and 10. According to the weight w_q of the l parameters, see Eq. (3.4), and the degrees of difficulty D_{kqi}, the design-based complexity factors is defined as follows (Su et al., 2010):

$$Cf_{D,i} = \sum_{q=1}^{l}\left(w_q \cdot \frac{1}{e} \cdot \sum_{k=1}^{e} D_{kqi}\right) \qquad (i = 1, \ldots, m) \qquad (3.5)$$

Previous research in the electromechanical field established that the relationship between DPU and Cf_P and Cf_D follows a power-law behavior (Shibata, 2002; Galetto, Verna, Genta, et al., 2020; Verna et al., 2020c), according to Eq. (3.6):

$$DPU_i = a \cdot (Cf_{P,i})^b \cdot (Cf_{D,i})^c \qquad (3.6)$$

where a, b and c may be obtained by means of a power-law nonlinear regression. It should be noted that, although Eq. (3.6) is linearizable, a recent study has shown that it is preferable using a nonlinear regression model in the case of few nonrepeated data and affected by high variability, as in the case of defect rates, because of the well-known problem of the retransformation bias (Galetto, Verna, and Genta, 2020).

3.3.3 Structural complexity (Sinha-de Weck-Alkan model)

Assembly complexity of a product can also be evaluated by a different perspective, that of the structural complexity model introduced by Sinha et al. (2012) (Sinha et al., 2012; Alkan, 2019). In this model, Huckel's molecular orbital theory (Hückel, 1932) is applied to the engineering domain to analyze the complexity of cyber-physical systems. According to Sinha et al. (2012), any engineering system can be represented by several components that are connected in different ways. Each component can be thought of as an atom and the interfaces between them as inter-atomic interactions, i.e., chemical bonds (Alkan et al., 2017). Through this analogy, product complexity can be associated with the system's inherent structure and, therefore, with individual system entities and the effects of the system connectivity pattern (Alkan and Harrison, 2019). This approach was successfully validated using pressure recording devices (Alkan et al., 2017) and printing systems (Sinha, 2014) as case studies. Accordingly, in this research, the approach was applied to the wrapping machines assembly, slightly amended to reflect the division of the process into workstations.

Assembly complexity C_i related to each i-th workstation can be defined as (Sinha, 2014; Alkan, 2019):

$$C_i = C_{1,i} + C_{2,i} \cdot C_{3,i} \tag{3.7}$$

In Eq. (3.7), $C_{1,i}$ represents the sum of complexities of individual product parts in each i-th workstation and is calculated as follows:

$$C_{1,i} = \sum_{p=1}^{N_i} \gamma_{pi} \tag{3.8}$$

where, for each i-th workstation ($i = 1, \dots, m$), N_i is the total number of product parts and γ_{pi} is the handling complexity of part p. Each complexity γ_{pi} may be intended as the ergonomic difficulty to interact with the part and can be measured according to the structural characteristics that cause difficulties during its handling (Alkan, 2019). As suggested by Alkan (Alkan, 2019), handling complexity γ_{pi} can be estimated as a function of the standard handling time of the part p, that involves the localization of the relevant box, moving arm to pick position, picking the relevant part and returning arm to work position.

$C_{2,i}$ is the complexity of liaisons related to the i-th workstation and is the sum of the complexities of pair-wise connections that exist in the product structure assembled in the workstation, as follows:

$$C_{2,i} = \sum_{p=1}^{N_i} \sum_{r=1}^{N_i} \varphi_{pri} \cdot A_{pri} \tag{3.9}$$

where, for each i-th workstation (i=1,…,m), φ_{pri} is the complexity in achieving a liaison between parts p and r and can be expressed by the relationships between the linked components and the nature of the connection, and A_{pri} defines the binary adjacency matrix representing the connectivity structure of the system, as indicated in Eq. (3.10):

$$A_{pri} = \begin{cases} 1 \text{ if there is a connection between } p \text{ and } r \text{ in the } i - \text{th workstation} \\ 0 \text{ otherwise} \end{cases} \tag{3.10}$$

The interface complexity φ_{pri} may be estimated based on the standard completion time of the liaison between parts p and r in isolated conditions. In addition to the handling of the connections, the completion time includes locating the connection areas, orienting and positioning the parts and the connector, placing the connectors and joining the parts, adjusting the connections, and a final check (Alkan, 2019).

Finally, $C_{3,i}$ is the topological complexity of the i-th workstation and represents the complexity related to the architectural pattern of the assembled product. According to Sinha (2014), it can be obtained from the matrix energy (also called graph energy) E_{Ai} of the adjacency matrix related to the i-th workstation (Nikiforov, 2007), as shown in Eq. (3.11). E_{Ai} is designated by the sum of singular values δ_{pi} of the adjacency matrix of the product assembled in the i-th workstation

$$C_{3,i} = \frac{E_{Ai}}{N_i} = \frac{\sum_{p=1}^{N_{Si}} \delta_{pi}}{N_i} \tag{3.11}$$

where N_{Si} is the total number of singular values of the product connectivity matrix related to i-th workstation. It is recalled that, given a matrix $\boldsymbol{A}$, the singular values are defined as the square roots of non-negative eigenvalues of the matrix $\boldsymbol{A}^T\cdot\boldsymbol{A}$.

As observed by Sinha (2014), matrix energy regime for graphs with a given number of nodes can be divided into (i) hyperenergetic, and (ii) hypoenergetic. An intermediate or transition regime between these two also exists (Xueliang Li et al., 2012). The hyperenergetic regime is defined by graph energy greater than or equal to that of a fully connected graph, and the hypoenergetic regime is defined as shown in Eq. (3.12):

$$E_{Ai} = \begin{cases} \geq 2(N_i - 1) & \text{hyperenergetic} \\ < N_i & \text{hypoenergetic} \end{cases} \tag{3.12}$$

Hence, in terms of topological complexity metric, the regimes are defined as:

$$C_{3,i} = \begin{cases} \geq 2\left(1 - \frac{1}{N_i}\right) \approx 2 & \text{hyperenergetic} \\ < 1 & \text{hypoenergetic} \end{cases} \quad (3.13)$$

Note that for hyperenergetic regimes, $C_{3,i}$ can be approximated to 2 when N_i is sufficiently large (Xueliang Li et al., 2012). Translating the graph structures to system architectural pattern, typical topological complexity metric $C_{3,i}$ values can be associated to those forms, again when N_i is sufficiently large: (i) $C_{3,i} < 1$ for a centralized architecture, (ii) $1 \leq C_{3,i} < 2$ for a hierarchical/layered architecture, and (iii) $C_{3,i} \geq 2$ for a distributed architecture (Sinha, 2014). Accordingly, $C_{3,i}$ increases as the system topology shifts from centralized architectures to more distributed architectures, as shown in Figure 3.4 (Alkan, 2019; Sinha et al., 2012).

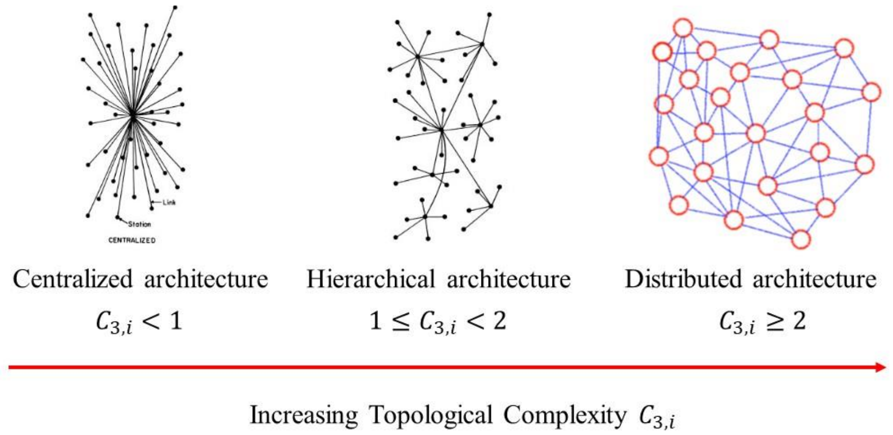
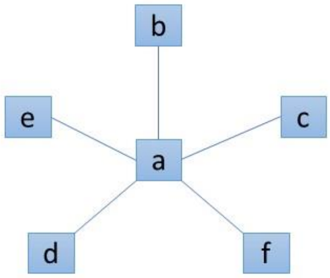


Figure 3.4 - Spectrum of architectural patterns based on topological complexity metric with their respective reference values (adapted from (Sinha, 2014)).

Therefore, $C_{3,i}$ represents the intricateness of structural dependency among assembly and requires knowledge of the complete architecture of the system and, in this sense, contrary to the previous terms $C_{1,i}$ and $C_{2,i}$, denotes a global effect whose influence could be perceived during the system integration phase (Sinha, 2014). Therefore, the term $C_{2,i} \cdot C_{3,i}$ in Eq. (3.7) can be referred to as a general indicator of the system integration effort that allows distinguishing product architectures with similar parts and connections complexities.

To clarify how the complexity $C_{3,i}$ can be obtained, a pedagogical example is proposed. Let us consider an assembly process made up by a single workstation in which a simple product composed of 6 parts is assembled, as represented in Figure 3.5. The graph energy of the associated adjacency matrix $\boldsymbol{A}$ is computed as the sum of its singular values, which are the square roots of non-negative eigenvalues of the matrix $\boldsymbol{A}^T \cdot \boldsymbol{A}$. In detail, the eigenvalues of the matrix $\boldsymbol{A}^T \cdot \boldsymbol{A}$ are λ_1=0 and λ_2=5. Thus, $E_A = \sqrt{5} = 2.24$. According to Eq. (3.11), it is obtained that $C_3 = \frac{2.24}{6} = 0.37$. Since $C_3 < 1$, the product topology can be qualified as a centralized architecture.



$$A = \begin{pmatrix} 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Figure 3.5 – Connectivity structure of a simple product composed of six parts and its associated adjacency matrix *A*.

3.3.4 A novel prediction model based on the structural complexity paradigm

This section aims to develop a novel approach to predict assembly defects in manufacturing by adopting the structural complexity paradigm (see Section 3.3.3). Two are the Research Questions (RQ) specifically addressed:

RQ1: *Is there a relationship between product defects and its structural complexity?*

RQ2: *To what extent the structural complexity affects the estimation of defects in electromechanical manufacturing?*

In order to answer these questions, a novel defect prediction model is developed. A low-volume production of wrapping machines is considered as a case study, in which product complexity is approached by the novel paradigm proposed by Alkan (2019) and Sinha (2014). Complexity is evaluated considering structural properties associated with handling and insertion of assembly parts and their architectural structure (Alkan, 2019). This approach, depending solely on physical design information, can be considered more practical from the design point of view, especially in the early design stages. Next, this model is compared with one of the most accredited in the literature, i.e., the Shibata-Su model (see 3.2.1.2).

The author believe that the novel approach based on the structural complexity paradigm can better support designers in the assembly quality-oriented design and optimization process. Furthermore, the novel prediction model can effectively help designers to get reliable defect estimates at early design stages and support decisions in the planning of quality inspections. Besides, by providing new insights into defects prediction, the present research should make a useful contribution to the field of low-volume production, where the inadequacy of traditional statistical approaches make quality control and inspection planning challenging (Galetto, Verna, Genta, et al., 2020; Verna et al., 2020e, 2020c; Koons and Luner, 1991).

3.3.4.1 Model definition

This section aims at proposing a novel approach to predict defects based on the structural complexity emulating the Shibata-Su model described in Section 3.3.2.

The model, shown in Eq. (3.14), uses the structural complexity as the unique predictor of *DPU*:

$$DPU_i = f(C_i) \tag{3.14}$$

The structure of the new defect prediction model reflects that of Eq. (3.6). However, the adoption of the concept of structural complexity (Section 3.3.3) introduces a novel paradigm. Furthermore, the proposed approach, depending solely on physical design information, can be considered more useful, especially in the early design stages, when real production data or the physical mockup are not available (as is the case for the model presented in Section 3.3.2).

In the next section, the proposed model is applied to a real case study in the electromechanical assembly field and compared with the Shibata-Su model described in 3.2.2.

3.3.4.2 Model development in the electromechanical field

Wrapping machines assembly

The model defined in Section 3.3.4.1 was applied to the real assembly of wrapping machines. Wrapping machines are electromechanical products employed at the end of production lines to pack palletized loads with a stretch plastic film. Typically, three main categories of wrapping machines are produced: (i) turntable, (ii) rotating arm and (iii) rotating ring. In this study, the rotating ring wrapping machines are analyzed in detail, in particular those produced by the Italian company Tosa Group S.p.A., represented in Figure 3.6. In a typical year, the production of these machines is of about 50 units. Furthermore, each assembled machine is highly customized, making it almost a unique piece. For these reasons, such a manufacturing process can be classified as a low-volume manufacturing process.

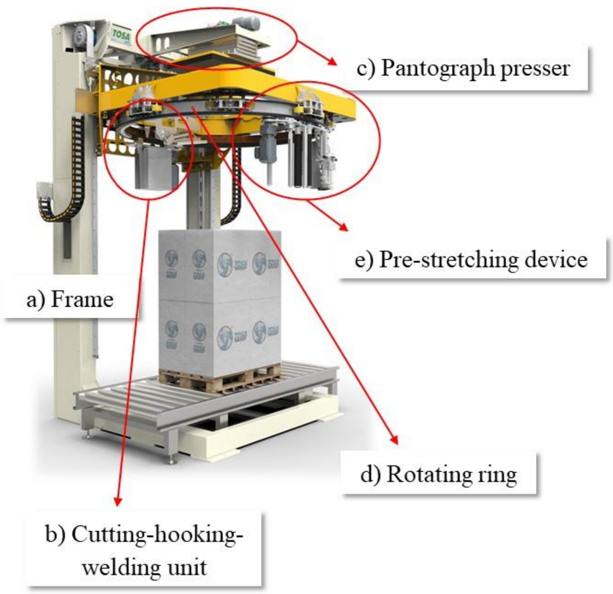


Figure 3.6 - Representation of the mechanical group and its main components of a rotating ring wrapping machine produced by the company Tosa Group S.p.A. (Italy).

The rotating wrapping machines consist of three central units: (i) mechanical, (ii) electrical and electronic and (iii) software. As shown in Figure 3.6, in the mechanical unit, a fixed and a mobile part can be distinguished. In particular, the fixed part is made up of:

a) a frame, i.e., the load-bearing structure, dimensioned to guarantee strength and durability, composed by boxes and profiles in high-strength sheet steel;
b) a cutting-hooking-welding unit that automatically cuts the plastic film employing a heated metal wire and heat-seals the last tail to the load with a specific plate;
c) a pantograph presser, which stabilizes the palletized load, exerting pressure on its top during the wrapping process.

In the mobile part, two devices are assembled:

d) a rotating ring, built with a calendered steel profile, light but very resistant and, therefore, suitable for high speeds. It is moved by a belt connected to an electric motor. The rotation of the ring around the palletized load is combined, during the wrapping cycle, with a vertical sliding;
e) a pre-stretching device, fixed to the rotating ring that allows: (i) the pulling/unwrapping, (ii) the pre-stretch and positioning of the plastic film, (iii) the wrapping of the pallet with the required number of wrappings.

The electrical and electronic unit includes all the wiring of the components, sensors and motors onboard the machine, and the general electrical panel. The software unit, whose programming and configuration is entrusted to a specialized external supplier, is designed to control the machine, as well as to communicate with the operator.

During a typical work cycle, the palletized load is transported by a roller or belt conveyor system within the area delimited by the trolley. Subsequently, the pantograph presser descends by pressing on the top of the palletized load to ensure stability during the film wrapping phase. The trolley descends, the ring starts to rotate and, at the same time, the plastic film moves through the pretensioner and is distributed around the load. After a variable number of wrappings that depends on the palletized load, the wrapping cycle ends, the cutting-hooking-welding unit removes the tail of the plastic film and the load is left free to be transported to the next station. Finally, a new pallet enters the perimeter of the machine ring, and the cycle is repeated.

Owing to the complexity and the high number of components of the wrapping machine, the assembly of a single part, i.e., the pre-stretching device, is considered in detail. The main reason is that, although each machine differs from the others for some details, this device is common to all rotating ring wrapping machines. Nonetheless, the proposed approach can be extended and implemented to the overall wrapping machine.

The pre-stretching device, illustrated in Figure 3.7, is installed on a support structure called frame plate. The stretch film runs through two rubber rollers, each one connected by a belt drive system to a brushless motor: the speeds of the two rollers are therefore independent of each other. In contact with the surface of the two rollers, the film is stretched proportionally to the speed difference, thus determining a significant increase in the length of the film that is wrapped on the load. The electronic system measures the speed using specific sensors and keeps the tension of the film constant during its application on the entire surface of the pallet. Besides, the pre-stretching device may be equipped with a patent spindle which automatically replaces the empty film reel.

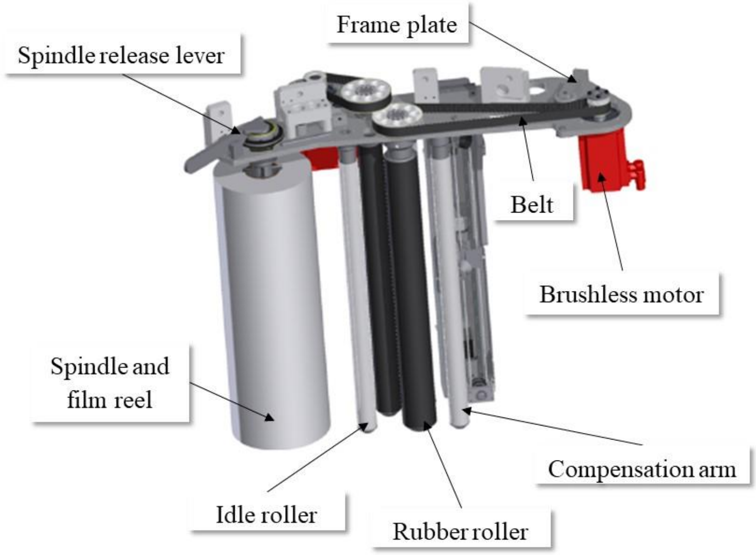


Figure 3.7 - 3D CAD model of the pre-stretching device showing its main components.

Table 3.2 shows the subdivision of the assembly process of the pre-stretching device into 29 workstations. These workstations are assembly steps defined within operation standards, i.e., instruction sheets for work procedure (Shibata, 2002; Su et al., 2010). As evidenced in Table 3.2, the first nine workstations are assembled on the bench, whilst the remaining are assembled on the frame plate. Moreover, Table 3.2 reports experimental values of defects per unit (*DPU*) occurring under stable process conditions in each workstation. These values are obtained by drawing on the company historical data collected over the last five years and, therefore, provide an indication of the average defectiveness rate of the assembly process in optimal working condition.

Table 3.2 - Subdivision of the assembly process of the pre-stretching device into workstations (WS) with the related experimental *DPU*.

WS no.	WS description	Bench assembly	Assembly on the frame plate	Experimental DPU_i
1	Motor no. 1 bench assembly	X		0.0364
2	Motor no. 2 bench assembly	X		0.0364
3	Support plate of motor no. 2 bench assembly	X		0.0182
4	Spindle bench assembly	X		0.0000
5	Rubber tires bench assembly	X		0.1091
6	Idle rolls bench assembly	X		0.0545
7	Rubberized pads bench assembly	X		0.0000
8	Belt tensioner device bench assembly	X		0.0364
9	Driven wheels of transmission system bench assembly	X		0.0000
10	Pre-stretch frame plate preparation		X	0.0182
11	Rubber rollers on pre-stretch frame plate assembly		X	0.0182
12	Idle rollers on pre-stretch frame plate assembly		X	0.0182
13	Motor no. 1 on frame plate assembly		X	0.0000
14	Transmission system of motor no. 1 assembly		X	0.0000
15	Motor no. 2 on frame plate assembly		X	0.0182
16	Transmission system of motor no. 2 assembly		X	0.0364
17	Motor no. 1 bracket on pre-stretch frame plate assembly		X	0.0000
18	Belt tensioner on pre-stretch frame plate assembly		X	0.0364
19	Transmission system of motor no. 1 calibration		X	0.0364
20	Transmission system of motor no. 2 calibration		X	0.0364
21	Spindle preparation for assembly on pre-stretch frame plate		X	0.0000
22	Spindle group on pre-stretch frame plate assembly		X	0.0364
23	Rubber pads on pre-stretch frame plate assembly		X	0.0000
24	Motor assembly no. 1 final steps		X	0.0545
25	Motor assembly no. 2 final steps		X	0.0545
26	Spindle release lever bench assembly		X	0.0000
27	Spindle release lever on pre-stretch frame plate assembly		X	0.0000
28	Compensation arm bench assembly		X	0.0909
29	Compensation arm on pre-stretch frame plate assembly		X	0.0000

The novel model: DPU vs. structural complexity

Table 3.3 reports, for each i-th workstation, the complexities $C_{1,i}$, $C_{2,i}$ and $C_{3,i}$, evaluated according to Eqs. (3.8), (3.9), and (3.11) respectively, and the final assembly complexity C_i derived by Eq. (3.7). Specifically, $C_{1,i}$ is estimated considering the standard handling time of the parts that are assembled in the corresponding workstation, and $C_{2,i}$ the standard completion time of the connection between the parts. Finally, $C_{3,i}$ is obtained from the graph energy of the adjacency matrix related to the i-th workstation and the number of parts assembled N_i. For instance, in the workstation no. 14, only two parts are assembled: the driven wheel and the drive belt. As shown in Table 3.3, the standard handling time of the two parts is 0.19 min and the time for connecting them is 0.78 min. For these two parts, the adjacency matrix is $\boldsymbol{A} = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ and its graph energy E_A is 1 (the eigenvalue of the matrix $\boldsymbol{A}^T \cdot \boldsymbol{A}$ is λ_1=1). Thus, the resulting complexity C_3 is 0.50. Consequently, by applying Eq. (3.7), product complexity of this workstation is 0.58 min.

To relate DPU_i versus C_i, different models were tested and compared (see Table 3.4). The adequacy of the models was assessed based on the analysis of regression residuals and of the S value as a measure of goodness-of-fit. A power curve fitting (model no. 3 in Table 3.4) was found to be the best model to define such a relationship. Accordingly, the final model developed for wrapping machines assembly is the following:

$$DPU_i = 3.05 \cdot 10^{-3} \cdot (C_i)^{1.58} \tag{3.15}$$

Figure 3.8 illustrates the novel defect prediction model defined in Eq. (3.15) and the corresponding residual plots. The Normal Probability Plot indicates that the residuals do not show significant departures from normal distribution, as also demonstrated by performing the Anderson-Darling test which does not reject normality of residuals with a confidence level of 95% (Devore, 2011). Besides, the plot of residuals versus order does not reveal any systematic effects in the data due to time or data collection order. The S value is 0.018, indicating that the experimental values of DPU fall a standard distance of 0.018 units from the DPU values predicted by Eq. (3.15).

Table 3.3 - Variables and predictions related to the novel defect prediction model: DPU vs C.

WS no.	N_i	$C_{1,i}$ [min]	$C_{2,i}$ [min]	$C_{3,i}$	C_i [min]	Predicted DPU_i
1	14	2.19	5.11	0.60	5.27	0.0424
2	14	2.28	5.33	0.59	5.41	0.0443
3	10	1.19	4.77	0.80	5.01	0.0391
4	3	0.78	3.14	0.25	1.57	0.0062
5	14	1.24	11.13	0.47	6.47	0.0587
6	12	1.63	6.53	0.62	5.68	0.0478
7	4	0.73	2.91	0.25	1.46	0.0055
8	8	0.25	2.22	1.90	4.47	0.0327
9	4	0.08	0.33	0.25	0.16	0.0002
10	11	0.99	3.97	0.75	3.97	0.0271
11	26	1.07	4.27	0.88	4.83	0.0369
12	39	1.19	4.77	0.83	5.15	0.0409
13	5	0.74	2.96	0.25	1.48	0.0057
14	2	0.19	0.78	0.50	0.58	0.0013
15	16	1.73	6.90	0.48	5.01	0.0391
16	2	0.09	0.80	3.14	2.60	0.0139
17	3	0.20	0.78	0.25	0.39	0.0007
18	5	0.18	1.64	1.97	3.41	0.0213
19	12	1.74	4.05	0.69	4.55	0.0336
20	12	1.90	4.43	0.66	4.81	0.0366
21	15	0.45	1.79	0.25	0.90	0.0026
22	34	1.36	12.23	0.44	6.730	0.0625
23	5	0.47	1.89	0.25	0.94	0.0028
24	3	0.12	1.04	2.88	3.09	0.0182
25	3	0.12	1.08	2.77	3.11	0.0184
26	6	0.24	0.95	0.25	0.48	0.0009
27	6	0.80	7.20	0.25	2.60	0.0139
28	20	1.26	11.32	0.60	8.05	0.0830
29	4	0.56	5.00	0.25	1.81	0.0078

Table 3.4 - Comparison of different models defining the relationship between defects per unit and assembly complexity.

No.		Model	S (Standard error of the regression)
(1)	Linear model with intercept	$DPU_i = 9.82 \cdot 10^{-3} \cdot C_i - 8.16 \cdot 10^{-3}$	0.01859
(2)	Power model with intercept	$DPU_i = 9.91 \cdot 10^{-3} \cdot C_i^{1.61} + 3.50 \cdot 10^{-4}$	0.01861
(3)	Power model	$DPU_i = 3.05 \cdot 10^{-3} \cdot C_i^{1.58}$	0.01826
(4)	Exponential model	$DPU_i = 6.45 \cdot 10^{-3} \cdot e^{0.34 \cdot C_i}$	0.01848

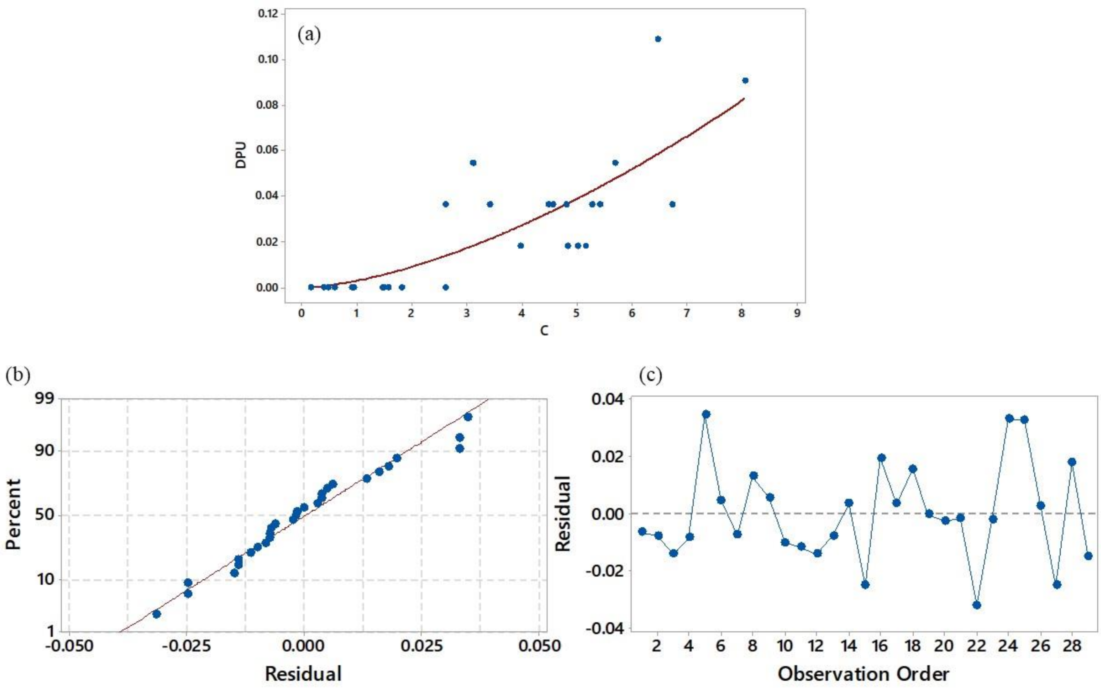


Figure 3.8 - (a) *DPU* vs. *C*: defect prediction model and experimental data; Residual plots: (b) Normal Probability Plot and (c) Residuals vs. Order.

Shibata-Su model: DPU vs. process- and design-based complexity

This section presents the implementation of the defect prediction model relating *DPU* with the Shibata-Su model, described in Section 3.3.2, in order to compare the obtained predictions with those obtained by using the new model shown in Eq. (3.15).

Regarding the first predictor, $Cf_{P,i}$, see Eq. (3.3), each workstation was subdivided into a certain number of elementary operations, $N_{a,i}$, ranging from 1 to 12 (see Table 3.5). Concerning assembly times, instead of using Sony Standard Time (typical of Sony's home audio products), the time of each job element was evaluated by considering the average value of 3 measurements of the assembly standard time spent by the operator in the job element. The threshold assembly time t_0 was set at 0.04 min, which corresponds to the time required to perform the least complex job element. The assembly time TAT_i is shown in Table 3.5, as well as the final value of the first predictor, $Cf_{P,i}$, calculated according to Eq. (3.3), separately for each *i*-th workstation.

As far as the second predictor is concerned, Cf_D, the adopted methodology is the one developed by Su et al. (2010) for electromechanical products because the wrapping machine is substantially an electromechanical equipment. In this case, regarding Eqs. (3.4) and (3.5), 11 design parameters were selected by adapting Ben Arieh's approach to the case of wrapping machines, see Table 3.5. Two engineers and four assembly operators were asked to compare the relative importance of each parameter in determining the difficulty of inserting a part into a product. The evaluation scale used for the relative importance between each pair of parameters ranges from a minimum of 1, which indicates equal importance of the two parameters, to a maximum of 9, which represents the dominant importance of the considered parameter with respect to the other. Six paired comparison matrices were obtained, whose individual evaluations were then aggregated into a single paired comparison matrix representative of the group judgment by using the geometric mean, as suggested by Dong and Saaty (2014). From this matrix, reported in Table 3.6, the weights w_q of the l parameters were derived, according to Eq. (3.4), and are listed in Table 3.7. For instance, taking parameter P1 as an example, the corresponding weight w_q (q=1) is obtained as: $w_1 = \frac{1.761}{12.693} = 0.139$.

Table 3.5– Variables and predictions related to the Shibata-Su defect prediction model: DPU vs. Cf_P and Cf_D.

WS no.	$N_{a,i}$	TAT_i [min]	$Cf_{P,i}$ [min]	$Cf_{D,i}$	Predicted DPU_i
1	6	7.30	7.1	4.38	0.0214
2	6	7.61	7.4	4.56	0.0250
3	3	5.96	5.8	5.06	0.0287
4	3	3.92	3.8	4.31	0.0126
5	12	12.37	11.9	5.69	0.0715
6	12	8.16	7.7	4.89	0.0320
7	3	3.64	3.5	2.76	0.0030
8	3	2.47	2.4	3.48	0.0045
9	2	0.41	0.3	3.68	0.0012
10	3	4.96	4.8	4.21	0.0142
11	4	5.34	5.2	5.35	0.0312
12	6	5.96	5.7	5.14	0.0298
13	1	3.70	3.7	5.09	0.0205
14	2	0.97	0.9	5.40	0.0084
15	4	8.63	8.5	4.94	0.0355
16	2	0.89	0.8	4.94	0.0060
17	1	0.98	0.9	4.22	0.0041
18	2	1.82	1.7	4.27	0.0067
19	2	5.79	5.7	5.19	0.0306
20	2	6.33	6.3	5.21	0.0332
21	2	2.24	2.2	5.20	0.0147
22	6	13.59	13.4	5.59	0.0738
23	2	2.36	2.3	4.13	0.0075
24	1	1.15	1.1	4.07	0.0041
25	1	1.20	1.2	4.25	0.0049
26	1	1.19	1.2	4.06	0.0042
27	3	8.00	7.9	4.72	0.0293
28	9	12.58	12.2	5.54	0.0672
29	3	5.56	5.4	4.96	0.0257

Table 3.6 - Paired comparison matrix of design parameters for evaluating the design-based assembly complexity.

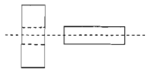
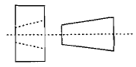
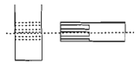
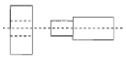
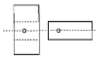
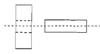
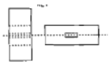
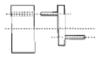
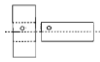
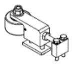
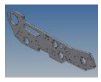
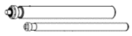
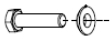
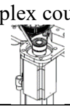
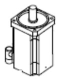
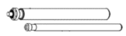
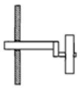
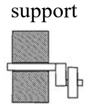
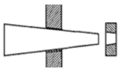
Design parameter	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	$\left(\prod_{r=1}^{l} a_{qr}\right)^{\frac{1}{l}}$
P1	1.00	1.32	1.96	0.78	0.60	2.59	5.58	2.72	2.93	1.53	2.38	1.761
P2	0.76	1.00	3.05	0.83	1.26	0.79	1.67	3.63	2.51	1.27	2.89	1.529
P3	0.51	0.33	1.00	1.26	3.04	1.26	3.80	2.12	5.10	4.93	7.41	1.907
P4	1.29	1.21	0.79	1.00	2.74	4.39	3.53	1.36	3.37	5.13	3.69	2.151
P5	1.66	0.79	0.33	0.53	1.00	1.47	1.02	1.10	3.45	5.44	0.97	1.192
P6	0.39	1.26	0.79	0.23	0.68	1.00	3.52	1.41	5.38	2.67	1.21	1.161
P7	0.18	0.60	0.26	0.28	0.98	0.28	1.00	1.28	1.76	1.31	3.69	0.714
P8	0.37	0.28	0.47	0.73	0.91	0.71	0.78	1.00	2.00	1.51	1.85	0.810
P9	0.34	0.40	0.20	0.30	0.29	0.19	0.57	0.50	1.00	1.51	1.24	0.466
P10	0.66	0.79	0.20	0.20	0.18	0.37	0.76	0.66	0.66	1.00	1.69	0.523
P11	0.42	0.35	0.13	0.27	1.03	0.82	0.27	0.54	0.81	0.59	1.00	0.480
											$\sum_{q=1}^{l}\left(\prod_{r=1}^{l} a_{qr}\right)^{\frac{1}{l}}$	12.693

Table 3.7 - Parameters selected from those in Table 1 for evaluating the design-based complexity factor and their weights.

Design parameter	Ref. Table 1	Design parameter description	Weight w_q
P1	(A)	Shape of mating objects	0.139
P2	(B)	Force required	0.120
P3	(D)	Alignment of components	0.150
P4	(C)	Mating direction	0.169
P5	(H)	Ratio of the mating component's weight to the mated one	0.094
P6	(G)	Ratio of length to width (diameter) of the mating component	0.091
P7	(M)	Reachability to the assembled component	0.056
P8	(E)	Mating component's length	0.064
P9	(L)	Amount of support required for the assembly	0.037
P10	(I)	Stability of the resultant assembly	0.041
P11	(F)	Length of components intersection	0.038

Besides, the e = 6 experts were asked to evaluate the degree of difficulty of each design parameter in each workstation. More in detail, the question asked to the experts was the following: *"How much does the q-th parameter affect the assembly difficulty in the i-th workstation on a scale from 0 to 10, where 0 corresponds to no difficulty and 10 corresponds to maximum difficulty?"*. To cope with the alignment of the assessment scales, the framework provided in Table 3.8 was explained to each expert. This tool entailed the adoption of a standard scale of judgments by defining conventional degrees of difficulty.

Table 3.8 - List of parameters used to evaluate the design-based assembly complexity, with examples of the degrees of difficulty to be assigned during the assessment.

Parameter	**Parameter description**	**Degree of difficulty 0-3**	**Degree of difficulty 3-6**	**Degree of difficulty 6-10**
P1	Shape of mating objects			
P2	Force required	Simple coupling (no manual tool required)	Forced coupling (manual tool required)	Coupling with hydraulic press (20000 kg)
P3	Alignment of components	Mechanical stop 	Stop with reference 	No reference stop 
P4	Mating direction	Axial 	Eccentric axial 	Eccentric radial 
P5	Ratio of the mating component's weight to the mated one	Bearing lift (approx. 1 kg)	Idle roller lift (approx. 4 kg)	Frame plate lift (approx. 7 kg)
P6	Ratio of length to width (diameter) of the mating component	Belt tensioner device 	Frame plate 	Roller 
P7	Reachability to the assembled component	Simple coupling 	Medium complexity coupling	Complex coupling 
P8	Mating component's length	Flanged sleeve 	Brushless motor 	Roller 
P9	Amount of support required for the assembly	No support 	Medium stable support 	Very stable support 
P10	Stability of the resultant assembly	Very stable resultant assembly	Medium stable resultant assembly	Poorly stable resulting assembly
P11	Length of components intersection	Low component coupling length	Medium component coupling length	High component coupling length

Six matrices were obtained, one for each expert. Then, by averaging the evaluations of the six experts, for each *q*-th parameter in each *i*-th workstation, the matrix of the degrees of difficulty was derived (see Table 3.9). To clarify these evaluations, a single workstation is analyzed in detail: the workstation no. 22, i.e., the spindle group on pre-stretch frame plate assembly. In such a workstation, 6 elementary operations are performed: (1) pre-tightening the spindle on a pre-stretch frame plate, repeated 12 times; (2) spindle clamping on pre-stretch frame plate, repeated 12 times; (3) tightening the screws on the intermediate spindle ring, repeated 3 times; (4) tightening the screws on the spindle brake support plate, repeated 4 times; (5) tightening the first spindle ring nut; (6) tightening the second spindle ring nut. To perform these operations, the assembly operator uses, in addition to his hands, simple equipment, including a wrench and a torque wrench. As shown in Table 3.9 for workstation 22, the degrees of difficulty range from a minimum of 4.50 to a maximum of 6.83. These values are mainly within the intermediate difficulty range (fourth column of Table 3.8) since the operations performed are mainly screw tightening activities on the spindle, requiring manual equipment and medium-complex couplings. Accordingly, they do not entail any particular assembly difficulties. The only exception is for parameter P8, whose degree of difficulty is almost 7, due to the high coupling length of the components to be assembled.

Table 3.9 - Degrees of difficulty matrix for evaluating the design-based assembly complexity.

	Design parameter										
Workstation	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
1	4.00	4.17	4.17	4.50	5.17	3.67	4.33	3.17	6.00	5.83	5.50
2	4.33	4.33	4.17	4.50	5.17	3.67	5.67	3.33	6.00	5.83	6.33
3	5.83	6.50	5.50	4.33	4.00	3.50	5.00	4.00	6.50	5.00	6.00
4	3.67	4.00	3.50	3.33	4.83	3.83	6.00	5.17	6.00	6.83	6.67
5	4.17	7.33	4.83	5.33	4.67	6.33	5.83	6.67	7.83	6.50	7.33
6	3.83	5.67	4.83	3.50	4.00	5.83	5.00	6.50	6.33	6.50	6.67
7	2.83	3.50	3.00	2.67	1.50	2.00	2.67	1.67	3.00	4.00	4.83
8	3.83	4.17	4.17	3.17	2.33	1.83	3.50	1.83	4.67	5.00	5.50
9	5.00	2.83	6.00	2.83	2.33	2.67	2.83	2.33	1.17	6.17	5.17
10	4.17	3.50	5.00	2.00	6.17	5.33	2.67	4.33	5.67	5.83	4.83
11	4.00	4.67	6.17	3.67	6.33	7.17	4.50	7.67	5.33	6.83	5.67
12	4.00	4.00	6.00	3.67	6.00	6.83	4.50	7.17	5.00	7.17	5.33
13	3.83	5.17	6.67	4.83	5.83	4.83	3.50	5.00	5.50	5.33	5.00
14	6.17	5.00	6.67	6.33	3.17	4.00	6.00	3.83	3.17	6.67	6.17
15	4.17	5.00	6.50	4.50	5.17	5.00	4.17	4.83	5.17	5.00	3.67
16	5.50	4.83	5.83	6.00	2.67	3.67	6.00	3.00	2.83	6.17	6.17
17	3.17	3.67	6.33	5.00	4.00	3.33	3.33	3.17	3.17	4.83	4.00
18	3.67	3.67	6.50	5.17	3.00	3.33	4.00	2.83	3.00	6.33	2.67
19	4.33	5.17	7.33	5.67	3.50	5.00	5.83	3.00	3.83	6.83	4.67
20	4.33	5.17	7.33	5.67	3.50	4.50	5.50	3.83	3.83	6.67	5.67
21	3.50	4.17	6.17	4.83	6.33	7.00	4.50	7.17	4.33	4.50	4.67
22	5.50	5.67	5.33	5.17	5.67	6.50	6.33	6.83	5.17	4.50	4.67
23	3.50	4.67	4.67	4.00	3.50	3.17	4.33	3.67	3.67	5.83	6.17
24	3.17	3.17	5.17	5.33	3.83	3.00	4.67	2.67	3.17	5.00	4.83
25	3.33	3.33	5.67	5.50	3.83	3.17	4.50	3.17	3.00	5.00	4.83
26	4.00	2.83	5.50	5.00	2.50	3.33	3.67	4.00	2.83	5.00	4.83
27	4.33	4.67	5.83	5.00	4.17	3.50	4.50	4.83	3.33	6.00	5.17
28	4.83	4.33	6.33	5.17	5.17	6.17	5.17	7.33	5.33	6.83	6.33
29	3.83	4.50	5.83	5.83	3.33	5.00	4.67	6.00	3.00	5.83	6.83

The design-based complexity factor of each workstation, $Cf_{D,i}$, is finally obtained by applying Eq. (3.5) and by combining the weights of the parameters and the degrees of difficulty matrix reported respectively in Table 3.7 and Table 3.9. The obtained values are listed in Table 3.5.

Experimental *DPU*s were analyzed using the power-law regression model shown in Eq. (3.6) by using the software *MATLAB*®. The defect prediction model obtained, which will be marked henceforth with an asterisk (*) to distinguish it from the novel model reported in Eq. (3.15), is the following (see also Figure 3.9):

$$DPU_i^* = 5.04 \cdot 10^{-5} \cdot (Cf_{P,i})^{0.77} \cdot (Cf_{D,i})^{3.08} \tag{3.16}$$

The *DPU*s predicted by using Eq. (16) are listed in Table 5. Finally, as shown in Figure 3.9 (b) and (c), the analysis of the residuals between experimental *DPU* and predicted *DPU* suggests that the power-law model describes well the trend of the *DPU* as a function of the assembly complexity. The Normal Probability Plot (NPP) indicates that the residuals do not show significant departures from normal distribution, even though a slight hypernormality is evidenced, indicating a higher concentration of residuals around the central value. Furthermore, by performing the Anderson-Darling test, the null hypothesis that the residuals follow a normal distribution cannot be rejected with a confidence level of 95% (Devore, 2011). The plot of residuals versus order shows a horizontal band around the residual line (value 0) and no systematic effects in the data due to time or data collection order are shown. The *S* value, known both as the standard error of the regression and as the standard error of the estimate, representing a measure of goodness of fit of the model to be used instead of R^2 for nonlinear models (Bates and Watts, 1988; Spiess and Neumeyer, 2010), is equal to 0.024. Such a value indicates that the experimental values of *DPU* fall a standard distance (roughly an average absolute distance) of 0.024 units from the *DPU* values predicted by Eq. (3.16).

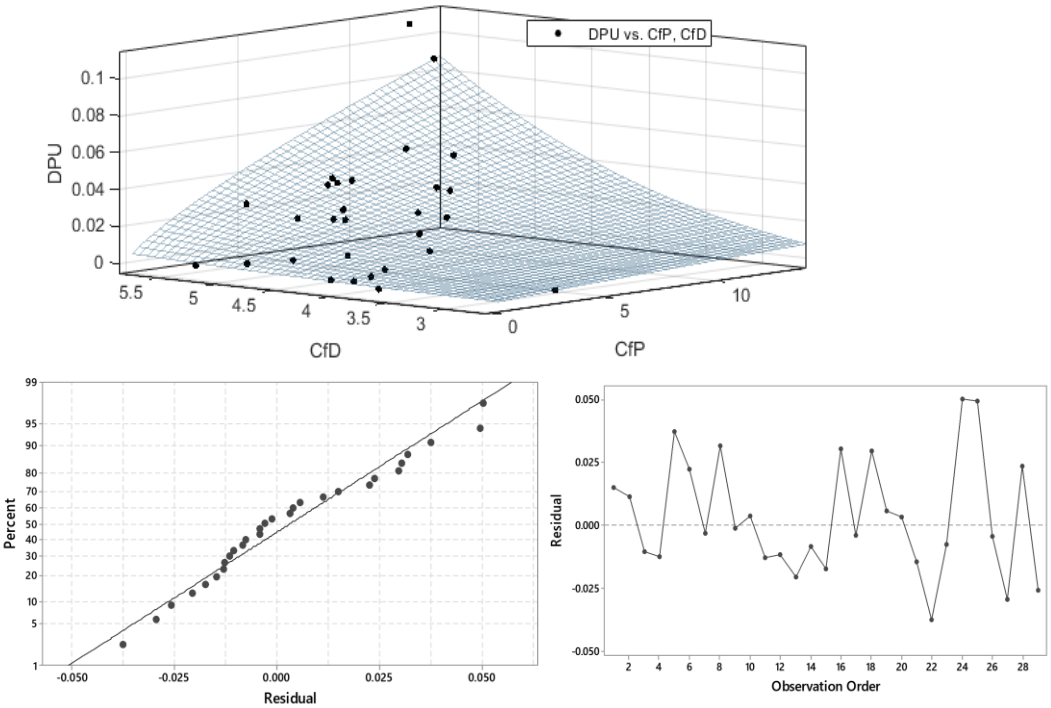


Figure 3.9 - (a) *DPU* vs Cf_P and Cf_D: defect prediction model and experimental data; Residual plots: (b) Normal Probability Plot and (c) Residuals vs Order.

Results analysis

As shown in Eq. (3.16), the novel defect prediction model follows a power-law behavior. Thus, defectiveness rate is low for workstations with lower product complexity and super-linearly grows as complexity increases. These results are in line with previous findings obtained in the literature, e.g., Alkan (2019) and Sinha (2014), in which the complexity is found to be in a super-linear relationship with real assembly time (not standard time), thus evaluated also considering possible errors and reworks.

The same behavior of the two curves, i.e., Eqs. (3.15) and (3.16), is not surprising because the theoretical formulation of the complexities used as predictors in both models is comparable. Indeed, in the Shibata-Su model described in Section 3.3.2, process-based complexity $Cf_{P,i}$ is estimated considering standard assembly times, see Eq. (3.3), that are strictly related to the handling complexity of parts and their connections complexity. Besides, $Cf_{D,i}$ considers product design complexity, as shown in Eq. (3.5), that is related to the design and architectural pattern of the product. Analogously, product complexity C_i defined in Eq. (3.7), which is the predictor of the novel model proposed in this study, being defined by assembly times and structural characteristics (design), incorporates in a single factor both the complexity of the process and the design. As a consequence, it represents the equivalent of $Cf_{P,i}$ and $Cf_{D,i}$, using, however, an objective perspective. While $Cf_{P,i}$ is estimated based on objective characteristics of the process, i.e., standard times, $Cf_{D,i}$ is obtained from the subjective evaluations provided by inspectors and, therefore, is much closer to a perceived complexity than an objective one. Thus, despite the analogy between the predictors of the models, they may differ due to the different perceptions that operators have of the complexity. As observed by Alkan (2019), perceived complexity does not correspond precisely to product complexity, because operators start to perceive the assembly operations as complex when the product complexity reaches a stagnation point.

Moreover, it should be noted that decoupling the complexity into the two factors of the model shown in Eq. (3.16) can be considered artificial. In practical applications, there is no clear distinction between the complexity due to the process and the complexity due to the design, as these are often related. To make this concept clearer, just think of the times for handling components or connecting parts. These are not only process-related but are also closely associated with the characteristics of the parts to be assembled and the nature of their connections. Therefore, since process and design coexist together, Eq. (3.15) seems to be more suitable to evaluate the complexity of the product as a whole, because it considers the complexity of individual components, connections and product topology, without however making a clear distinction between process and design.

Table 3.10 reports the 95% prediction interval obtained for the *DPU* estimated using defect prediction models shown in Eq. (3.15) and (3.16), separately for each workstation, showing both the limits and the width of the interval. These prediction intervals, obtained by using *MINITAB*®, represent the ranges in which the predicted responses for single new observations are expected to fall. It should be noted that negative values of the lower limits of prediction intervals of *DPU* are set equal to zero. Accordingly, for most workstations, the prediction interval is not symmetric with respect to the predicted DPU_i.

According to results provided in Table 3.10 and by comparing Figure 3.8 and Figure 3.9, it is observed that the model proposed in this study allows obtaining more accurate estimates of *DPU* because the average absolute distance between experimental values and the regression model is 0.018, while for the other model is 0.024. Furthermore, *DPU* values estimated by implementing the proposed model are also generally more precise since the related uncertainty in the estimate is tendentially lower (see the limits and the width of the prediction intervals in Table 3.10).

Table 3.10 - Comparison of predictions obtained using the novel defect prediction model, see Eq. (3.15), and an alternative one existing in the literature, see Eq. (3.16).

	95% prediction interval for $\boldsymbol{DPU_i}$		95% prediction interval for $\boldsymbol{DPU_i^*}$	
WS no.	**Range**	**Width**	**Range**	**Width**
1	(0.0038;0.0810)	0.0772	(0.0000;0.0755)	0.0755
2	(0.0056;0.0829)	0.0773	(0.0000;0.0788)	0.0788
3	(0.0005;0.0777)	0.0771	(0.0000;0.0802)	0.0802
4	(0.0000;0.0442)	0.0442	(0.0000;0.0639)	0.0639
5	(0.0189;0.0985)	0.0796	(0.0134;0.1295)	0.1161
6	(0.0090;0.0865)	0.0775	(0.0000;0.0843)	0.0843
7	(0.0000;0.0435)	0.0435	(0.0000;0.0538)	0.0538
8	(0.0000;0.0713)	0.0713	(0.0000;0.0551)	0.0551
9	(0.0000;0.0376)	0.0376	(0.0000;0.0512)	0.0512
10	(0.0000;0.0657)	0.0657	(0.0000;0.0663)	0.0663
11	(0.0000;0.0755)	0.0755	(0.0000;0.0849)	0.0849
12	(0.0023;0.0795)	0.0772	(0.0000;0.0815)	0.0815
13	(0.0000;0.0436)	0.0436	(0.0000;0.0730)	0.0730
14	(0.0000;0.0388)	0.0388	(0.0000;0.0618)	0.0618
15	(0.0006;0.0777)	0.0771	(0.0000;0.0883)	0.0883
16	(0.0000;0.0524)	0.0524	(0.0000;0.0573)	0.0573
17	(0.0000;0.0382)	0.0382	(0.0000;0.0544)	0.0544
18	(0.0000;0.0600)	0.0600	(0.0000;0.0573)	0.0573
19	(0.0000;0.0722)	0.0722	(0.0000;0.0826)	0.0826
20	(0.0000;0.0752)	0.0752	(0.0000;0.0850)	0.0850
21	(0.0000;0.0402)	0.0402	(0.0000;0.0682)	0.0682
22	(0.0221;0.1029)	0.0808	(0.0155;0.1322)	0.1167
23	(0.0000;0.0405)	0.0405	(0.0000;0.0581)	0.0581
24	(0.0000;0.0569)	0.0569	(0.0000;0.0544)	0.0544
25	(0.0000;0.0571)	0.0571	(0.0000;0.0553)	0.0553
26	(0.0000;0.0385)	0.0385	(0.0000;0.0545)	0.0545
27	(0.0000;0.0524)	0.0524	(0.0000;0.0828)	0.0828
28	(0.0362;0.1297)	0.0935	(0.0113;0.1230)	0.1117
29	(0.0000;0.0459)	0.0459	(0.0000;0.0771)	0.0771

The comparison between the two models pointed out that, despite the architectural similarities, the novel defect prediction model allows for more accurate and precise estimates of *DPU*. This may depend on the different perspectives used to formulate complexity in the two approaches. In the novel model, product complexity is approached based on objective product characteristics, while an objective perspective is combined with a subjective evaluation provided by experts in the Shibata-Su model. Besides, the objective perspective seems to be preferable as it considers in a combined factor both the complexity due to the process and the design, without separating the two aspects. The proposed model, although specifically designed for wrapping machines assembly, can be used in other similar industrial contexts to predict defects in low-volume productions.

Furthermore, the method can provide a framework for future explorations on other products, particularly for electromechanical and mechanical products. The novel model can act both as a tool for quantitatively estimating defects of newly developed wrapping machines and as a decision support tool for the assembly quality-oriented wrapping machine design and optimization. Indeed, engineers can employ this prediction model to get a quantitative estimation of *DPU* and accordingly design or re-design the process of wrapping machines trying to minimize the defectiveness rates, by reducing assembly complexity. Future research will be aimed at exploiting this novel defect prediction to support the design of quality-inspection strategies in low-volume manufacturing and evaluate its effect on the inspection planning process.

3.4 Defect prediction models for offline inspections[2]

In the literature, a scant number of defect prediction models specific for offline inspections have been proposed. In this section, a probabilistic model suitable to predict defects occurring in low-volume manufacturing processes is developed. The methodology proposed includes the definition of input and output variables, the determination of the mathematical relationship among these variables, the identification of all the uncertainty contributions and the estimation of probabilities of occurrence of defective-output variables.

The proposed approach, which has a general validity and can be adopted in a wide variety of possible industrial situations, is applied by way of example to a case study belonging to an Additive Manufacturing (AM) production in the automotive industry. In the Additive Manufacturing (AM) field, only a few authors proposed analytical methods for in-process defect detection and control strategies to implement corrective or adaptive actions once a defect has been detected during the process (Tapia and Elwany, 2014; Everton et al., 2016; Rao et al., 2015; Grasso and Colosimo, 2017; Colosimo, 2018; Tsung et al., 2018). As a result, quality inspections performed on AM products are mainly restricted to offline controls, i.e., carried out at the end of the production process. In the practical application considered in this section, the technique of Selective Laser Melting (SLM) has been

[2] Part of the work described in this section was also previously published in:

- Verna E., Genta G., Galetto M., and Franceschini F. (2020e). “Planning Offline Inspection Strategies in Low-Volume Manufacturing Processes.” *Quality Engineering* In press, DOI: 10.1080/08982112.2020.1739309.
- Galetto M., Genta G., Maculotti G., and Verna E. (2020). “Defect Probability Estimation for Hardness-Optimised Parts by Selective Laser Melting.” *International Journal of Precision Engineering and Manufacturing* 21 (9), 1739-1753.

examined in detail. Indeed, although extensive research has been carried out on the optimization of material properties of SLM parts to prevent defects and guarantee part quality, a major void still concerns the quantification of their extent in terms of probability of defects occurring during the process, although it is optimized. Considering these issues, the novel approach proposed in this section may be of assistance to both researchers and practitioners for quantifying the probability of occurrence of defects in parts inspected through offline inspections.

3.4.1 Estimation of defective-output variable probability

In order to evaluate the probability of occurrence of defects in the final part, the AM manufacturing process, in optimal working conditions, should be modeled as represented in Figure 3.10. Specifically, m process variables, also called input variables, may affect the final quality of the AM product. In order to evaluate product quality, n output variables are measured on the AM part, using the most appropriate inspection method to detect the defect, e.g., dimensional verifications, mechanical tests, or visual checks (See, 2012; Savio et al., 2016; Bress, 2017). In this situation, each input variable may potentially influence each output variable at different intensity levels. As represented in Figure 3.10, each input variable is denoted as X_i, ($i = 1,\ldots,m$) and each output variable is indicated as Y_j ($j = 1,\ldots,n$). Furthermore, for each output variable Y_j, a probability of occurrence of a defect, called p_{Y_j}, may be defined. It is worth remarking that the manufacturing process considered is in optimal working conditions, meaning that each input variable is set at its optimum value. Under such conditions, each p_{Y_j} should be zero; however, in realistic cases, this almost never happens because of uncertainty. Consequently, it is of the utmost importance to estimate such probabilities of occurrence of defects in order to effectively and efficiently plan quality inspections on the final product (Verna et al., 2019).

The probabilities of occurrence of defects, p_{Y_j}, are closely related to the intrinsic characteristics of the process. Accordingly, they can be evaluated by using empirical methods, e.g., historical data, previous experience on similar processes, knowledge of the process, or by implementing probabilistic models (Franceschini et al., 2018; Genta et al., 2018; Galetto et al., n.d.). In the case of AM productions, which are small-sized lots or even unique parts, the historical data are often not available, requiring the formulation of a probabilistic model that exploits the knowledge of the production process.

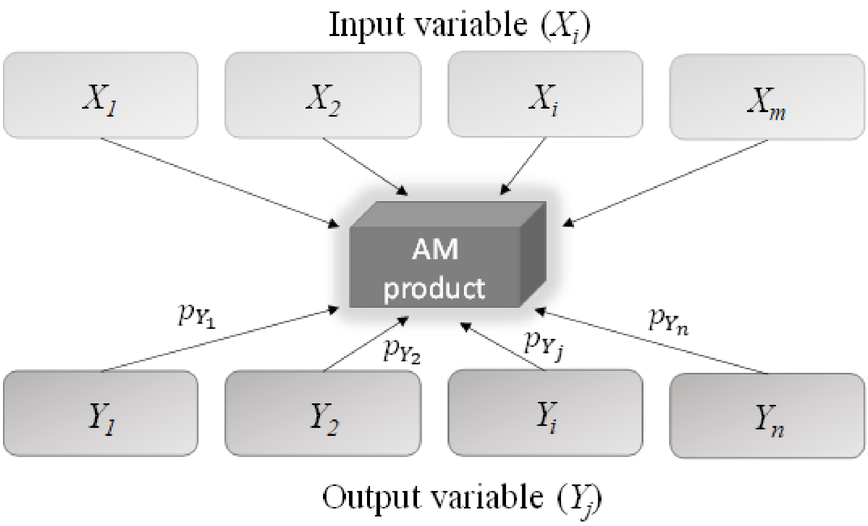


Figure 3.10 - Schematic of a production process with *m* input variables and *n* output variables and the related probabilities of occurrence of defects $\left(p_{Y_j}\right)$.

The underlying assumption of the model is that there is a relationship between input and output variables. Consequently, if a defective-output variable occurs, it may be caused by some input variables. The probabilities of occurrence of defective-output variables may be therefore obtained using the mathematical function relating input variables to output variables (Montgomery, 2017). Besides, the proposed methodology requires the knowledge of the input variables values that result in the best values of the responses. Finally, the specification limits of the output variables (upper specification limit, USL_j, and lower specification limit, LSL_j) are needed in order to determine whether the products meet the specifications imposed by regulations and/or company standards. Input variables can be discrete or continuous variables. This section proposes the methodologies adopted to estimate the probabilities of occurrence of defective-output variables, separately for continuous and discrete variables.

3.4.1.1 Continuous input variables

Consider, for example, a case with only one output variable, denoted as Y, and one input variable, called X. The relationship between the two variables is given by the function $Y = f(X)$. However, in realistic cases, this function is not exactly defined, i.e., the coefficients of the mathematical model are affected by uncertainty. Furthermore, also the optimal value of the input variable (x^*), i.e., the value that optimizes the response output, is not exactly defined because of the uncertainty of the measurement device. For that reason, a variability range must be associated with it (by defining an upper UL and a lower LL variation limit, as illustrated in Figure 3.11). The probability distribution associated with X depends on the characteristics of the input variable. For instance, if the values are all equiprobable in the interval, a uniform distribution should be considered. As shown in Figure 3.11, the variance of the probability distribution of the output variable may be estimated by composing the uncertainties associated with both the input variable and the mathematical function, through the law of composition of variances (Ver Hoef, 2012).

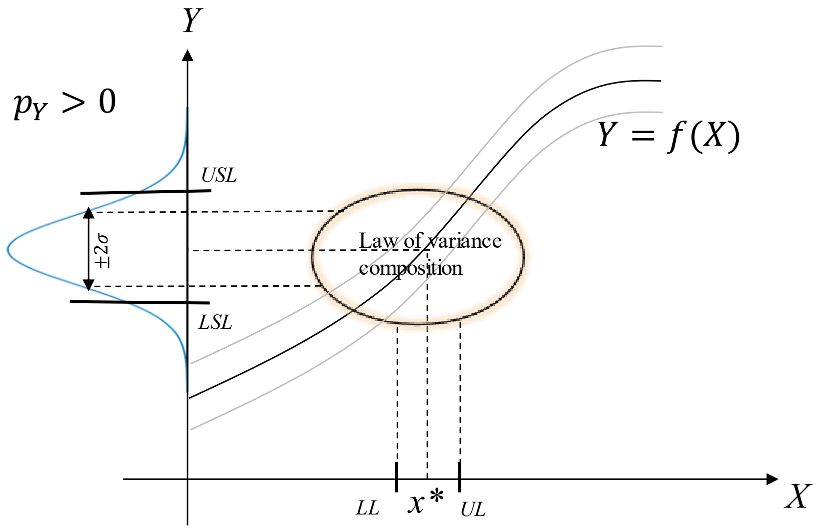


Figure 3.11 - Estimation of the probability of occurrence of defective-output variable ($\boldsymbol{p_Y}$).

More in general, if there are m input variables, $\boldsymbol{X} = [x_1, \dots, x_m]^{\mathrm{T}}$, the uncertainty of each one contributes to the variance of the related Y_j output variable, together with the contribution of the mathematical function coefficients, $\boldsymbol{A} = [a_0, a_1, \dots, a_m]^{\mathrm{T}}$, as shown in Eq. (3.17), which is expressed in matrix form:

$$VAR(Y_j) \approx \left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right]^T \cdot cov(\boldsymbol{K}) \cdot \left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right] \qquad (j = 1, \dots, n) \tag{3.17}$$

where $\boldsymbol{K}$ is the vector of size $2m$+1 of the input variables and the coefficients of the mathematical function, defined as $\boldsymbol{K} = [\boldsymbol{X}, \boldsymbol{A}]^{\mathrm{T}}$, $cov(\boldsymbol{K})$ is the variance-covariance matrix and $\left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right]$ is the vector of the partial derivatives of Y_j with respect to each component of $\boldsymbol{K}$. In $cov(\boldsymbol{K})$, the element in the l, q position is the covariance between K_l and K_q, defined as:

$$\mathrm{cov}(K_l, K_q) = \rho_{l,q} \cdot \sqrt{VAR(K_l)} \cdot \sqrt{VAR(K_q)} \tag{3.18}$$

where $\rho_{l,q}$ is the Pearson correlation coefficients between the parameters K_l and K_q (Devore, 2011).

Given that the distribution of the output variable Y_j originates by many different random contributions, according to the central limit theorem (Montgomery, 2012), it can be approximated to a Normal distribution. Hence, the probability of occurrence of the defective-output variable p_{Y_j}, which represents the probability that Y_j falls outside the specification limits (LSL_j and USL_j), may be estimated by computing the area of the normal distribution outside the two specification limits by Eq. (3.19):

$$p_{Y_j} = 1 - P(LSL_j \leq Y_j \leq USL_j) \tag{3.19}$$

3.4.1.2 Discrete input variables

The probability of occurrence of the j-th defective-output variable, p_{Y_j}, can be derived from the probabilities of occurrence of defects in the final product caused by the input variables. Accordingly, in the model, each i-th input variable is associated with the probability p_{X_i}, i.e., the probability of occurrence of defects in the final part due to the input variable X_i.

The relation between input and output variables is represented in the model through the probability $p_{Y_j}^{X_i}$, i.e., the probability of occurrence of the defective-output variable Y_j due to the input variable X_i. Besides, each input variable may be the source of more than one defective-output variable. In this situation, the probability that the input variable X_i causes k defective-output variables is denoted as $p_{Y_1 \cap Y_2 \cap \ldots \cap Y_k}^{X_i}$, with $k \leq n$. Similarly, each defective-output variable may be caused by more than one input variable. In such a case, the probability that s input variables cause the defective-output variable Y_j is identified with the probability $p_{Y_j}^{X_1 \cap X_2 \cap \ldots \cap X_s}$, with $s \leq m$.

Consider an exemplifying process with 3 input variables and 4 output variables, as shown in Figure 3.10.

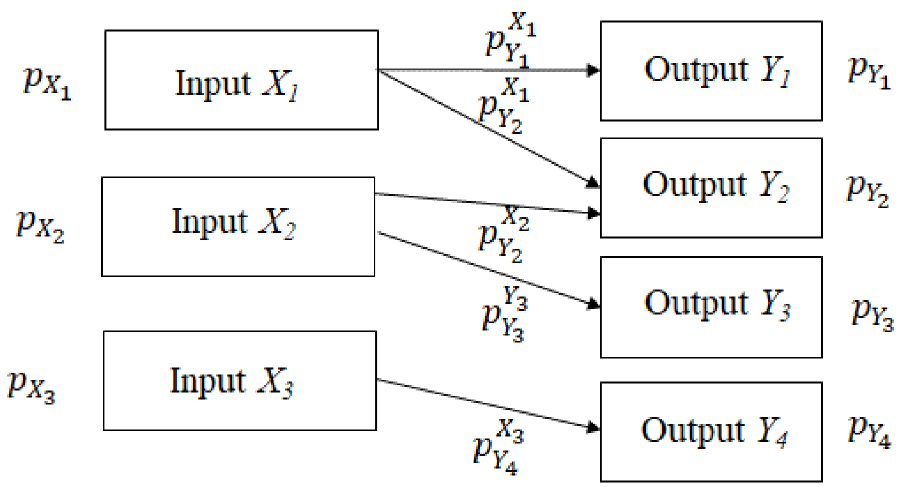


Figure 3.12 - Representation of an exemplifying process with 3 input variables and 4 output variables.

In this specific example, the probabilities of occurrence of defects in the product due to the input variables, p_{X_i} (i=1,2,3), are:

$$p_{X_1} = p_{Y_1}^{X_1} + p_{Y_2}^{X_1} - p_{Y_1 \cap Y_2}^{X_1} \tag{3.20}$$

$$p_{X_2} = p_{Y_2}^{X_2} + p_{Y_3}^{X_2} - p_{Y_2 \cap Y_3}^{X_2} \tag{3.21}$$

$$p_{X_3} = p_{Y_4}^{X_3} \tag{3.22}$$

More in general, p_{X_i} can be calculated, for each $i \in \{1,2,\ldots,m\}$, as follows:

$$p_{X_i} = \sum_{j=1}^{k} p_{Y_j}^{X_i} - \sum_{j_1<j_2} p_{Y_{j_1}\cap Y_{j_2}}^{Xi} + \cdots + (-1)^{r+1} \cdot \sum_{j_1<j_2<\cdots<j_r} p_{Y_{j_1}\cap Y_{j_2}\cap\ldots\cap Y_{j_r}}^{X_i} + \cdots + (-1)^{k+1} \cdot p_{Y_1\cap Y_2\cap\ldots\cap Y_k}^{Xi} \tag{3.23}$$

where each sum $\sum_{j_1<j_2<\cdots<j_r}$ is calculated for all the $\binom{k}{r}$ possible subsets of r elements of the set $\{1,2,\ldots,k\}$, and k is the total number of defective-output variables caused by the input variable X_i, with $k \le n$.

At this point, the probabilities of occurrence of defective-output variables of the example illustrated in Figure 3.12, p_{Y_j} (j=1,2,3,4), can be derived as follows:

$$p_{Y_1} = p_{Y_1}^{X_1} \tag{3.24}$$

$$p_{Y_2} = p_{Y_2}^{X_1} + p_{Y_2}^{X_2} - p_{Y_2}^{X_1\cap X_2} \tag{3.25}$$

$$p_{Y_3} = p_{Y_3}^{X_2} \tag{3.26}$$

$$p_{Y_4} = p_{Y_4}^{X_3} \tag{3.27}$$

where the probability $p_{Y_2}^{X_1\cap X_2}$ in Eq. (3.25) can be calculated, according to the Bayes's theorem (Schervish, 2012), as follows:

$$p_{Y_2}^{X_1\cap X_2} = \begin{cases} p_{Y_2}^{X_1} \cdot p_{Y_2}^{X_2} & \text{if the occurrence of } X_1 \text{ and that of } X_2 \text{ are independent} \\ p_{Y_2}^{X_2|X_1} \cdot p_{Y_2}^{X_1} & \text{if the occurrence of } X_1 \text{ and that of } X_2 \text{ are dependent} \\ & \text{(the occurrence of } X_1 \text{is the conditioning event)} \\ p_{Y_2}^{X_1|X_2} \cdot p_{Y_2}^{X_2} & \text{if the occurrence of } X_1 \text{ and that of } X_2 \text{ are dependent} \\ & \text{(the occurrence of } X_2 \text{is the conditioning event)} \end{cases} \tag{3.28}$$

In Eq. (3.28), $p_{Y_2}^{X_1|X_2}$ is the probability that the defective-output variable Y_2 caused by X_1 occurs, given that the defective-output variable Y_2 caused by X_2 has occurred (or *vice versa* for $p_{Y_2}^{X_2|X_1}$).

More in general, p_{Y_j} can be calculated, for each $j \in \{1,2,\ldots,n\}$, as follows:

$$p_{Y_j} = \sum_{i=1}^{s} p_{Y_j}^{X_i} - \sum_{i_1<i_2} p_{Y_j}^{X_{i_1}\cap X_{i_2}} + \cdots + (-1)^{r+1} \cdot \sum_{i_1<i_2<\cdots<i_r} p_{Y_j}^{X_{i_1}\cap X_{i_2}\cap\ldots\cap X_{i_r}} + \cdots + (-1)^{s+1} \cdot p_{Y_j}^{X_1\cap X_2\cap\ldots\cap X_s} \tag{3.29}$$

where each sum $\sum_{j_1<j_2<\cdots<j_r}$ is calculated for all the $\binom{s}{r}$ possible subsets of r elements of the set $\{1,2,\ldots,s\}$, and s is the total number of input variables that cause the defective-output variable Y_j jointly, with $s \le m$. The generic probability $p_{Y_j}^{X_{i_1}\cap X_{i_2}\cap\ldots\cap X_{i_r}}$, expressed in Eq. (3.29), can be derived by exploiting the Bayes's theorem (Schervish, 2012) and according to the logic-causal criteria between input variables. However, in manufacturing, it can be assumed the independence between the input variables, as shown in Eq. (3.30), because they are the controlled independent inputs of the process affecting the quality of the finished product.

$$p_{Y_j}^{X_{i_1} \cap X_{i_2} \cap \ldots \cap X_{i_r}} = p_{Y_j}^{X_{i_1}} \cdot p_{Y_j}^{X_{i_2}} \cdot \ldots \cdot p_{Y_j}^{X_{i_r}} \qquad j \in \{1, 2, \ldots, n\} \tag{3.30}$$

3.4.2 Practical applications to Selective Laser Melting Process

Consider the low-volume production of components by Additive Manufacturing process based on Selective Laser Melting (SLM) technique, also called Direct Metal Laser Sintering (DMLS). In this process, a high-density object is built up layer by layer through the consolidation of metal powder particles with a focused laser beam that selectively scans the surface of the powder bed (Gibson et al., 2014). In this process, several input variables can influence the quality of the finished product, including continuous variables, such as laser power, scan speed and hatching distance, and discrete variables, e.g., the use of recycled powder and the layer thickness (Sufiiarov et al., 2017; Delgado et al., 2012; Ardila et al., 2014; Asgari et al., 2017).

In this section, the two proposed methodologies to predict the probability of occurrence of defects for continuous and discrete input variables are applied to the SLM process. In detail, regarding the first category of variables, the effect of laser power, scan speed and hatching distance on the defectiveness in terms of surface roughness and macro-hardness was investigated in Section 3.4.2.1. The methodology described in Section 3.4.1.1 was applied to obtain the probabilities of occurrence of defective-output variables. On the other hand, the example proposed in Section 3.4.2.2 shows how to obtain the probabilities of occurrence of defective-output variables from discrete variables (see Section 3.4.1.2), i.e., use of recycled powder and layer thickness, and how they can be used to plan quality inspections.

3.4.2.1 Continuous input variables

The aluminium samples, produced using the AlSi10Mg alloy, were prepared by SLM with an EOS M290 machine. In this machine, a powerful ytterbium (Yb) fiber laser system in an argon atmosphere is used to melt powders with a continuous power up to 400 W, a scanning rate up to 7 m/s, and a spot size of 100 μm. During the production process, three areas can be identified in the parts: up-skin, down-skin and in-skin, as shown in Figure 3.13 (a). The up-skin is the region on the part layer above which there is no area to be exposed. The bottom region, which is in contact with the building platform below it and laser exposed areas above it, is called down-skin. The third area, the in-skin, is the region where there are above and below exposed areas. For each layer, a contour of the layer structure is exposed with the contour speed and the laser power. After that, the inner area is solidified by means of the laser beam which moves line after line several times. The distance between the lines is called hatching distance. Once the inner area is solidified, a second exposure of the exterior part contour is carried out in order to increase the accuracy of the building process (Calignano et al., 2013). Several studies (Krishnan et al., 2014; Tian et al., 2017; Trevisan et al., 2017) have shown that this region-wise differentiated parameter setting can achieve control of material properties, such as surface finishing and mechanical properties. In fact, according to Figure

3.13 (a), up- and down-skin parameters are related to surface properties, while in-skin parameters to the core average properties of the component.

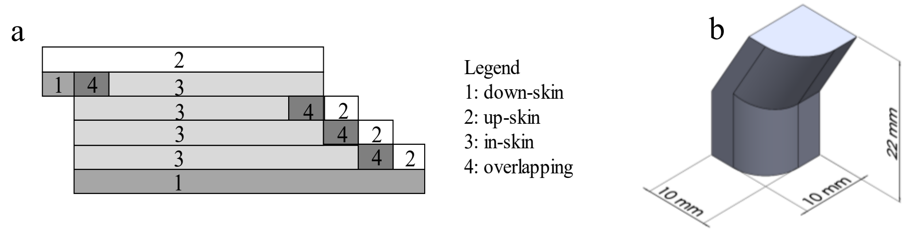


Figure 3.13 - (a) Schematic of up-skin, in-skin and down-skin areas; (b) Geometry of specimen.

Output variables optimization

In this case study, the output variables measured on the specimens were macro-hardness and up-skin roughness. It is evident from the literature that controlling and changing process variables may result in different quality outputs of the parts. Specifically, the most influencing process variables on the hardness of the parts are laser power, scan speed and hatching distance of the in-skin (Krishnan et al., 2014). For the surface roughness, process parameters chosen were laser power, scan speed and hatching distance of the up-skin (Calignano et al., 2013). The specimens, whose dimensions are 22x10x10 mm, were designed, according to Figure 3.13 (b), in order to measure both surface roughness and hardness. The different inclinations of the sample will allow evaluating how the roughness changes with the variation of the surface considered. In this study, the roughness of the upper surface is analyzed in detail.

In order to obtain optimal process parameters that result in the best values of hardness and roughness, two experimental plans were designed. Specifically, two 3^3 full factorial design were performed in order to investigate possible quadratic effects of input variables. For the first response, the hardness, the three input variables relevant to the in-skin, laser power (*PI*), scan speed (*vI*) and hatching distance (h_dI), were kept at three levels. Similarly, three levels were chosen for the three input variables for up-skin, laser power (*PU*), scan speed (*vU*) and hatching distance (h_dU) (see Table 3.11). In this experiment, the down-skin roughness was not specifically investigated. Variable values used were the same as those of the up-skin. Consequently, the results achieved for the up-skin can also be reasonably exploited for the assessment of the down-skin. The choice of the levels of the process variables set in both the experimental plans allowed to get a wide range of energy density function, ψ, which is calculated as follows:

$$\psi = \frac{P}{h_d \cdot v \cdot t}\left[\frac{J}{\mathrm{mm}^3}\right] \tag{3.31}$$

where P and v are respectively the laser power and scan speed, h_d is hatching distance and t is layer thickness. Specifically, in the first experiment ψ varied from 35.09 to 124.58 J/mm^3 and in the second from 44.97 to 134.47 J/mm^3. Energy density is strictly related to the degree of consolidation of the powder particles and may cause defects by creating turbulence in the melt pool (Read et al., 2015).

Consequently, it is often adopted in literature as a reference parameter for the setup of a planned experimentation (Trevisan et al., 2017). The experiments were not randomized because the high repeatability of the machine allowed building the samples in a single job, by varying process parameters for each sample (Calignano et al., 2013; Read et al., 2015). This approach, as a first approximation, is the one adopted in the computer experiment field (Sacks et al., 1989).

Table 3.11 - Process parameters values used in the two planned experimentations.

Hardness HB [HB]				Roughness Ra [µm]			
Process Variable	Values	Fixed Parameter	Value	Process Variable	Values	Fixed Parameter	Value
PI [W]	340 – 355 - 370	Layer thickness [µm]	30	PU [W]	340-355-370	Layer thickness [µm]	30
vI [mm/s]	900 – 1300 - 1700	Spot size [mm]	0.1	vU [mm/s]	800-1000-1200	Spot size [mm]	0.1
h_dI [mm]	0.11 – 0.15 – 0.19	PU [W]	355	h_dU [mm]	0.11-0.16-0.21	PI [W]	355
		vU [mm/s]	100			vI [mm/s]	1300
		h_dU [mm]	0.16			h_dI [mm]	0.15

After the production, the 27 specimens for hardness measurements were polished. Then, the Brinell hardness test was performed according to the industrial standard ISO 6506-1:2014 (ISO 6506-1:2014, 2014). The test was carried out using a sphere with a diameter of 2.5 mm and applying a force of 62.5 kgf, thus evaluating Brinell hardness in the scale HBW 2.5/62.5. For simplicity of notation, the measurement unit of Brinell hardness will henceforth be indicated with the symbol HB. Three measures for each specimen were taken and the average value was examined. The coefficient of variation of the three hardness measurements ranges from a minimum of 1% to a maximum of 7% (see Table 5.2).

The surface roughness on the top surface of the other 27 samples was measured according to industrial standards ISO 4287 and ISO 4288, using a contact stylus, Veeco Dektak 150 Surface Profiler, with a 2 µm radius stylus tip (ISO 4287:2009, 2009; ISO 4288:2000, 2000). The roughness parameter calculated from the filtered roughness profile was Ra, defined as the average value of the ordinates from centerline. For surfaces having a periodic profile, such as the top surfaces of the samples, the prescribed sampling length is based on the mean width of profile elements (RSm). When RSm is included between 0.13 mm and 0.4 mm, it is recommended to use a sampling length for filtering of 0.8 mm and to perform measurements over five consecutive sampling lengths, resulting in an evaluation length of 4 mm (ISO 4288:2000, 2000). Three measurements, each 1 mm apart, in the direction perpendicular to the scan path were performed on each sample, and the average value was examined. The coefficient of variation of the three roughness measurements ranges from a minimum of 1% to a maximum of 18%, except for a single sample which reaches 48% (see Table 5.4). Such high value may be attributed to the peculiarities of the measurement activity. Indeed, due the discrete nature of the measurements obtained using the contact stylus, each roughness measurement may be sensitive to localized defects. However, considering the mean value of three measurements, the roughness value obtained can be considered representative of the up-skin. The use of a non-contact device, such as a Point Autofocus Instrument (PAI), could help to reduce measurements' uncertainty and the related inspection errors.

The arrangement of the two 3^3 full factorial designs with the indication of the three measurements, the resulting mean value, standard deviation and coefficient of variation for the hardness and the up-skin roughness are reported in Table 5.2 and Table 5.4, respectively.

The Response Surface Methodology (RSM) was used to analyze the results and optimize the process for both the experimental designs (Montgomery, 2017). The arrangement of the two full factorial design allowed the development of an appropriate empirical equation, a second-order polynomial multiple regression equation. The standard stepwise regression was adopted to obtain a model containing exclusively significant factors. This method both adds and removes predictors at each step, according to selected Alpha-to-Enter and Alpha–to-Remove values (Devore, 2011). These two values were set at 10% to allow entering terms very close to the significance level of 5%. The software Minitab®, which was used to perform the analysis, provided the coefficients of the significant regression terms with their relevant standard errors, reported in Table 3.12, and the regression equations showed in Eqs. (3.32) and (3.33). The analysis of residuals, i.e., the differences between the observed and the corresponding fitted value, for both hardness and roughness, showed a random pattern of residuals and the absence of systematic errors. Furthermore, the R^2 value, a measure of goodness model fit, shows that the variation in the response explained by the model is 92.32 % for HB and 72.50 % for Ra. Moreover, the S value, also known as the standard error of the regression or as the standard error of the estimate (Devore, 2011), is 4.55 for HB and 4.13 for Ra. The 3D surface plots representing how the fitted responses are related to the process variables are reported in Figure 3.14 and Figure 3.15.

$$HB = a_0 + a_1 \cdot PI + a_2 \cdot vI + a_3 \cdot h_d I + a_4 \cdot vI \cdot vI + a_5 \cdot vI \cdot h_d I \tag{3.32}$$

$$Ra = b_0 + b_1 \cdot vU + b_2 \cdot h_d U + b_3 \cdot PU \cdot PU + b_4 \cdot PU \cdot vU + b_5 \cdot PU \cdot h_d U \tag{3.33}$$

In order to find the best values of laser power, scan speed and hatching distance, two response optimizations were performed. The objective functions were the maximization of hardness and the minimization of surface roughness. Parameters setups and the respective value of energy density ψ are summarized in Table 3.13, together with the predicted value of responses.

Table 3.12 - Estimates of regression models' parameters (see Eqs. (3.32) and (3.33)), with their standard errors (SE), separately for the hardness HB [HB] and roughness Ra [µm]. The standard error of the estimate is 4.55 for HB and 4.13 for Ra.

Hardness HB [HB]				Roughness Ra [µm]			
Variable	Parameter	Parameter estimate	Parameter SE estimate	Variable	Parameter	Parameter estimate	Parameter SE estimate
constant	a_0 [HB]	$-5.12\cdot10^{1}$	$3.57\cdot10^{1}$	constant	b_0 [µm]	$8.71\cdot10^{1}$	$8.45\cdot10^{1}$
PI	a_1 [HB/W]	$-1.42\cdot10^{-1}$	$7.16\cdot10^{-2}$	vU	b_1 [µm/(mm/s)]	$-2.99\cdot10^{-1}$	$1.41\cdot10^{-1}$
vI	a_2 [HB/(mm/s)]	$2.19\cdot10^{-1}$	$3.28\cdot10^{-2}$	h_dU	b_2 [µm/mm]	$9.85\cdot10^{2}$	$5.64\cdot10^{2}$
h_dI	a_3 [HB/mm]	$4.85\cdot10^{2}$	$1.10\cdot10^{2}$	$PU\cdot PU$	b_3 [µm/W^2]	$-5.85\cdot10^{-4}$	$6.68\cdot10^{-4}$
$vI\cdot vI$	a_4 [HB/(mm/s)^2]	$-5.46\cdot10^{-5}$	$1.16\cdot10^{-5}$	$PU\cdot vU$	b_4 [µm/(W·mm/s)]	$8.76\cdot10^{-4}$	$3.96\cdot10^{-4}$
$vI\cdot h_dI$	a_5 [HB/(mm^2/s)]	$-2.69\cdot10^{-1}$	$8.22\cdot10^{-2}$	$PU\cdot h_dU$	b_5 [µm/(W·mm)]	$-2.58\cdot10^{0}$	$1.59\cdot10^{0}$

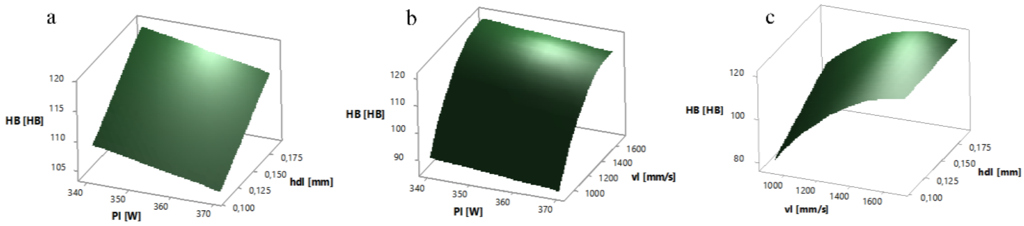


Figure 3.14 - Surface plot of HB [HB] versus: (a) h_dI [mm] and PI [W] (vI was set to 1300 mm/s); (b) vI [mm/s] and PI [W] (h_dI was set to 0.15 mm); (c) h_dI [mm] and vI [mm/s] (PI was set to 355 W).

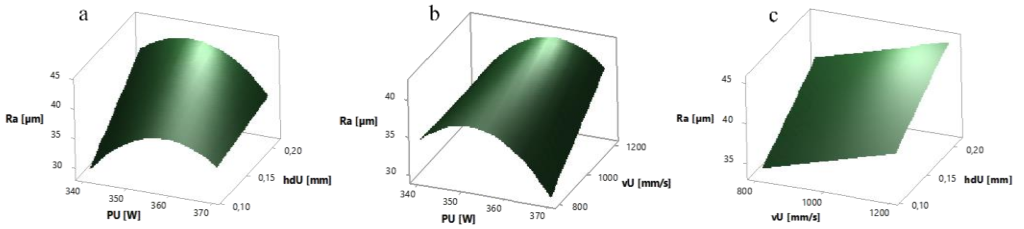


Figure 3.15 - Surface plot of Ra [µm] versus: (a) h_dU [mm] and PU [W] (vU was set to 1000 mm/s); b) vU [mm/s] and PU [W] (h_dU was set to 0.16 mm); c) h_dU [mm] and vU [mm/s] (PU was set to 355 W).

Table 3.13 - Responses optimization (max. HB and min. Ra): process setups and predicted values.

Control factors				HB predicted value	Control factors				Ra predicted value
PI [W]	vI [mm/s]	hdI [mm]	ψ [J/mm^3]	Mean value [HB]	PU [W]	vU [mm/s]	hdU [mm]	ψ [J/mm^3]	Mean value [µm]
340	1538	0.19	38.78	122.45	340	1200	0.11	85.85	29.68

Estimation of the probabilities of occurrence of defective-output variables

Once the input parameters optimizing the responses were obtained, the variances of the output variables were derived, according to Eq. (3.28), by propagating the uncertainty of both the mathematical function parameters (see Table 3.12) and the input variables, evaluated as the resolution of the AM machine (see Table 3.14). The AM measuring device that displays the values of input variables is digital. In such a case, the distribution of the resolution contribution is uniform because the measurand can be assumed to have an equal probability of occurrence at any point in the range associated with the displayed value, i.e., the resolution interval (JCGM 100:2008, 2008). Accordingly, the standard deviations of the input variables are calculated considering a uniform distribution and are reported in Table 3.14 (JCGM 100:2008, 2008). The Pearson correlation coefficients between the parameters of the regression models used in the variance-covariance matrix (see Eq. (3.29)) were derived by the software Minitab®. The computations were performed using the software MATLAB® and the obtained variances of hardness and roughness are reported in Eqs. (3.34) and (3.35) respectively.

Table 3.14 - Variability range (i.e., resolution interval) and standard deviation of input variables, under the assumption of uniform distributions.
It is reminded that the variance of a uniform distribution is σ2=a2/3, where a is half of the variability range.

Up-skin and in-skin process variables	Resolution of AM machine	Process variable variability range	Process variable standard deviation
Laser power [W]	0.1	$(PI \pm 0.05)$ $(PU \pm 0.05)$	$\sqrt{\frac{0.05^2}{3}} = 2.89 \cdot 10^{-2}$
Scan speed [mm/s]	0.1	$(vI \pm 0.05)$ $(vU \pm 0.05)$	$\sqrt{\frac{0.05^2}{3}} = 2.89 \cdot 10^{-2}$
Hatching distance [mm]	0.01	$(h_dI \pm 0.005)$ $(h_dU \pm 0.005)$	$\sqrt{\frac{0.005^2}{3}} = 2.89 \cdot 10^{-3}$

$$VAR(HB) \approx \left[\frac{\partial HB}{\partial \boldsymbol{K}_{HB}}\right]^T \cdot cov(\boldsymbol{K}_{HB}) \cdot \left[\frac{\partial HB}{\partial \boldsymbol{K}_{HB}}\right] = 4.62 \text{ HB}^2 \qquad (3.34)$$

where $\boldsymbol{K}_{HB} = [PI, vI, h_dI, vI \cdot vI, vI \cdot h_dI, a_0, a_1, a_2, a_3, a_4, a_5]^{\mathrm{T}}$.

$$VAR(Ra) \approx \left[\frac{\partial Ra}{\partial \boldsymbol{K}_{Ra}}\right]^T \cdot cov(\boldsymbol{K}_{Ra}) \cdot \left[\frac{\partial Ra}{\partial \boldsymbol{K}_{Ra}}\right] = 6.55 \text{ µm}^2 \qquad (3.35)$$

where $\boldsymbol{K}_{Ra} = [PU, vU, h_dU, PU \cdot PU, PU \cdot vU, PU \cdot h_dU, b_0, b_1, b_2, b_3, b_4, b_5]^{\mathrm{T}}$.

The distributions of the two responses (*HB* and *Ra*) were also obtained through a computer simulation. In both cases, the normality of the distributions cannot be rejected by the Anderson-Darling test at a significance level of 5%. Thus, under the hypothesis of normal distribution, the probabilities of occurrence of the defective-output variables may be obtained. Given the mean values, reported in Table 3.13, the variances of Eqs. (3.34) and (3.35), and the specification limits, the probabilities of occurrence of defects, p_{HB} and p_{Ra}, were derived by applying Eq. (3.30). The specification limits were fixed according to technological requirements for the produced parts (for hardness a lower specification limit, LSL_{HB}, was set to 114 HB and for roughness an upper specification limit, USL_{Ra}, was set to 36 μm). The two resulting probabilities are shown in Eqs. (3.36) and (3.37).

$$p_{HB} = P(HB \leq LSL_{HB}) = 0.55\% \tag{3.36}$$

$$p_{Ra} = P(Ra \geq USL_{Ra}) = 0.67\% \tag{3.37}$$

To summarize, by providing a quantitative assessment of defect probabilities, this methodology can help researchers and practitioners in their understanding of the SLM process in terms of defect generation. Operatively, the approach herein presented has the great potential of supporting inspection designers in the planning of effective quality inspection strategies during the early phases of inspection planning (see next Chapter 5).

3.4.2.2 Discrete input variables

The use us recycled powder may be considered a Boolean variable (use or not of the recycled powder). The second variable, the layer thickness, is primarily chosen based on the particle size and cannot be thinner than the largest particle in the powder (Hutmacher et al., 2004). Besides, in AM machines, the layer thickness can typically assume discrete values in the permissible range. For instance, in the machine EOSIN M 270, the layer thickness can vary from 20 μm to 100 μm, depending on the material, and assuming the following values: 20 μm, 30 μm, 40 μm, 50 μm, 60 μm, 70 μm, 80 μm, 90 μm and 100 μm. In the scientific literature, extensive studies have shown the effect of recycled powder and layer thickness on porosity, tensile strength and dimensional accuracy of components produced with SLM technique. In particular, some authors found empirically that the use of recycled powder has a significant effect on porosity and mechanical properties, including tensile strength (Ardila et al., 2014; Asgari et al., 2017; Hadadzadeh et al., 2018), while layer thickness on dimensional accuracy as well as tensile properties (Basalah et al., 2016; Delgado et al., 2012; Xu et al., 2015). Although recycled powder and layer thickness may also affect other output variables, e.g., surface roughness (Z. Chen et al., 2018), this example is restricted to analyzing porosity, tensile strength and dimensional accuracy. However, the proposed approach can be extended to further output variables. The recycled powder is denoted as RP and the layer thickness is denoted as LT. The output variables, i.e., porosity, tensile strength and dimensional accuracy, are denoted as PO, TS, DA, respectively (see Figure 3.16).

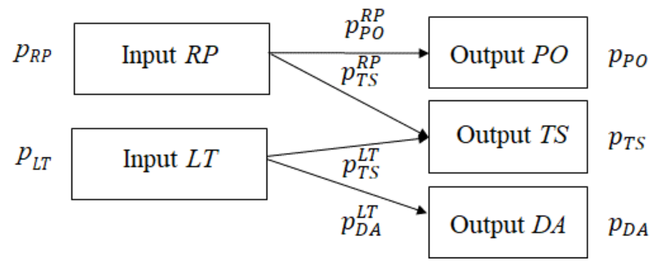


Figure 3.16 - Schematic of the SLM process with 2 input variables and 3 output variables with the related probabilities.

Let us assume that the probabilities of occurrence of defects in the product due to *RP* and *LT*, p_{RP} and p_{LT}, are respectively 2% and 3%. Regarding *RP*, see Eq. (3.38), the probability that it causes defects of porosity, p_{PO}^{RP}, is 2% and defects of tensile strength, p_{TS}^{RP}, is 1%. Besides, *RP* jointly produces defects of porosity and tensile strength with a probability $p_{PO\cap TS}^{RP}$ of 1%. Regarding *LT,* see Eq. (3.39), it causes defects of tensile strength with a probability p_{TS}^{LT} of 2%, defects of dimensional accuracy with a probability p_{DA}^{LT} of 3% and jointly defects of tensile strength and dimensional accuracy with a probability $p_{TS\cap DA}^{LT}$ of 2%.

$$p_{RP} = p_{PO}^{RP} + p_{TS}^{RP} - p_{PO\cap TS}^{RP} = 2\%+1\%-1\%=1\% \tag{3.38}$$

$$p_{LT} = p_{TS}^{LT} + p_{DA}^{LT} - p_{TS\cap DA}^{LT} = 2\%+3\%-2\%=3\% \tag{3.39}$$

Accordingly, the probabilities of occurrence of defective-output variables can be derived, according to Eqs. (3.29) and (3.30):

$$p_{PO} = p_{PO}^{RP} = 2\% \tag{3.40}$$

$$p_{TS} = p_{TS}^{RP} + p_{TS}^{LT} - p_{Y_2}^{RP\cap LT} = 1\%+2\%-(1\%\cdot 2\%)=2.98\% \tag{3.41}$$

$$p_{DA} = p_{DA}^{LT} = 3\% \tag{3.42}$$

At this point, once the probabilities of occurrence of defective-output variables are derived from the relationships existing with the input variables, the probabilities that these defective-output variables occur jointly can be obtained. Such probabilities can be derived from the related conditional probabilities. For instance, let us assume that the following conditional probabilities occur in the SLM process:

$$p_{TS|PO} = 60\% \tag{3.43}$$

$$p_{DA|PO} = 20\% \tag{3.44}$$

$$p_{(TS\cap DA)|PO} = 10\% \tag{3.45}$$

$$p_{DA|TS} = 15\% \tag{3.46}$$

By exploiting the Bayes's theorem (Schervish, 2012), the probabilities that the defective-output variables occur jointly are derived, as follows:

$$p_{TS\cap PO} = p_{TS|PO} \cdot p_{PO} = 1.2\% \tag{3.47}$$

$$p_{DA\cap PO} = p_{DA|PO} \cdot p_{PO} = 0.4\% \tag{3.48}$$

$$p_{TS\cap DA\cap PO} = p_{(TS\cap DA)|PO} \cdot p_{PO} = 0.2\% \tag{3.49}$$

$$p_{DA\cap TS} = p_{DA|TS} \cdot p_{TS} = 0.45\% \tag{3.50}$$

Chapter 4 : Inspection strategies modeling and performance measurement

For years, manufacturing companies have exploited traditional approaches to design quality-inspections (Montgomery, 2012; Mandroli et al., 2006). Nowadays, the increasing complexity and customization of products require more sophisticated, flexible and, therefore, expensive quality control strategies (Colledani et al., 2014; Eger et al., 2018). There are several aspects that inspection designers have to consider during the design of inspections, including (i) the typology of production to be inspected, and (ii) the kind of quality control to be performed. The low production rate and the high level of complexity and customization of low-volume productions often require the execution of specific inspection strategies. Consequently, assessing whether one inspection procedure is better than another in terms of both efficiency and cost is often critical for these productions.

Although this topic is attracting increasing interest from researchers and practitioners, there remains a paucity of quantitative methods that can be used to evaluate both in-process and offline inspection performances of low-volume productions. To this aim, this chapter extends the studies proposed by Franceschini et al. (2018) and Genta et al. (2018) by adapting the two practical performance measures conceived for in-process inspections to offline inspections. In detail:

- Section 4.1 reviews the methodology proposed by Franceschini et al. (2018) and Genta et al. (2018) to assess inspection effectiveness and cost in the case of in-process inspection strategies.
- Section 4.2 aims to adapt the methodology proposed in Section 4.1 to the case of offline inspections. The approach also involves possible interactions between process and inspection variables, in terms of cause-and-effect relationships, in addition to potential imperfect inspections.
- Section 4.3 enrich the proposed method by providing an approach to evaluate the uncertainty of the performance measures, both in the case of in-process and offline inspections.

4.1 In-process inspections

In the case of in-process inspections, Franceschini et al. (2018) and Genta et al. (2018) proposed to decompose the manufacturing process into a certain number of steps, i.e., specific operations providing an added value to the end product. Further, they developed a probabilistic model with the aim to define two performance indicators for inspection strategies related to inspection effectiveness and affordability. In detail, the inspection strategy modeling and the probabilistic model are described in Section 4.1.1, while the performance measures are review in Section 4.1.2. The probabilistic model and, accordingly, the two indicators of effectiveness and total cost, used to depict an inspection strategy, may be integrated with the defect generation models that have been proposed in Section 3.3.

4.1.1 Inspection strategy modeling

As highlighted in the previous Section 3.3, an overall assembly manufacturing process, in optimal settings condition, may be modeled by decomposing it into several process steps, also called workstations (Shibata, 2002; Su et al., 2010; Genta et al., 2018; Franceschini et al., 2018). Each of such workstations produces an outcome, henceforth called workstation-output, whose conformity can be tested through different inspection activities. Quality control activities are performed on the workstation-output according to the specific kind of defect to be detected. They include, for instance, dimensional verifications, visual checks, comparison with reference exemplars, mechanical tests, etc. (Savio et al., 2016; See, 2012; Bress, 2017). The combination of the inspection activities performed on the workstations defines an inspection strategy for the assembly process. Inspection designers can choose between several alternative strategies to inspect an overall manufacturing process. For example, a strategy may require all workstations to be inspected or only some of them. Alternatively, the choice may concern a strategy where all workstations are inspected by visual checks or another one where only mechanical tests are performed, and so on.

According to Franceschini et al. (2018), it is assumed that (i) for each workstation there can be one-and-only-one defect typology, (ii) defects originated in different workstations are uncorrelated, (iii) the occurrence of defects and that of inspection errors are uncorrelated.

When performing an inspection activity, two types of inspection errors may occur: there are a risk of detecting a defect when it is not present (type I error) and a risk of not detecting the defect when it is actually present (type II error). Although such risks can be reduced through sophisticated quality monitoring techniques, manual and/or automatic, they should not be neglected (C. H. Wang, 2007; Ko et al., 2013; Sarkar and Saren, 2016; Tang and Schneider, 1987).

In the modeling of a manufacturing process and inspection strategy, the outcome of each i-th workstation is modeled by a Bernoulli distribution (Montgomery, 2012). Thus, each i-th workstation (where i=1,…,m) can be associated with three variables (Franceschini et al., 2018):

- p_i: probability of occurrence of a defective-workstation-output in optimal operating conditions;
- α_i: probability of erroneously detecting a defective-workstation-output (i.e., type-I inspection error);
- β_i: probability of erroneously not detecting a defective-workstation-output (i.e., type-II inspection error).

The first variable, p_i, is strictly related to the quality of the process relative to the i-th workstation. It should be emphasized that such defect probability is due to a physiological condition of the process; therefore, it is not affected by occasional failures or errors. On the other hand, the inspection errors α_i and β_i depend on the quality of the inspection activity, that involves the inspection typology and procedure, the technical skills and experience of the operators, the environmental conditions, etc. (Duffuaa and Khan, 2005; C. W. Kang et al., 2018; Tzimerman and Herer, 2009; Tang and Schneider, 1987). In practical applications, the variables p_i, α_i and β_i can be estimated by the use of simulations, prediction models and/or empirical methods, based on historical data, previous experience on similar processes, and process knowledge (Franceschini et al., 2018; Genta et al., 2018; Galetto, Verna, Genta, et al., 2020). In particular, the probability of occurrence of at least one defect in each workstation i (p_i) may be estimated as the fraction of nonconforming units in the workstation i (Montgomery, 2012). Accordingly, p_i may be calculated, in the case of low-volume productions, by exploiting the defect rates obtained using the defects rates predicted by the models described in Section 3.3 and the number of job elements in the relative workstation, as shown in Eq. (4.1) (Genta et al., 2018):

$$p_i = 1 - \left(1 - \frac{DPU_i}{N_{a,i}}\right)^{N_{a,i}} \tag{4.1}$$

It should be remarked that Eq. (4.1) is obtained under the assumptions that: (i) each job element may introduce at most one defect; and (ii) for each workstation i, the probability of occurrence of a defect is the same for each job element (Hinckley, 1994; Genta et al., 2018).

According to Franceschini et al. (2018), the following probabilities can be calculated for each i-th workstation:

$$P(\text{signalling a defective-workstation output in the workstation } i) \\ = p_\mathrm{i} \cdot (1 - \beta_i) + (1 - p_\mathrm{i}) \cdot \alpha_\mathrm{i} \tag{4.2}$$

and

$$P(\text{not signalling a defective-workstation output in the workstation } i) \\ = p_\mathrm{i} \cdot \beta_i + (1 - p_\mathrm{i}) \cdot (1 - \alpha_\mathrm{i}) \tag{4.3}$$

where $i = 1, \ldots, m$, i.e. the total number of workstations.

In the case a defective-workstation-output is signaled, this will be true with a probability $p_i \cdot (1\text{-}\beta_i)$ or false with a probability $(1\text{–}p_i) \cdot \alpha_i$ (see Eq. (4.2)). On the other hand, in the case no defect is signaled, this will be the result of an inspection error with a probability $p_i \cdot \beta_i$, or will be due to the real absence of any defect with a probability $(1\text{-}p_i) \cdot (1\text{-}\alpha_i)$ (see Eq. (4.3)).

Considering the m Bernoulli random variables X_i, they are defined as (Franceschini et al., 2018):

- $X_i = 0$: when (i) a defective-workstation-output is correctly signaled, or (ii) no defect is present in the i-th workstation;
- $X_i = 1$: when a defective-workstation-output is erroneously not signaled in the i-th workstation.

4.1.2 Inspection performance measures: effectiveness and total cost

A typical inspection strategy performance may be assessed by two inspection indicators that depict the overall effectiveness and economic convenience of an inspection strategy (Savio et al., 2016; De Ruyter et al., 2002; Avinadav and Perlman, 2013; Verna et al., 2020e). As explained in recent studies (Franceschini et al., 2018; Genta et al., 2018; Galetto, Verna, Genta, et al., 2020), the inspection effectiveness of an inspection strategy may be represented using a practical indicator, D_{tot}, defining the mean total number of defective-workstation-outputs which are erroneously not detected after completing the overall inspection strategy, as follows (Genta et al., 2018; Franceschini et al., 2018):

$$D_{tot} = \sum_{i=1}^{m} E(X_i) = \sum_{i=1}^{m} D_i = \sum_{i=1}^{m} p_i \cdot \beta_i \tag{4.4}$$

where D_i represents the mean number of real defects undetected in the i-th workstation. The indicator D_{tot} is obtained by assuming that the variables p_i, α_i and β_i related to both the same workstations and to different ones are uncorrelated.

The total cost related to the inspection strategy may be estimated by the total cost indicator, C_{tot}, that includes the cost of the specific inspection activity, the necessary- and the unnecessary-repair costs, and the cost of undetected defects, as defined in Eq. (4.5) (Franceschini et al., 2018; Galetto, Verna, Genta, et al., 2020):

$$C_{tot} = \sum_{i=1}^{m} C_{tot,i} = \sum_{i=1}^{m}[c_i + NRC_i \cdot p_i \cdot (1-\beta_i) + URC_i \cdot (1-p_i) \cdot \alpha_i + NDC_i \cdot p_i \cdot \beta_i] \tag{4.5}$$

where:

- $C_{tot,i}$ is the total cost related to the i-th workstation;
- c_i is the cost of the control performed in the i-th workstation;
- NRC_i is the Necessary-Repair Cost, namely the necessary cost for repairing/removing the defective-workstation-outputs (or in some cases the cost of rejection);
- URC_i is the Unnecessary-Repair Cost, i.e., the cost incurred when identifying false defective-workstation outputs; e.g., despite there is no cost required for defective-workstation-outputs removal, the overall process can be slowed down, with a consequent extra cost.
- NDC_i is the cost of undetected defective-workstation-outputs, namely the external failure costs related to the missing detection of defective-workstation-outputs, including legal fees related to customer lawsuits, loss of future sales from dissatisfied customers, product recalls, product return costs, after-sales repair costs, etc. (Verna et al., 2020e).
- NDC_i is the cost of undetected defects, i.e., the cost related to the missing detection of defects.

Apart from the estimate of the probabilities p_i, α_i and β_i, the calculation of the total cost indicator requires the estimate of additional quantities. In general, c_i and NRC_i are known costs, URC_i is likely to be relatively easy to estimate, while NDC_i is difficult to estimate since it may depend on difficult-to-quantify factors. It is noted that among the parameters in Eq. (4.5) only c_i, α_i and β_i are related to the inspection strategy adopted. Indeed, the costs NRC_i, URC_i and NDC_i depend on the cost concerning (in)appropriate defect repair or missing defect detection, while p_i is associated with the process propensity to generate defects.

Even this indicator is obtained under the assumption of absence of statistical correlation between the variables p_i, α_i and β_i related both to the same workstations and to different ones.

The indicator C_{tot} gives a trade-off among different cost components. For each i-th workstation, the first cost component c_i is always present, in the case an inspection is performed, while the second component $NRC_i \cdot p_i \cdot (1-\beta_i)$ generally has an opposite behavior with respect to the latter two components $URC_i \cdot (1-p_i) \cdot \alpha_i$ and $NDC_i \cdot p_i \cdot \beta_i$. In fact, when the defect is detected and repair is performed correctly, we certainly do not incur in the third and fourth cost components. Consider the i-th workstation and suppose that the parameters p_i, c_i,

NRC_i, URC_i, and NDC_i are known and fixed. The first cost component c_i is independent of α_i and β_i, the second and fourth component are functions of β_i, and the third component is a function of α_i, as shown in Figure 4.1.

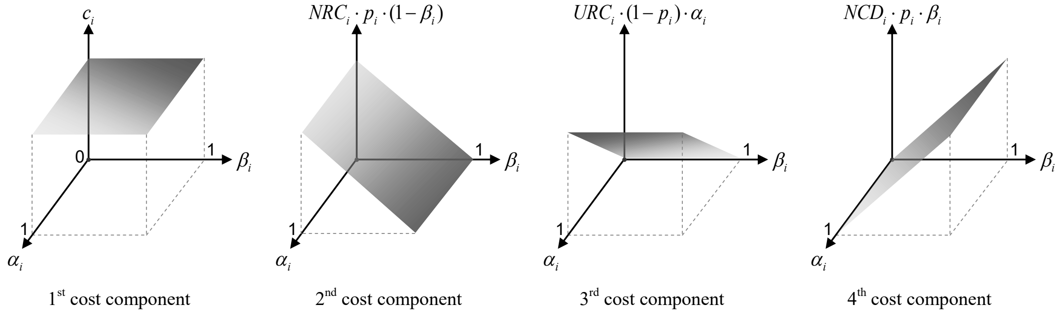


Figure 4.1 - Cost components as functions of the probabilities α_i and β_i for a generic *i*-th workstation (Franceschini et al., 2018).

It is worth remarking that, as the quality of the inspections is improved (i.e., α_i and β_i are likely to decrease, while c_i is likely to increase, due to the improved testing activities), then the contributions $URC_i \cdot (1 - p_i) \cdot \alpha_i$ and $NDC_i \cdot p_i \cdot \beta_i$ will tend to decrease, while $NRC_i \cdot p_i \cdot (1 - \beta_i)$ and c_i will tend to increase. The indicator C_{tot} may be consequently affected by compensation effects.

The indicator C_{tot} provides a preliminary indication of the total cost related to the inspection strategy in use. In this sense, it can be used as a proxy for the economic convenience of an inspection procedure.

4.2 Offline inspections[3]

The probabilistic model and the two performance measures describe in Section 4.1 are now adapted to the case of offline inspections. In particular, the purpose of this section is to quantify inspection effectiveness and cost to support designers in offline inspection planning. After having modeled the inspection strategy in Section 4.2.1, two practical performance indicators are developed to assist designers in choosing the best compromise between effectiveness and cost of alternative inspection strategies in the next Section 4.2.2. Besides, the method proposed is improved in Section 4.2.3 by including possible interaction between model variables and costs occurring during the inspection process. An excerpt of the application of the method to a real case study in the field of Additive Manufacturing processes is also proposed.

[3] Part of the work described in this section was also previously published in Verna E., Genta G., Galetto M., and Franceschini F. (2020c). "Planning Offline Inspection Strategies in Low-Volume Manufacturing Processes." *Quality Engineering* In press, DOI: 10.1080/08982112.2020.1739309

4.2.1 Inspection strategy modeling

With reference to the manufacturing process modeling described in Section 3.4.1, to check the conformity of the product, many different inspection strategies aimed at evaluating the output variables may be performed, such as dimensional verifications, visual checks, comparison with reference exemplars, mechanical tests, etc. (Savio et al., 2016; See, 2012; Bress, 2017). For each inspection activity, there is a risk of detecting a defect when it is not present (type I error), and a risk of not detecting it when it is actually present (type II error). Although these risks can be minimized by using sophisticated (manual and/or automatic) quality monitoring techniques, they can never be eliminated. Accordingly, the following probabilities can be associated with each j-th output variable:

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

The probability p_{Y_j} concerns the quality of the process and it is strictly related to the intrinsic characteristics of the process and its propensity to generate defects. The inspection errors α_{Y_j} and β_{Y_j} depend on the quality of the j-th output variable inspection activity. They are strongly related to factors such as the technical skills and experience of the inspectors, the type of inspection performed, the time allowed for inspection, the work environment, and other work- and inspection-related factors (C. W. Kang et al., 2018; Tzimerman and Herer, 2009; Duffuaa and Khan, 2005; Tang and Schneider, 1987). In practical applications, the probabilities p_{Y_j}, α_{Y_j} and β_{Y_j} may be a priori estimated using adequate probabilistic models, empirical methods (historical data, previous experience on similar processes, process knowledge, etc.) or simulations (Franceschini et al., 2018; Genta et al., 2018; Sarkar and Saren, 2016; De Ruyter et al., 2002; Galetto, Verna, Genta, et al., 2020).

4.2.2 Inspection performance measures

According to Verna et al. (Verna et al., 2020e), for each j-th output variable (j=1,…,n) the following probabilities can be obtained:

$$P(\text{classify the output variable } Y_j \text{ as defective}) = p_{Y_j} \cdot \left(1 - \beta_{Y_j}\right) + \left(1 - p_{Y_j}\right) \cdot \alpha_{Y_j} \tag{4.6}$$

$$P(\text{classify the output variable } Y_j \text{ as not defective}) = p_{Y_j} \cdot \beta_{Y_j} + \left(1 - p_{Y_j}\right) \cdot \left(1 - \alpha_{Y_j}\right) \tag{4.7}$$

In the case a defective-output variable is classified, this will be true with a probability $p_{Y_j} \cdot \left(1 - \beta_{Y_j}\right)$ or false with a probability $\left(1 - p_{Y_j}\right) \cdot \alpha_{Y_j}$, see Eq. (4.6). On the other hand, in case no defective-output variable is classified, this will be the result of an inspection error with a probability $p_{Y_j} \cdot \beta_{Y_j}$, or will be due to the real absence of any defective-output variable with a probability $\left(1 - p_{Y_j}\right) \cdot \left(1 - \alpha_{Y_j}\right)$, see Eq. (4.7). Figure 4.2 depicts this scenario. The above probabilities represent the "elementary bricks" for the construction of two indicators depicting the performance of inspection strategies in terms of effectiveness and cost (Franceschini et al., 2018; Genta et al., 2018).

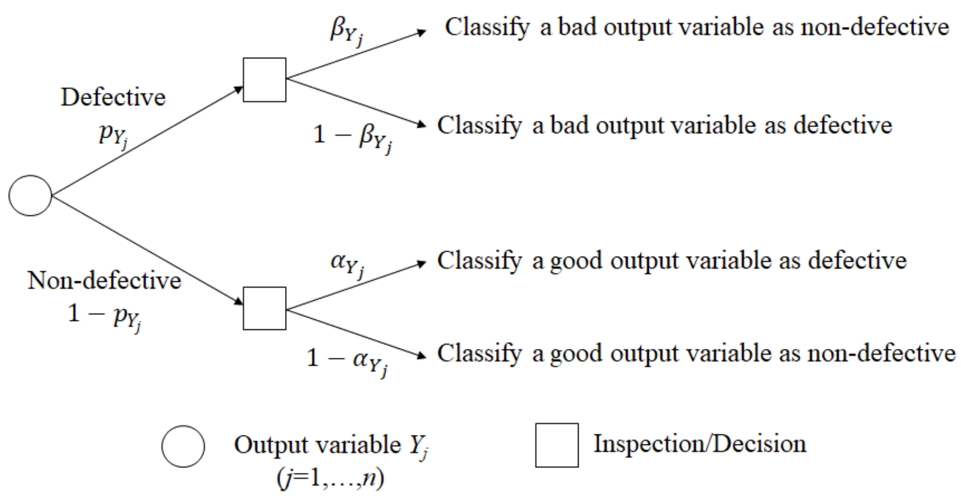


Figure 4.2 – Tree diagram of the inspection process of each j-th output variable.

Next, 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 detected as such or (ii) the output variable Y_j is not defective;
- W_j =1, the truly defective output variable Y_j is not detected as such.

According to Eq. (4.6) and (4.7), the following two relationships are obtained (j = 1, … , n):

$$P(W_j = 0) = p_{Y_j} \cdot \left(1 - \beta_{Y_j}\right) + \left(1 - p_{Y_j}\right) \tag{4.8}$$

$$P(W_j = 1) = p_{Y_j} \cdot \beta_{Y_j} \tag{4.9}$$

Indeed, an authentic defective-output variable is detected with a probability $p_{Y_j} \cdot \left(1 - \beta_{Y_j}\right)$ and not detected with a probability $p_{Y_j} \cdot \beta_{Y_j}$. Instead, when no defective-output variable is actually present, a defect may be detected with a probability $\left(1-p_{Y_j}\right)\cdot\alpha_{Y_j}$ and not detected with a probability $\left(1-p_{Y_j}\right)\cdot\left(1-\alpha_{Y_j}\right)$. Of course, the sum of the latter two probabilities is the probability that no defect is present, i.e. $\left(1-p_{Y_j}\right)$.

Therefore, the mean number of real defective-output undetected for the *j*-th output-variable is:

$$D_{Y_j}=E\left(W_j\right)=p_{Y_j}\cdot\beta_{Y_j} \tag{4.10}$$

When considering the overall inspection strategy, the mean total number of defective-output variables which are erroneously not detected can be defined as:

$$D_{tot}=\sum_{j=1}^{n}E\left(W_j\right)=\sum_{j=1}^{n}p_{Y_j}\cdot\beta_{Y_j} \tag{4.11}$$

The variable D_{tot} is assumed as a first approximation of inspection effectiveness since it provides a measure of the overall effectiveness of the inspection strategy performed on the product. It should be pointed out that Eq. (4.11) is obtained under the hypothesis of no interaction between inspection errors and defect probabilities of different output variables. As a consequence, the two output variables can be considered decoupled.

Regarding each output variable Y_j, the total cost for inspection and defects removal can be expressed as (Genta et al., 2018):

$$\begin{aligned}C_{Y_j}=FC_j+c_j+NRC_j\cdot p_{Y_j}\cdot\left(1-\beta_{Y_j}\right)+URC_j\cdot\left(1-p_{Y_j}\right)\cdot\\ \alpha_{Y_j}+NDC_j\cdot p_{Y_j}\cdot\beta_{Y_j}\end{aligned} \tag{4.12}$$

where:

- FC_j is the fixed cost for controlling and keeping the input variables at the values which result in the best values of the response, and within their variability range;
- c_j is the cost of the *j*-th inspection activity (e.g., manual or automatic inspection activities);
- NRC_j is the necessary-repair cost, i.e., the necessary cost for removing defects of the *j*-th output variable;
- URC_j is the unnecessary-repair cost, i.e., the cost incurred when identifying false defective-output variables; e.g., despite there is no cost required for defective-output variables removal, the overall process can be slowed down, with a consequent extra cost;
- NDC_j is the cost of undetected defective-output variables, i.e., the cost related to the missing detection of defective-output variables.

As shown in Eq. (4.12), C_{Y_j} is composed of five cost components. The first cost component, FC_j, depends on the quality of the inspection used to control the input variables that affect the j-th output variable. The second cost component, c_j, is always present in the case an inspection is performed, and it is strictly related to the quality of the inspection. The third cost component, $NRC_j \cdot p_{Y_j} \cdot \left(1-\beta_{Y_j}\right)$, generally has an opposite behavior with respect to the latter two components, $URC_j \cdot \left(1-p_{Y_j}\right) \cdot \alpha_{Y_j}$ and $NDC_j \cdot p_{Y_j} \cdot \beta_{Y_j}$. Indeed, when the quality of the inspections improves, it is probable that α_{Y_j} and β_{Y_j} decrease and c_j increase, due to the enhancement of controls. As a result, the contributions of the fourth and fifth cost components will tend to decrease, being respectively functions of α_{Y_j} and β_{Y_j}, whilst the third cost component, together with the inspection cost c_j, will tend to increase.

In addition to the estimates of the probabilities p_{Y_j}, α_{Y_j} and β_{Y_j}, the evaluation of the costs FC_j, c_j, NRC_j, URC_j, NDC_j, which are considered fixed parameters as a preliminary approximation, is required. Typically, FC_j, c_j and NRC_j are known costs. URC_j is usually relatively easy to estimate, while NDC_j is usually hard to estimate since it may depend on difficult-to-quantify factors, such as external failure costs including legal fees related to customer lawsuits, loss of future sales from dissatisfied customers, product recalls, product return costs, after-sales repair costs, etc. (Verna et al., 2020e).

The total cost for inspection and defective-output variables removal related to the overall inspection strategy (n output variables) can be expressed as:

$$C_{tot} = \sum_{j=1}^{n} C_{Y_j} = \sum_{j=1}^{n} \Big[FC_j + c_j + NRC_j \cdot p_{Y_j} \cdot \left(1-\beta_{Y_j}\right) + URC_j \cdot \left(1-p_{Y_j}\right) \cdot \alpha_{Y_j} + NDC_j \cdot p_{Y_j} \cdot \beta_{Y_j}\Big] \tag{4.13}$$

Eq. (4.13) can be considered a preliminary approximation of the total cost of the inspection strategy. Even for this indicator, it is assumed that no interaction between inspection errors and defect probabilities of different output variables occurs. Furthermore, Eq. (4.13) does not consider possible cost-sharing between the output variables. As a result, in some circumstances C_{tot} might overestimate the costs related to the inspection strategy.

4.2.3 Interaction between model variables

As mentioned above, Eqs. (4.11) and (4.13) are obtained under the assumption of no interaction between defects and inspections errors of different output variables. This allows to decouple the corresponding output variables and, therefore, to consider the related events as mutually exclusive, i.e., disjoint events. However, in practical situations, different defective-output variables can occur jointly, requiring the proposed model and performance indicators to be refined. Besides, when several output variables are considered together, the interaction between the costs related to their inspections should also be considered in the final cost indicator.

It is worth noting that, in this study, possible interactions between variables are intended as cause-and-effect relationships and not merely as correlations. Indeed, a correlation is a statistical measure of the relationship between two or more variables that, however, does not provide information about the cause-and-effect relationship of the data (Eger et al., 2018; Murdoch and Barnes, 1973).

Consider for example two output variables denoted by Y_1 and Y_2 that are 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 possibilities in such an inspection process, including some cases of misclassifications and other of correct classifications. This scenario is depicted in Figure 4.3.

It should be highlighted that the events represented in Figure 4.3, both related to the occurrence of defects and inspection errors, are considered independent. For instance, the occurrence of the defective-output variable Y_2 is independent from the occurrence of the defective output-variable Y_1. Besides, inspections on Y_1 and Y_2 are performed separately, as it happens in most practical cases, and the corresponding inspection errors do not depend on the typology of the defect. Accordingly, as shown in Figure 4.3, the type-I and type-II inspection errors are the same in all the paths of the graphical model. In graphical terms, this situation is indicated by the absence of any direct arrow between the nodes of the events in the tree diagram.

However, in real situations, the assumption of independence between the defective-output variables can be an oversimplification. In general, probabilities are context sensitive. For example, the probability of occurrence of the defective-output variable Y_2 can be conditioned on the occurrence of the other defective-output variable Y_1, or *vice versa*. In such a case, i.e., when there is a dependence between the occurrence of defective-output variables, the scenario is depicted in Figure 4.4. The four possible combinations of defects in such a scenario 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 Figure 4.4. Specifically, the probability that the two defective-output variables occur jointly, $p_{Y_1 \cap Y_2}$, can be obtained by exploiting Bayes's theorem (Schervish, 2012), as follows:

$$p_{Y_1 \cap Y_2} = \begin{cases} p_{Y_2} \cdot p_{Y_1} & \text{if the occurrence of } Y_1 \text{ and that of } Y_2 \text{ are independent} \\ p_{Y_2|Y_1} \cdot p_{Y_1} & \text{if the occurrence of } Y_1 \text{ and that of } Y_2 \text{ are dependent} \\ & \text{(the occurrence of } Y_1 \text{ is the conditioning event)} \\ p_{Y_1|Y_2} \cdot p_{Y_2} & \text{if the occurrence of } Y_1 \text{ and that of } Y_2 \text{ are dependent} \\ & \text{(the occurrence of } Y_2 \text{ is the conditioning event)} \end{cases} \tag{4.14}$$

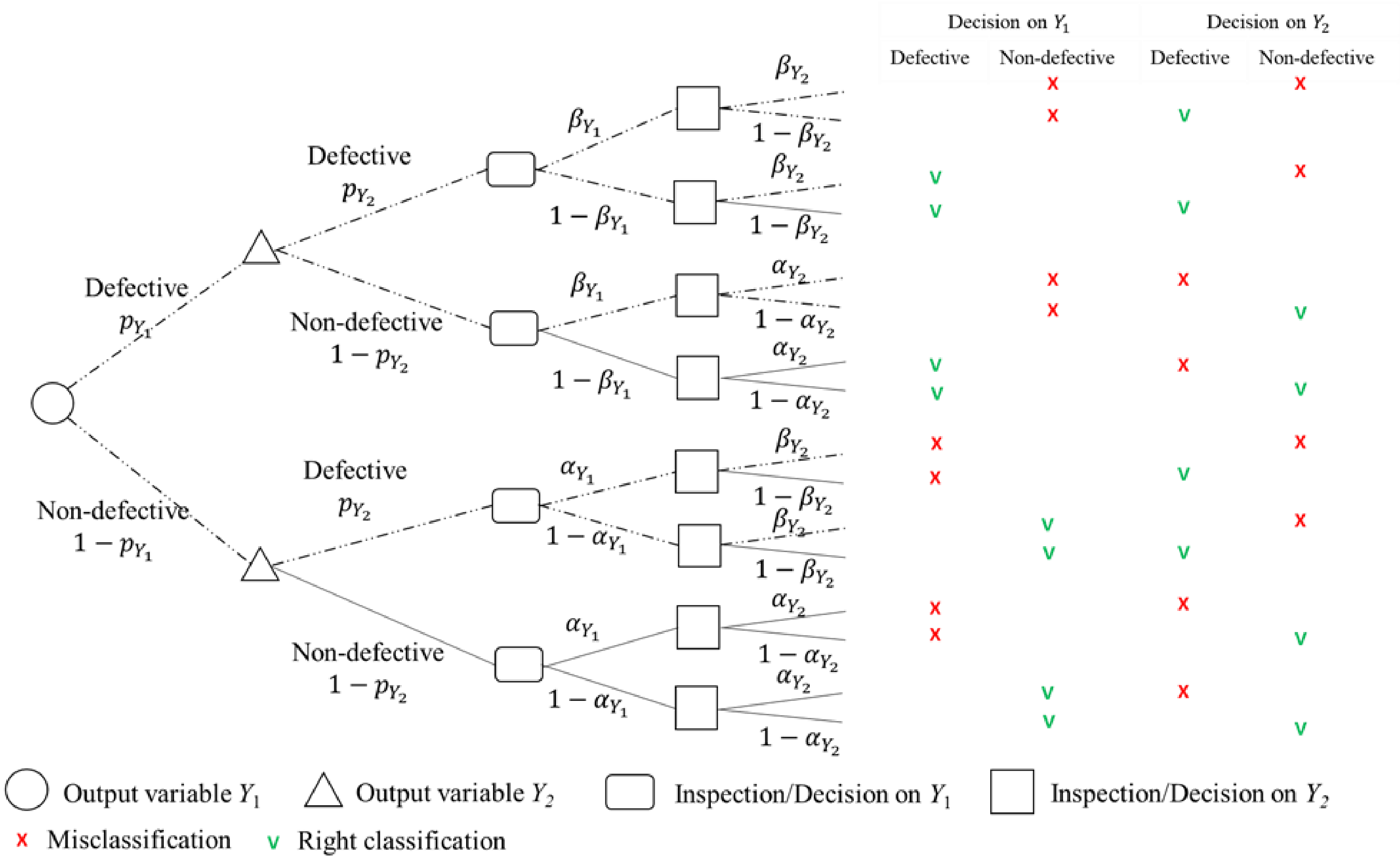


Figure 4.3 – Tree diagram of the inspection process of 2 output variables in case of independence between the occurrence of defects, inspection errors and both.

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 Figure 4.4, $p_{Y_1 \cap Y_2}$ should be replaced by the probabilities reported in Eq. (4.14). It should be noted that, when the occurrence of Y_1 and that of Y_2 are independent, the diagram in Figure 4.4 can lead back to the diagram in Figure 4.3.

As far as inspection errors are concerned, their probability could also be related to the occurrence of the defective-output variables, i.e., to the four different events (A), (B), (C) and (D). In this case, simple probabilities should be replaced by conditional probabilities, as shown in Figure 4.5. In detail, four different inspection errors can occur when inspecting Y_1 ($\beta_{Y_1|A}$, $\beta_{Y_1|B}$, $\alpha_{Y_1|C}$ and $\alpha_{Y_1|D}$), and other four when inspecting Y_2 ($\beta_{Y_2|A}$, $\beta_{Y_2|C}$, $\alpha_{Y_2|B}$, $\alpha_{Y_2|D}$). However, 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 inspectors, and other work- and inspection-related factors (Mehmood Khan et al., 2011; Dorris and Foote, 1978). For that reason, as a first approximation, the model and indicators proposed in this study rely on the independence between inspection errors and the occurrence of defects.

More in general, when considering n output variables inspected, the possible combinations in which the defects can occur in the product are 2^n, each one associated with 2^n possible combinations of inspection errors, resulting in a total of 2^{2n} combinations.

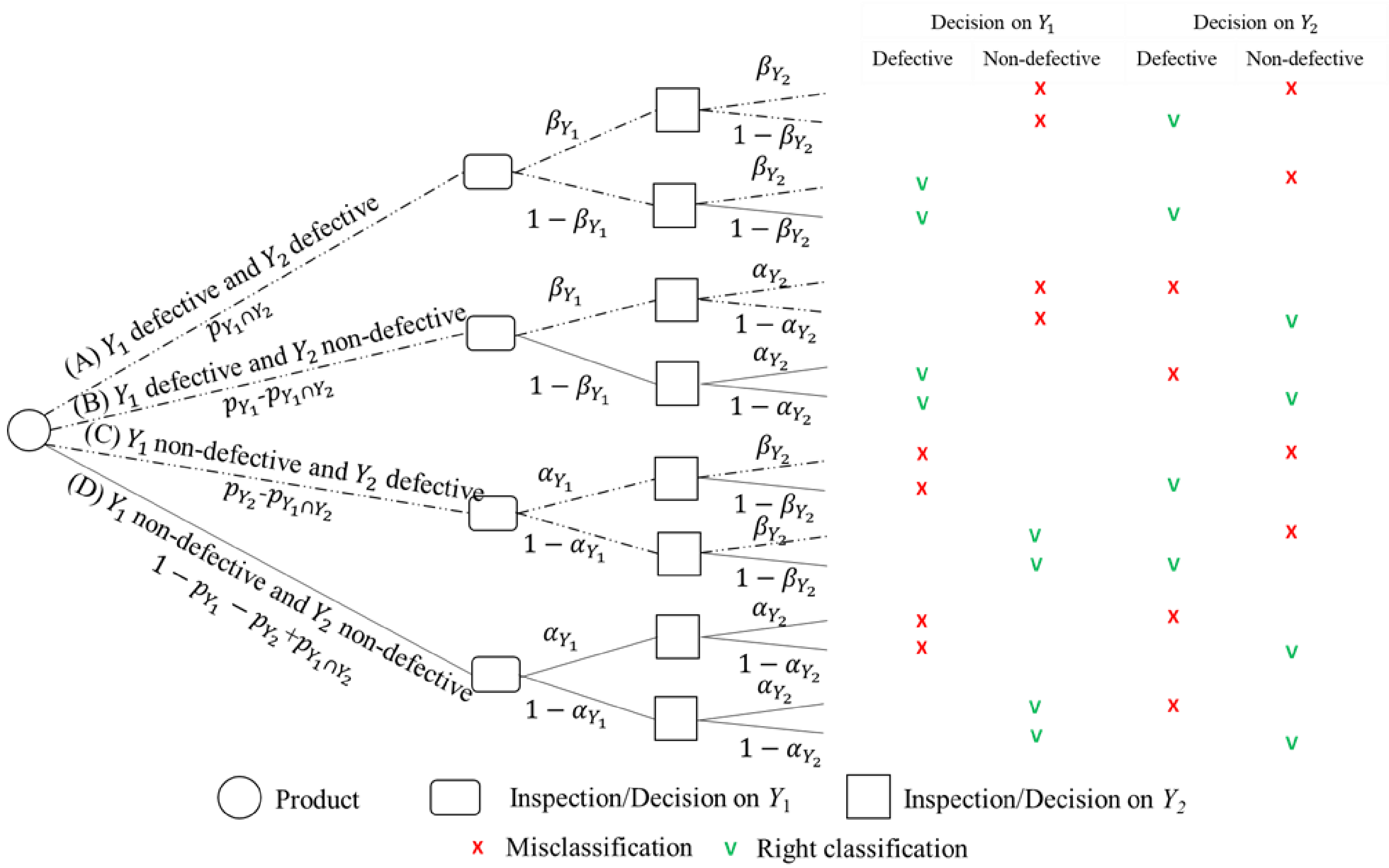


Figure 4.4 – Tree diagram of the inspection process of 2 output variables in case of independence between inspection errors, and between inspection error and the occurrence of defects.

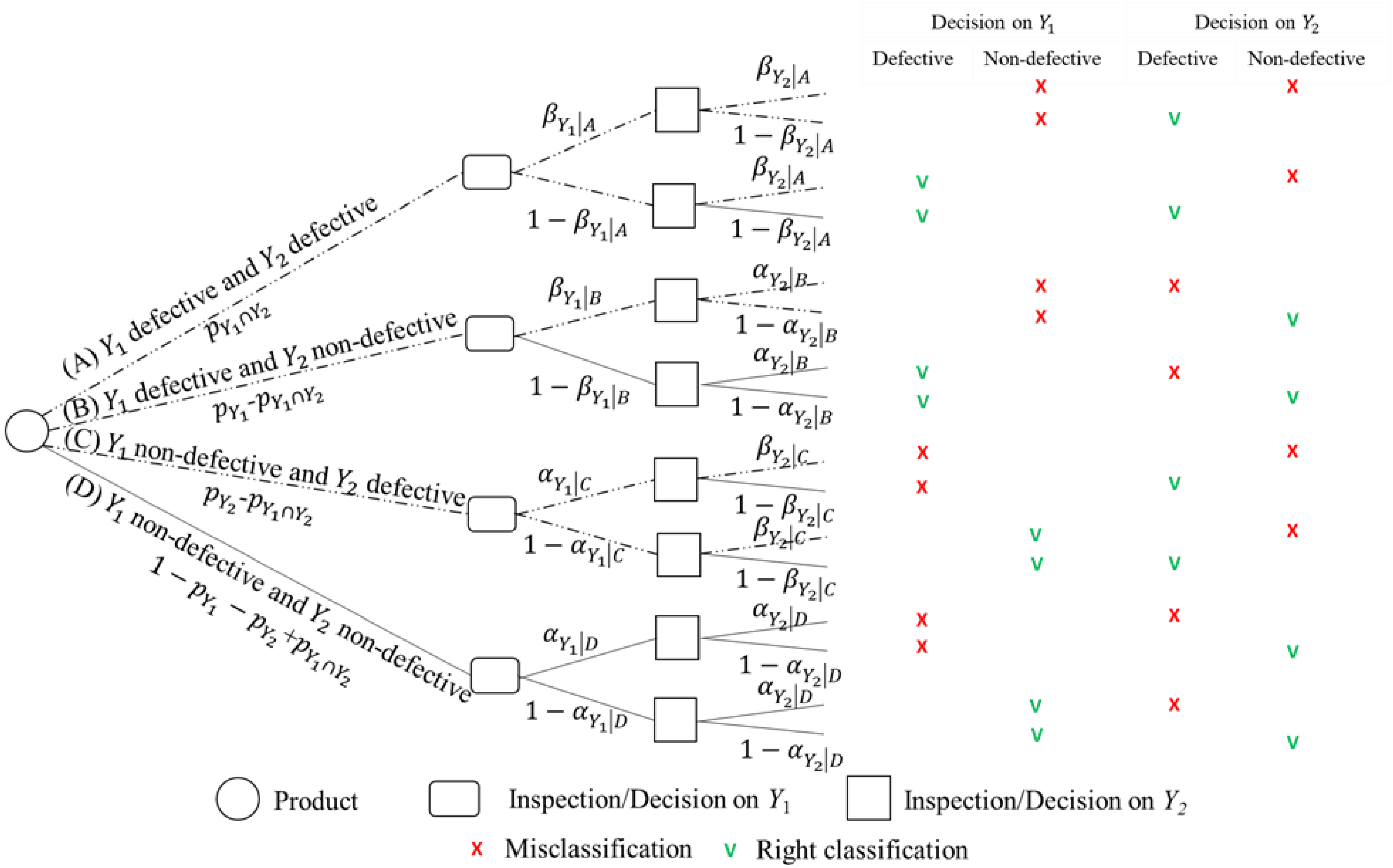


Figure 4.5 - Tree diagram of the inspection process of 2 output variables in case of independence between inspection errors.

4.2.3.1 Inspection effectiveness

Let us now define a Bernoulli random variable (W) as follows:

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

According to the graphical models of Figure 4.3, Figure 4.4 and Figure 4.5, $P(W = 0)$ can be obtained by multiplying the probabilities on the paths with continuous lines, while $P(W = 1)$ can be derived by multiplying the probabilities on the paths with dotted lines. In the specific case of independence between inspection errors and the related defective-output variables (see Figure 4.4), the following two relationships are obtained:

$$P(W = 0) = 1 - p_{Y_1} \cdot \beta_{Y_1} - p_{Y_2} \cdot \beta_{Y_2} + p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \tag{4.15}$$

$$P(W = 1) = p_{Y_1} \cdot \beta_{Y_1} + p_{Y_2} \cdot \beta_{Y_2} - p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \tag{4.16}$$

Therefore, according to Eqs. (4.15) and (4.16), the mean total number of defective-output variables which are erroneously not detected in the inspection process can be defined as:

$$D'_{tot} = E(W) = p_{Y_1} \cdot \beta_{Y_1} + p_{Y_2} \cdot \beta_{Y_2} - p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} \tag{4.17}$$

Thus, if the inspection process is examined in its totality and, therefore, the two output variables are not decoupled, Eq. (4.17) differs from Eq. (4.11) for the component $p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2}$, which represents the mean total number of undetected defects of Y_1 and Y_2 when they occur jointly in the product.

More in general, if there are *n* output variables to be inspected on the product, by exploiting the total probability theorem (Schervish, 2012), the inspection effectiveness indicator becomes:

$$\begin{aligned} D'_{tot} = &\sum_{j=1}^{n} \left(p_{Y_j} \cdot \beta_{Y_j}\right) - \sum_{j_1<j_2} \left[\left(p_{Y_{j_1} \cap Y_{j_2}}\right) \cdot \left(\beta_{Y_{j_1}} \cdot \beta_{Y_{j_2}}\right)\right] + \cdots + (-1)^{t+1} \\ &\cdot \sum_{j_1<j_2<\cdots<j_t} \left[\left(p_{Y_{j_1} \cap Y_{j_2} \cap \ldots \cap Y_{j_t}}\right) \cdot \left(\beta_{Y_{j_1}} \cdot \beta_{Y_{j_2}} \cdot \ldots \cdot \beta_{Y_{j_t}}\right)\right] + \cdots \\ &+ (-1)^{n+1} \cdot \left[\left(p_{Y_1 \cap Y_2 \cap \ldots \cap Y_n}\right) \cdot \left(\beta_{Y_1} \cdot \beta_{Y_2} \cdot \ldots \cdot \beta_{Y_n}\right)\right] \\ &= \sum_{j=1}^{n} (-1)^{j+1} \cdot \sum_{1 \le k_1 < \cdots < k_j \le n} \left[\left(p_{\cap_{q=1}^{j} Y_{k_q}}\right) \cdot \left(\prod_{q=1}^{j} \beta_{Y_{k_q}}\right)\right] \end{aligned} \tag{4.18}$$

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, D'_{tot} 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 Eq. (4.18) is formulated for the case in which there is independence between inspection errors and the related defective-output variables, it can be considered a good approximation of the indicator of inspection effectiveness when *n* defective-output variables can occur jointly in the product.

4.2.3.2 Inspection cost

Similar to the inspection effectiveness indicator, the indicator of inspection total cost is first evaluated considering only two output variables that can occur jointly in the product, and then its expression is generalized to the case of *n* output variables.

When considering all the variables together, an interaction between the costs related to the different output variables may occur.

The first kind of interaction may incur when the same input variables cause different defective-output variables. In this case, there will be an allocation of the fixed costs *FC* among the variables. Such interaction is introduced in the total cost indicator using the variable I_{FC_j}, which is a weight between 0 and 1 to be assigned to corresponding fixed cost FC_j, as follows:

$$I_{FC_j} = \begin{cases} = 1 & \text{if the variable } Y_j \text{ is not affected by the same input variables of other output variables} \\ \in [0,1) & \text{if the variable } Y_j \text{ is affected by the same input variables of other output variables} \end{cases} \quad (4.19)$$

The second kind of interaction occurs when inspecting a single output variable also provides information on the defectiveness of other output variables. In such a case, an interaction between the costs c_j should be introduced. The interaction between the inspection costs is considered in the total cost indicator using the functions I_{c_j}, which is defined as:

$$\boldsymbol{I_{c_j}} = \begin{cases} \boldsymbol{= 1} & \text{if inspecting other variables different from } \boldsymbol{Y_j} \text{ does not provide information on the defectiveness of } \boldsymbol{Y_j} \\ \boldsymbol{\in [0,1)} & \text{if inspecting other variables different from } \boldsymbol{Y_j} \text{ provides information on the defectiveness of } \boldsymbol{Y_j} \end{cases} \quad (4.20)$$

Furthermore, the necessary-repair costs of different output variables (as well as the unnecessary repair costs) may be correlated when the cost for repairing multiple output variables is different from the sum of the costs for repairing them individually. Such a situation occurs, for instance, when the repair action is the same or when the presence of defects leads to the rejection of the piece. For instance, consider two output variables Y_1 and Y_2. The necessary repair cost for repairing both is denoted as $NRC_{1,2}$. Generally, the range of the cost $NRC_{1,2}$ is defined as follows:

$$max(NRC_1, NRC_2) \leq NRC_{1,2} \leq NRC_1 + NRC_2 \tag{4.21}$$

Although repairing multiple output variables together is generally less expensive than repairing them individually, when the repair of both defects is more expensive than the sum of the individual repair costs, the range of $NRC_{1,2}$ becomes:

$$NRC_{1,2} \geq NRC_1 + NRC_2 \tag{4.22}$$

Similarly, the costs of undetected defects may be correlated when not detecting multiple defective-output variables implies an increase or decrease in costs with respect to the individual undetected defect cost. Such a situation could occur when the after-sales repair action is the same for multiple variables or when the presence of defects leads to the rejection of the product. Conversely, multiple undetected defects in the same product may results in an increase of the undetected costs because of the more significant external failure costs (legal fees, product recalls, etc.) that result in not identifying multiple defects jointly. Always considering the two output variables Y_1 and Y_2, in the first case the range of the cost of not detecting both the defects, $NDC_{1,2}$, is defined as:

$$max(NDC_1, NDC_2) \leq NDC_{1,2} \leq NDC_1 + NDC_2 \tag{4.23}$$

On the other hand, in the second case, the range is as follows:

$$NDC_{1,2} \geq NDC_1 + NDC_2 \tag{4.24}$$

Moreover, an interaction may occur between the costs of reworking and repairing activities on the product. In particular, if several defects (authentic or not) occur at the same time, they are considered by the operator as real defects and therefore a reduction, or less frequently, an increase of the repair cost if compared to the sum of the individual costs may occur, In such a case, the total cost which combines the costs *NRC* and *URC* is called repair cost *RC*. When dealing with two output variables Y_1 and Y_2, two different repair costs should be considered. The first one which includes NRC_1 and URC_2 is denoted as RC_{N_1,U_2}. This cost is defined in the range:

$$max(NRC_1, URC_2) \leq RC_{N_1.U_2} \leq NRC_1 + URC_2 \tag{4.25}$$

However, when repairing both the defects (authentic and not) is more expensive than repairing them individually, the range of RC_{N_1,U_2} becomes:

$$RC_{N_1,U_2} \geq NRC_1 + URC_2 \tag{4.26}$$

The second repair cost involves the costs URC_1 and NRC_2 and is denoted as RC_{U_1,N_2}. Even this cost is typically included in the following range:

$$max(\,URC_1, NRC_2) \leq RC_{U_1,N_2} \leq URC_1 + NRC_2 \tag{4.27}$$

Nevertheless, occasionally, may be defined in the range:

$$RC_{U_1,N_2} \geq URC_1 + NRC_2 \tag{4.28}$$

Finally, the costs *NRC* (or *URC*) and *NDC* are not reasonably correlated, except in negligible cases in which repairing defects (authentic or not) lead to a reduction/increase of the costs of the undetected defect. For that reason, this kind of interaction is not considered in the final cost indicator.

According to Figure 4.6, the indicator of the total cost may be derived by multiplying the cost component of each path of the graphical model by the corresponding probabilities.

As a result, the final cost indicator is:

$$\begin{aligned} C'_{tot} = {} & FC_1 + FC_2 + I_{c_1} \cdot c_1 + I_{c_2} \cdot c_2 + NDC_{1,2} \cdot p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2} + (NDC_1 \\ & + NRC_2) \cdot p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot (1 - \beta_{Y_2}) + (NRC_1 \\ & + NDC_2) \cdot p_{Y_1 \cap Y_2} \cdot (1 - \beta_{Y_1}) \cdot \beta_{Y_2} + NRC_{1,2} \cdot p_{Y_1 \cap Y_2} \cdot (1 - \beta_{Y_1}) \\ & \cdot (1 - \beta_{Y_2}) + (NDC_1 + URC_2) \cdot (p_{Y_1} - p_{Y_1 \cap Y_2}) \cdot \beta_{Y_1} \cdot \alpha_{Y_2} \\ & + NDC_1 \cdot (p_{Y_1} - p_{Y_1 \cap Y_2}) \cdot \beta_{Y_1} \cdot (1 - \alpha_{Y_2}) + RC_{N_1,U_2} \\ & \cdot (p_{Y_1} - p_{Y_1 \cap Y_2}) \cdot (1 - \beta_{Y_1}) \cdot \alpha_{Y_2} + NRC_1 \cdot (p_{Y_1} - p_{Y_1 \cap Y_2}) \\ & \cdot (1 - \beta_{Y_1}) \cdot (1 - \alpha_{Y_2}) + (URC_1 + NDC_2) \cdot (p_{Y_2} - p_{Y_1 \cap Y_2}) \cdot \alpha_{Y_1} \\ & \cdot \beta_{Y_2} + RC_{U_1,N_2} \cdot (p_{Y_2} - p_{Y_1 \cap Y_2}) \cdot \alpha_{Y_1} \cdot (1 - \beta_{Y_2}) + NRC_2 \\ & \cdot (p_{Y_2} - p_{Y_1 \cap Y_2}) \cdot (1 - \alpha_{Y_1}) \cdot (1 - \beta_{Y_2}) + NDC_2 \\ & \cdot (p_{Y_2} - p_{Y_1 \cap Y_2}) \cdot (1 - \alpha_{Y_1}) \cdot (1 - \beta_{Y_2}) + URC_{1,2} \cdot (1 - p_{Y_1} \\ & - \, p_{Y_2} + p_{Y_1 \cap Y_2}) \cdot \alpha_{Y_1} \cdot \alpha_{Y_2} + URC_1 \cdot (1 - p_{Y_1} - \, p_{Y_2} + p_{Y_1 \cap Y_2}) \\ & \cdot \alpha_{Y_1} \cdot (1 - \alpha_{Y_2}) + URC_2 \cdot (1 - p_{Y_1} - \, p_{Y_2} + p_{Y_1 \cap Y_2}) \cdot (1 - \alpha_{Y_1}) \\ & \cdot \alpha_{Y_2} \end{aligned} \tag{4.29}$$

It should be highlighted that, when there is no interaction between costs (i.e. when $I_{c_1} = 1, I_{c_2} = 1$, $NDC_{1,2} = NDC_1 + NDC_2$, $NRC_{1,2} = NRC_1 + NRC_2$, $RC_{N_1,U_2} = NRC_1 + URC_2$, $RC_{U_1,N_2} = URC_1 + NRC_2$, $URC_{1,2} = URC_1 + URC_2$), Eq. (4.29) corresponds to the total cost indicator calculated according to Eq. (4.13) without variables interaction, as follows:

$$\begin{aligned} C'_{tot} = {} & FC_1 + FC_2 + c_1 + c_2 + NRC_1 \cdot p_{Y_1} \cdot \left(1 - \beta_{Y_1}\right) + NRC_2 \cdot p_{Y_2} \cdot \left(1 - \beta_{Y_2}\right) \\ & + URC_1 \cdot \left(1 - p_{Y_1}\right) \cdot \alpha_{Y_1} + URC_2 \cdot (1 - p_2) \cdot \alpha_{Y_2} + NDC_1 \\ & \cdot p_{Y_1} \cdot \beta_{Y_1} + NDC_2 \cdot p_{Y_2} \cdot \beta_{Y_2} \end{aligned} \tag{4.30}$$

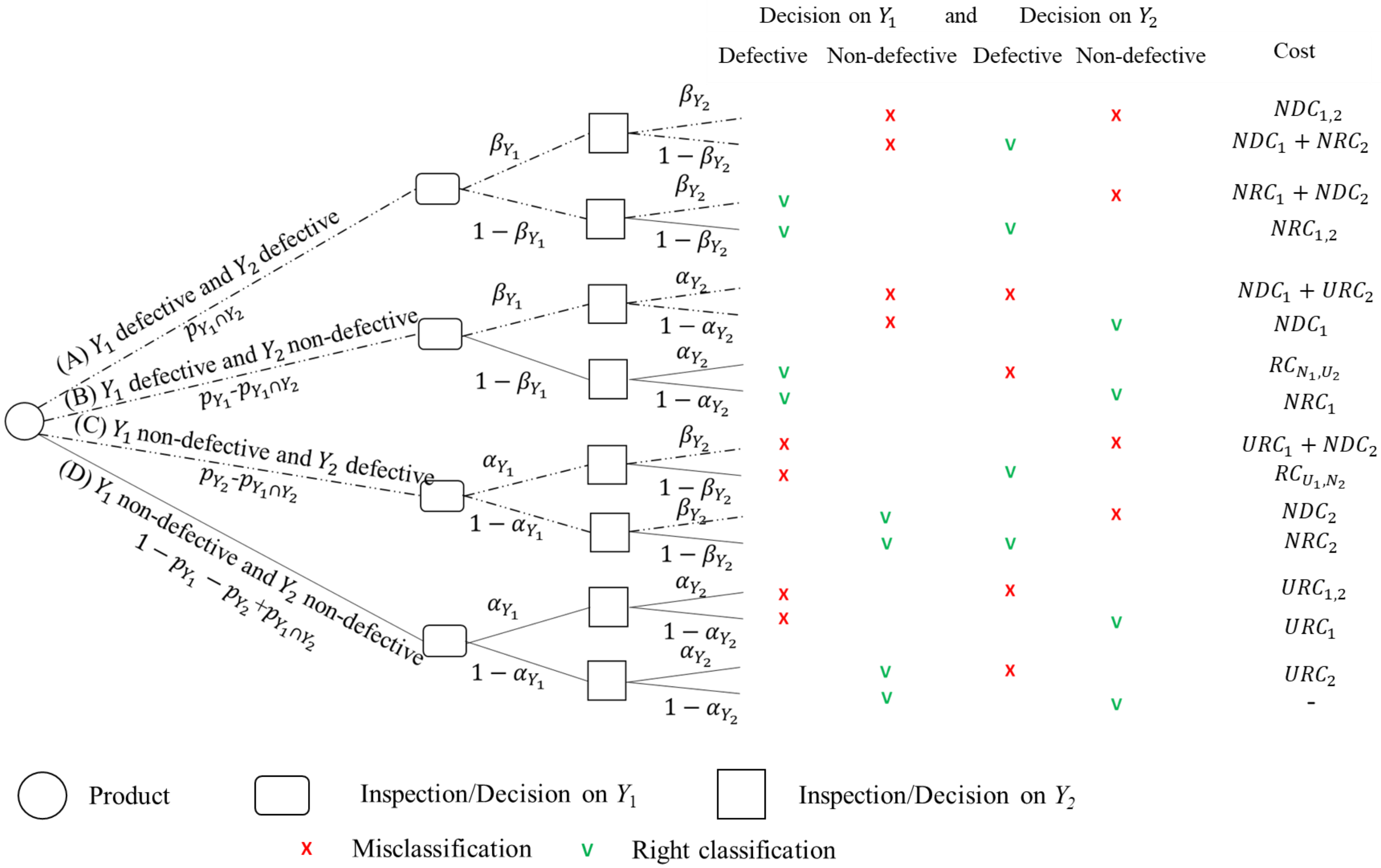


Figure 4.6 - Tree diagram of the inspection process of 2 output variables in case of independence between inspection errors, and between inspection error and the occurrence of defects. For each branch of the tree diagram, the related cost components are shown.

Indeed, the independence between the inspection errors and between them and the occurrence of defects, as well as the non-interaction between costs, lead to the decoupling of the two output variables.

The general expression of the total cost of an inspection strategy becomes highly complex when more than two output variables are considered. Indeed, the possible combinations of the output variables are 2^n, which have to be multiplied by the combinations of inspection errors, again 2^n, resulting in a total of 2^{2n} combinations. For instance, an inspection strategy concerning 4 output variables involves 256 different combinations and, as a consequence, as many cost components for the calculation of the cost indicator. For that reason, an approximated expression of the total cost indicator is proposed.

Firstly, by exploiting the graphical model of Figure 4.7, the probability that a defective-output variable is correctly classified as such, denoted by p_{NR}, can be derived as:

$$\begin{aligned} p_{NR} = \left(p_{Y_1} - p_{Y_1 \cap Y_2}\right) \cdot \left(1 - \beta_{Y_1}\right) + \left(p_{Y_2} - p_{Y_1 \cap Y_2}\right) \cdot \left(1 - \beta_{Y_2}\right) \\ + p_{Y_1 \cap Y_2} \cdot \left(1 - \beta_{Y_1} \cdot \beta_{Y_2}\right) \end{aligned} \tag{4.31}$$

The probability p_{NR} represents the probability that the product needs to be repaired or rejected because of the defective-output variables identified. As shown in Eq. (4.31), p_{NR} is the sum of the probability that (i) when only Y_1 is defective, it is classified as defective, (ii) when only Y_2 is defective, it is classified as such, and (iii) when both Y_1 and Y_2 are defective, both Y_1 and Y_2 are classified as defective.

Then, the probability that a defective-output variable is erroneously classified as such, denoted by p_{UR}, can be expressed as:

$$\begin{aligned} p_{UR} &= \left(p_{Y_2} - p_{Y_1 \cap Y_2}\right) \cdot \alpha_{Y_1} + \left(p_{Y_1} - p_{Y_1 \cap Y_2}\right) \cdot \alpha_{Y_2} \\ &\quad + \left(1 - p_{Y_1} - p_{Y_2} + p_{Y_1 \cap Y_2}\right) \cdot \left(\alpha_{Y_1} + \alpha_{Y_2} - \alpha_{Y_1} \cdot \alpha_{Y_2}\right) \\ &= \left(1 - p_{Y_1}\right) \cdot \alpha_{Y_1} + \left(1 - p_{Y_2}\right) \cdot \alpha_{Y_2} \\ &\quad - \left(1 - p_{Y_1} - p_{Y_2} + p_{Y_1 \cap Y_2}\right) \cdot \left(\alpha_{Y_1} \cdot \alpha_{Y_2}\right) \end{aligned} \tag{4.32}$$

Such probability defines the probability that the product needs to be unnecessarily repaired or rejected because of the misclassification of the defective-output variables. As shown in Eq. (4.32), p_{UR} is the sum of the probability that (i) when only Y_2 is defective, Y_1 is misclassified as defective, (ii) when only Y_1 is defective, Y_2 is misclassified as defective, minus the probability that (iii) when both Y_1 and Y_2 are non-defective, both Y_1 and Y_2 are misclassified as defective.

The probability that a defective-output variable is not classified as such, and therefore remains in the product, p_{ND}, is the probability derived in Eq. (4.16), that can also be rewritten as:

$$p_{ND} = p_{Y_1} \cdot \beta_{Y_1} + p_{Y_2} \cdot \beta_{Y_2} - \left(p_{Y_1 \cap Y_2} \cdot \beta_{Y_1} \cdot \beta_{Y_2}\right)$$
$$= \left(p_{Y_1} - p_{Y_1 \cap Y_2}\right) \cdot \beta_{Y_1} + \left(p_{Y_2} - p_{Y_1 \cap Y_2}\right) \cdot \beta_{Y_2} + p_{Y_1 \cap Y_2} \cdot \left(\beta_{Y_1} + \beta_{Y_2} - \beta_{Y_1} \cdot \beta_{Y_2}\right) \quad (4.33)$$

This probability is the sum of the probability that (i) when only Y_1 is defective, it is misclassified as non-defective, (ii) when only Y_2 is defective, it is misclassified as non-defective, and (iii) when both Y_1 and Y_2 are defective, only Y_1 is misclassified as non-defective, only Y_2 is misclassified as non-defective and both Y_1 and Y_2 are misclassified as non-defective.

Accordingly, the indicator of inspection total cost becomes:

$$C'_{tot} \approx FC_1 + FC_2 + I_{c_1} \cdot c_1 + I_{c_2} \cdot c_2 + \overline{NRC} \cdot\ p_{NR} + \overline{URC} \cdot p_{UR} + \overline{NDC} \cdot p_{ND} \quad (4.34)$$

where the cost $\overline{NRC}$ represents the average cost for repairing/rejecting the product due to real defective-output variables, while $\overline{URC}$ is the average unnecessary repair cost due to non-defective output variables identified as such, and $\overline{NDC}$ the average cost of non-detected defects. These costs can be evaluated, as a first approximation, as the average of the corresponding costs related to the single output variables Y_1 and Y_2, and the cost related to the two variables occurring jointly, as follows:

$$\overline{NRC} = \frac{NRC_1 + NRC_2 + NRC_{1,2}}{3} \quad (4.35)$$

$$\overline{URC} = \frac{URC_1 + URC_2 + URC_{1,2}}{3} \quad (4.36)$$

$$\overline{NDC} = \frac{NDC_1 + NDC_2 + NDC_{1,2}}{3} \quad (4.37)$$

More in general, when the inspection strategy involves *n* output variables, the indicator of total cost may be written as:

$$C'_{tot} \approx \sum_{j=1}^{n} (FC_j + I_{c_j} \cdot c_j) + \overline{NRC} \cdot\ p_{NR} + \overline{URC} \cdot p_{UR} + \overline{NDC} \cdot p_{ND} \quad (4.38)$$

where the average costs $\overline{NRC}$, $\overline{URC}$ and $\overline{NDC}$ are calculated by averaging the cost of the $2^n - 1$ possible cases in which the output variables can occur (individually, in pairs, in triplets, up to *n* together), as follows:

$$\overline{NRC} = \frac{\sum_{j=1}^{n}\left(NRC_j\right) + \sum_{j_1<j_2}\left(NRC_{j_1,j_2}\right) + \sum_{j_1<j_2<\cdots<j_t}\left(NRC_{j_1,j_2,\ldots,j_t}\right) + NRC_{1,2,\ldots,n}}{2^n - 1} \quad (4.39)$$

$$\overline{URC} = \frac{\sum_{j=1}^{n}\left(URC_j\right) + \sum_{j_1<j_2}\left(URC_{j_1,j_2}\right) + \sum_{j_1<j_2<\cdots<j_t}\left(URC_{j_1,j_2,\ldots,j_t}\right) + URC_{1,2,\ldots,n}}{2^n - 1} \quad (4.40)$$

$$\overline{NDC} = \frac{\sum_{j=1}^{n}\left(NDC_j\right) + \sum_{j_1<j_2}\left(NDC_{j_1,j_2}\right) + \sum_{j_1<j_2<\cdots<j_t}\left(NDC_{j_1,j_2,\ldots,j_t}\right) + NDC_{1,2,\ldots,n}}{2^n - 1} \quad (4.41)$$

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 $\{1,2,\dots,n\}$.

Besides, the probabilities in Eq. (4.38) can be expressed as:

$$\begin{aligned}\boldsymbol{p_{NR}} = \sum_{j=1}^{n}\Bigg[\Bigg(&\boldsymbol{p_{Y_j}} - \sum_{j=j_1<j_2}\boldsymbol{p_{Y_{j=j_1}\cap j_2}} - \sum_{j=j_1<j_2<\cdots<j_t}\boldsymbol{p_{Y_{j=j_1\cap j_2\cap\ldots\cap j_t}}} - \boldsymbol{p_{Y_{1\cap 2\cap\ldots\cap n}}}\Bigg) \\ &\cdot\left(\boldsymbol{1} - \boldsymbol{\beta_{Y_j}}\right)\Bigg] + \sum_{j_1<j_2}\left[\boldsymbol{p_{Y_{j_1\cap j_2}}}\cdot\left(\boldsymbol{1} - \boldsymbol{\beta_{Y_{j_1}}}\cdot\boldsymbol{\beta_{Y_{j_2}}}\right)\right] + \cdots \\ &+ \sum_{j_1<j_2<\cdots<j_t}\left[\boldsymbol{p_{Y_{j_1\cap j_2\cap\ldots\cap j_t}}}\cdot\left(\boldsymbol{1} - \boldsymbol{\beta_{Y_{j_1}}}\cdot\boldsymbol{\beta_{Y_{j_2}}}\cdot\ldots\cdot\boldsymbol{\beta_{Y_{j_t}}}\right)\right] + \cdots \\ &+ \left[\left(\boldsymbol{p_{Y_{1\cap 2\cap\ldots\cap n}}}\right)\cdot\left(\boldsymbol{1} - \boldsymbol{\beta_{Y_1}}\cdot\boldsymbol{\beta_{Y_2}}\cdot\ldots\cdot\boldsymbol{\beta_{Y_n}}\right)\right]\end{aligned} \tag{4.42}$$

$$\begin{aligned}\boldsymbol{p_{UR}} = &\sum_{j=1}^{n}\left[\left(\boldsymbol{1} - \boldsymbol{p_{Y_j}}\right)\cdot\left(\boldsymbol{\alpha_{Y_j}}\right)\right] \\ &- \left[\boldsymbol{1} - \left(\sum_{j=1}^{n}(\boldsymbol{-1})^{\boldsymbol{j+1}}\cdot\sum_{1\le k_1<\cdots<k_j\le n}\left(\boldsymbol{p_{\cap_{q=1}^{j}Y_{k_q}}}\right)\right)\right] \\ &\cdot\left(\prod_{j=1}^{n}\boldsymbol{\alpha_{Y_j}}\right)\end{aligned} \tag{4.43}$$

$$\boldsymbol{p_{ND}} = \sum_{j=1}^{n}(\boldsymbol{-1})^{\boldsymbol{j+1}}\cdot\sum_{1\le k_1<\cdots<k_j\le n}\left[\left(\boldsymbol{p_{\cap_{q=1}^{j}Y_{k_q}}}\right)\cdot\left(\prod_{q=1}^{j}\boldsymbol{\beta_{Y_{k_q}}}\right)\right] \tag{4.44}$$

4.2.3.3 Practical example

In order to better illustrate the proposed approach involving interactions between model variables, a practical example in the AM is provided. The indicators of effectiveness and total cost obtained in Eqs. (4.18) and (4.38), respectively, are evaluated for the inspection strategy adopted in the case study that was presented in Section 3.4.2.2 for a process with discrete input variables.

In detail, the inspection activities related to the three output variables, i.e., porosity, tensile strength and dimensional accuracy, are characterized by the inspection errors reported in Table 4.1. By combining the inspection errors of each output variable with the related defect probabilities, that were obtained in Section 3.4.2.2, the two indicators of effectiveness and cost may be derived.

Table 4.1 – Inspection errors related to porosity PO, tensile strength TS and dimensional accuracy DA.

Output variable	α_{Y_j} [%]	β_{Y_j} [%]
PO	5	4
TS	3	2
DA	2	1

When the interactions between variables are not considered, the effectiveness indicator can be derived by exploiting Eq. (4.11):

$$D_{tot} = p_{PO} \cdot \beta_{PO} + p_{TS} \cdot \beta_{TS} + p_{DA} \cdot \beta_{DA} = 1.70 \cdot 10^{-3} \tag{4.45}$$

Instead, when considering the interactions, the indicator of effectiveness becomes, according to Eq. (4.18), as follows:

$$\begin{aligned} D'_{tot} = {} & p_{PO} \cdot \beta_{PO} + p_{TS} \cdot \beta_{TS} + p_{DA} \cdot \beta_{DA} - (p_{TS \cap PO} \cdot \beta_{TS} \cdot \beta_{PO}) \\ & - (p_{DA \cap PO} \cdot \beta_{DA} \cdot \beta_{PO}) - (p_{DA \cap TS} \cdot \beta_{DA} \cdot \beta_{TS}) \\ & + (p_{TS \cap DA \cap PO} \cdot \beta_{TS} \cdot \beta_{DA} \cdot \beta_{PO}) = 1.68 \cdot 10^{-3} \end{aligned} \tag{4.46}$$

As can be noticed, the interactions between model variables result in a slight decrease in the mean number of undetected defective-output variables. In both cases (see Eqs. (4.45) and (4.46)), given production of 1000 components, there are nearly 2 defective-output variables which are erroneously not identified. Given that the production of SLM components can reach hundreds of parts per year, the number of undetected can be considered negligible.

Table 4.2 reports the costs of each output variable, estimated considering the time required for the activity and the labor cost of operators/inspectors. As a first approximation, the necessary and un-necessary repair costs are considered identical.

Table 4.2 – Cost estimates related to porosity PO, tensile strength TS and dimensional accuracy DA.

Output variable j	FC_j [€]	c_j [€]	NRC_j [€]	URC_j [€]	NDC_j [€]
PO	10	15	25	25	100
TS	20	18	50	50	120
DA	10	10	14	14	80

According to Eq. (4.13), the total cost indicator without interactions can be evaluated as:

$$\begin{aligned} C_{tot} = \sum_{j \in \{PO,TS,DA\}} & \Big[FC_j + c_j + NRC_j \cdot p_{Y_j} \cdot \left(1 - \beta_{Y_j}\right) + URC_j \cdot \left(1 - p_{Y_j}\right) \cdot \alpha_{Y_j} \\ & + NDC_j \cdot p_{Y_j} \cdot \beta_{Y_j}\Big] = 88.48 \text{ €} \end{aligned} \tag{4.47}$$

In the presence of interaction between model variables, the total cost indicator can be evaluated by using Eq. (4.38) and considering the cost components reported in Table 4.3. As shown in the table, in some circumstances, repairing the output variables together leads to a reduction in costs with respect to repairing the output variables independently, e.g., for *TS* and *PO*, and for *DA* and *PO*. Conversely, in some cases, the cost of the undetected defects is greater than the sum of the individual costs (see *NDC* for *TS*, *DA* and *PO*).

Table 4.3 – Cost estimates related to porosity PO, tensile strength TS and dimensional accuracy DA, when they occur jointly.

Output variables	NRC [€]	URC [€]	NDC [€]
TS and *PO*	70	70	220
DA and *PO*	35	35	180
DA and *TS*	64	64	200
TS, *DA* and *PO*	80	80	350

The average costs $\overline{NRC}$, $\overline{URC}$ and $\overline{NDC}$ can be calculated according to Eqs. (4.42), (4.43) and (4.44), by averaging the related cost components reported in Table 4.3. As a result, the following costs are obtained: $\overline{NRC} = \overline{URC} = 62.25$ € and $\overline{NDC} = 237.5$ €.

Furthermore, the probabilities p_{NR}, p_{UR} and p_{ND} can be obtained by using Eqs. (4.39), (4.40) and (4.41), as follows:

$$\begin{aligned} p_{NR} = {} & (p_{PO} - p_{TS\cap PO} - p_{DA\cap PO} - p_{TS\cap DA\cap PO}) \cdot (1 - \beta_{PO}) \\ & + (p_{TS} - p_{TS\cap PO} - p_{DA\cap TS} - p_{TS\cap DA\cap PO}) \cdot (1 - \beta_{TS}) \\ & + (p_{DA} - p_{DA\cap PO} - p_{DA\cap TS} - p_{TS\cap DA\cap PO}) \cdot (1 - \beta_{DA}) \\ & + p_{TS\cap PO} \cdot (1 - \beta_{TS} \cdot \beta_{PO}) + p_{DA\cap PO} \cdot (1 - \beta_{DA} \cdot \beta_{PO}) \\ & + p_{DA\cap TS} \cdot (1 - \beta_{DA} \cdot \beta_{TS}) + p_{TS\cap DA\cap PO} \\ & \cdot (1 - \beta_{TS} \cdot \beta_{DA} \cdot \beta_{PO}) = 5.48\% \end{aligned} \tag{4.48}$$

$$\begin{aligned} p_{UR} = {} & (1 - p_{PO}) \cdot \alpha_{PO} + (1 - p_{TS}) \cdot \alpha_{TS} + (1 - p_{DA}) \cdot \alpha_{DA} \\ & - (1 \\ & - (p_{PO} + p_{TS} + p_{DA} - p_{TS\cap PO} - p_{DA\cap PO} - p_{DA\cap TS} \\ & + p_{TS\cap DA\cap PO})) \cdot (\alpha_{TS} \cdot \alpha_{DA} \cdot \alpha_{PO}) = 9.75\% \end{aligned} \tag{4.49}$$

$$\begin{aligned} p_{ND} = {} & p_{PO} \cdot \beta_{PO} + p_{TS} \cdot \beta_{TS} + p_{DA} \cdot \beta_{DA} - (p_{TS\cap PO} \cdot \beta_{TS} \cdot \beta_{PO}) \\ & - (p_{DA\cap PO} \cdot \beta_{DA} \cdot \beta_{PO}) - (p_{DA\cap TS} \cdot \beta_{DA} \cdot \beta_{TS}) \\ & + (p_{TS\cap DA\cap PO} \cdot \beta_{TS} \cdot \beta_{DA} \cdot \beta_{PO}) = 0.17\% \end{aligned} \tag{4.50}$$

Finally, considering that no interaction between the costs c_j occurs because the inspection activities are performed separately, the weight I_{c_j} can be considered equal to one for all the output variables, i.e. $I_{c_j} = 1, \forall\, j \in \{PO, TS, DA\}$. Besides, since the output variables *PO* and *DA* are affected by the same input variables of *TS*, their fixed cost should not be considered in order not to count the same cost twice. Thus, $I_{FC_{PO}} = I_{FC_{DA}} = 0$, while $I_{FC_{TS}} = 1$.

Accordingly, the total cost indicator becomes:

$$C'_{tot} \approx \sum_{j \in \{PO,TS,DA\}} (I_{FC_j} \cdot FC_j + I_{c_j} \cdot c_j) + \overline{NRC} \cdot p_{NR} + \overline{URC} \cdot p_{UR} + \overline{NDC} \cdot p_{ND} = 72.88\ € \tag{4.51}$$

As can be seen from Eqs. (4.47) and (4.51), the total cost indicator calculated in the presence of interactions between variables and costs, C'_{tot}, is about 18% lower than the indicator which does not take the interactions into account, C_{tot}. The reason for such a difference is that, by decoupling the output variables, any joint effects between the variables are not addressed.

4.3 Uncertainty evaluation of performance measures[4]

The reliability of the two indicators of inspection strategy performance, for both cases, i.e., in-process and offline inspections, can be assessed by providing a quantitative evaluation of the variability of their estimates. The approach that can be used to this aim is the method based on the evaluation of uncertainty given in the GUM (Guide to the expression of Uncertainty in Measurement) (JCGM 100:2008, 2008). According to this approach, the uncertainty affecting all the model variables, i.e., probabilities of occurrence of defects, inspection errors, and costs, can be combined and propagated to the resulting indicators D_{tot} and C_{tot} (JCGM 100:2008, 2008; Ver Hoef, 2012). A detailed description and implementation of the method for in-process inspections is provided in the recent study of the author (Galetto, Verna, Genta, et al., 2020). Accordingly, the uncertainty, expressed in terms of variance, *VAR*, of the indicators of effectiveness and total cost for in-process inspections is, respectively:

$$VAR(D_{tot}) = \sum_{i=1}^{m} [\beta_i^2 \cdot VAR(p_i) + p_i^2 \cdot VAR(\beta_i)] \tag{4.52}$$

$$\begin{aligned} VAR(C_{tot}) \approx \sum_{i=1}^{m} [&(NRC_i - NRC_i \cdot \beta_i - URC_i \cdot \alpha_i + NDC_i \cdot \beta_i)^2 \cdot VAR(p_i) + \\ &+(URC_i - URC_i \cdot p_i)^2 \cdot VAR(\alpha_i) + (-NRC_i \cdot p_i + NDC_i \cdot p_i)^2 \cdot VAR(\beta_i) + VAR(c_i) + \\ &+(p_i - p_i \cdot \beta_i)^2 \cdot VAR(NRC_i) + (\alpha_i - p_i \cdot \alpha_i)^2 \cdot VAR(URC_i) + (p_i \cdot \beta_i)^2 \cdot VAR(NDC_i)] \end{aligned} \tag{4.53}$$

On the other hand, the uncertainty of the indicators of effectiveness and total cost for offline inspections is, respectively:

$$VAR(D_{tot}) = \sum_{j=1}^{n} \left[\beta_{Y_j}^2 \cdot VAR\left(p_{Y_j}\right) + p_{Y_j}^2 \cdot VAR\left(\beta_{Y_j}\right)\right] \tag{4.54}$$

[4] Part of the present Section was also published in Galetto M., Verna E., Genta G., and Franceschini F. (2020). "Uncertainty Evaluation in the Prediction of Defects and Costs for Quality Inspection Planning in Low-Volume Productions." *The International Journal of Advanced Manufacturing Technology* 108 (11), 3793–3805.

$$
\begin{aligned}
VAR(C_{tot}) \approx \sum_{j=1}^{n} \Big[& \left(NRC_{\mathrm{j}} - NRC_{\mathrm{j}} \cdot \beta_{Y_j} - URC_{\mathrm{j}} \cdot \alpha_{Y_j} + NDC_{\mathrm{j}} \cdot \beta_{Y_j}\right)^2 \cdot VAR\left(p_{Y_j}\right) + \\
& \left(URC_{\mathrm{j}} - URC_{\mathrm{j}} \cdot p_{Y_j}\right)^2 \cdot VAR\left(\alpha_{Y_j}\right) + \left(-NRC_j \cdot p_{Y_j} + NDC_j \cdot p_{Y_j}\right)^2 \cdot VAR\left(\beta_{Y_j}\right) + VAR(FC_j) + VAR(c_j) \\
& + \left(p_{Y_j} - p_{Y_j} \cdot \beta_{Y_j}\right)^2 \cdot VAR(NRC_j) + \left(\alpha_{Y_j} - p_{Y_j} \cdot \alpha_{Y_j}\right)^2 \cdot VAR(URC_j) + \left(p_{Y_j} \cdot \beta_{Y_j}\right)^2 \cdot VAR\left(NDC_{Y_j}\right) \Big]
\end{aligned}
\tag{4.55}
$$

It should be noted that the uncertainty of probabilities of occurrence of defective workstation-output can be obtained, with reference to in-process inspections, by composing the uncertainties of the defect prediction models' parameters (see Section 3.3). On the other hand, when considering offline inspections, the uncertainty of the probabilities of occurrence of defective-output variables can be estimated by using, for instance, simulative methods, and then composed with the uncertainty affecting the other random variables according to Eqs. (4.54) and (4.55).

Chapter 5 : Practical tools for supporting inspection planning

Several tools and methods have been proposed in the literature to support the inspection planning in mass productions. These include simulations (Neu et al., 2002, 2003; Münch et al., 2002), cost-benefit models (Savio, 2012), optimization and mathematical programming models (Hanne and Nickel, 2005; Shiau, 2003; Mohammadi et al., 2015). However, in the case of low-volume productions, such techniques may not be appropriate. In previous chapters, suitable models of defect prediction have been developed and methods to assess the performance of inspection strategies have been proposed, both for in-process and offline inspections. Despite this research enhancements, a practical tool allowing for the assessment of the adequacy of alternative inspection strategies is still lacking. To fill this gap, Chapter 5 provides new insight into the understanding of the inspection planning process by proposing a general framework to assess the effectiveness and cost of inspection strategies. The defect prediction models proposed in Chapter 3 and the practical indicators of inspection effectiveness and cost, that were described in Chapter 4, are now combined to develop a novel tool, named Inspection Strategy Map (ISM). Two are the main purposes of ISM:

(i) analyzing the positioning of different inspection strategies on the map, in terms of effectiveness and cost, allowing the designer to compare more alternatives (analysis tool);
(ii) supporting the designer in determining the conditions of effectiveness and cost to allow *a priori* inspection strategy positioning.

The framework tool proposed in this chapter is applied to (i) the low-volume assembly of wrapping machines, regarding in-process inspections, and (ii) the additive manufacturing process of SLM, as regards offline inspections.

This tool may provide an opportunity to advance the understanding of the inspection planning process, especially for low-volume productions where traditional techniques are not exploitable. By ISM, engineers are driven to identify alternative inspection procedures in order to make the inspection strategy more effective and cost-efficient.

In detail, Chapter 5 has been organized in the following way:

- Section 5.1 presents and discusses the novel tool, i.e., the Inspection Strategy Map.
- Section 5.2 describes different applications of ISM to the case study of assembly of wrapping machines and the additive manufacturing productions of automotive components.

5.1 Inspection Strategy Maps (ISM)[5]

As presented in Chapter 4, for each inspection strategy, whether in-process or offline, to be assessed and compared, two performance measures may be calculated by Eqs. (4.4) and (4.5) for in-process inspections and by Eqs. (4.18) and (4.38) for offline inspections. According to the scientific literature about Multi-Criteria Decision-Making (MCDM), several methods may be implemented to choose from different alternatives when multiple criteria and trade-offs are involved (Zeleny, 2011; Guo and Zhao, 2017; Ishizaka and Nemery, 2013; Bhushan and Rai, 2007). In the present study, a more straightforward and practical methodology is proposed to support quality inspection planning by Inspection Strategy Maps (ISMs). ISMs are defined on a plan whose axes are the two indicators D_{tot} and C_{tot} (see Figure 5.1). Each inspection strategy may be described by a point on the ISM.

A pair of thresholds (respectively D^*_{tot} and C^*_{tot}) defined by the designer limits the values of the two indicators. D^*_{tot} can be seen as a guarantee for the consumer because it represents the maximum average number of acceptable defective-workstation output remaining in the final product. The second threshold, C^*_{tot}, is a cost limit for the company, i.e. the maximum cost that the producer is willing to pay for the inspection strategy. Then, the following rules can be used to support inspection designers in the choice of the most appropriate inspection strategy according to their requirements.

For each s-th inspection strategy (where $s = 1,\dots, k$), a comparison between the upper limit of the 95% confidence interval of $D_{tot,s}$ and $C_{tot,s}$, identified as $D^U_{tot,s}$ and $C^U_{tot,s}$, is made with the thresholds D^*_{tot} and C^*_{tot}:

[5] Part of the research addressed in this section is also present in the paper Verna E., Genta G., Galetto M., and Franceschini F. (2020d). "Inspection planning by defect prediction models and inspection strategy maps for low-volume productions" Submitted to *Flexible Services and Manufacturing Journal*.

1) if $D^{U}_{tot,s} < D^*_{tot}$ and $C^{U}_{tot,s} < C^*_{tot}$, the strategy may be selected: the strategy is therefore in the acceptance region (see Figure 5.1);
2) if $D^{U}_{tot,s} > D^*_{tot}$ or $C^{U}_{tot,s} > C^*_{tot}$, the strategy is located in the rejection region (see Figure 5.1).

If more strategies lie in the acceptance region, and therefore their values of D_{tot} and C_{tot} are below the imposed thresholds, the designer can decide which strategy should be adopted. The preferred strategy is the one that minimizes both D_{tot} and C_{tot}. However, if among the alternatives no strategy minimizes both indicators, the designer can choose whether minimizing one or the other. Such choice strictly depends on the product specifications and on the certification constraints imposed by the product application sector. For example, in medical or aerospace sectors, the producer may be more inclined to select the strategy that minimizes D_{tot} instead of choosing the most cost-efficient one, because of the significant consequences external failures could have. Conversely, if the specifications are not so stringent, the manufacturer may be driven to choose the most economical strategy.

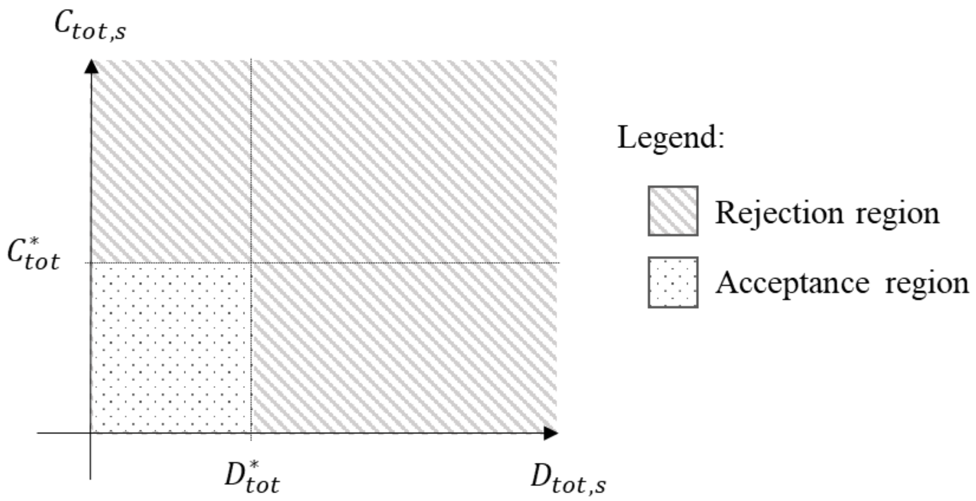


Figure 5.1 - Schematic representation of an Inspection Strategy Map.

The first aim of an ISM is to enable the analysis and positioning of the inspection strategies implemented by a manufacturing company. Indeed, according to a cost-benefit logic, the combined use of the inspection indicators and their uncertainty allows the positioning of alternative inspection strategies into the map and, consequently, designers are guided in choosing the most appropriate one. ISM may also be adopted to compare more alternative inspection strategies, such as partial inspections in selected workstations, or strategies in which current control activities are modified or improved. Apart from being an analysis tool, the ISM can also be used as a design tool. In other words, by setting an objective point on the map, it is possible to determine which conditions of effectiveness and cost may guarantee its achievement. Thus, ISM can represent a powerful and practical decision tool to assist the inspection designers in quality assessment and improvement. An example of the use of ISM for both functionalities is discussed in the next Section 5.2.

5.2 Application of ISM to real low-volume productions

In this section, the proposed ISM is applied to two case studies concerning in-process inspections and offline inspections, respectively, in Section 5.2.1 and 5.2. In the former, the low-volume production of wrapping machines is considered. The defects prediction models that have been described in Section 3.3 are incorporated in this decision support tool with the purpose of selecting the most suitable inspection strategy among several alternatives. On the other hand, the defect prediction model developed for offline inspection in Section 3.4 is combined with the inspection performance measures defined in Section 4.2 and applied to an automotive low-volume production by SLM process.

5.2.1 In-process inspections: wrapping machines assembly[6]

5.2.1.1. Inspection strategies positioning using the ISM

The two inspection strategy indicators of effectiveness and total cost developed for in-process inspections are evaluated for the current inspection strategy, denoted as IS-0, performed by the producer of wrapping machines, which is detailed in Table 5.1. Such a strategy requires each workstation to be checked through an inspection activity, needing specific equipment depending on the workstation-output (see Table 5.1). Table 5.2 reports the cost values used for estimating inspection total cost. Precisely, the estimates of c_i were calculated considering the time required for the inspection activity and the labor cost of operators/inspectors. NRC_i and URC_i, considered identical as a first approximation, were estimated starting from the time required for identifying and repairing possible defects (necessary or unnecessary) and the respective labor cost. Finally, NDC_i was estimated considering the after-sales repair costs, calculated as the time for the repairs/substitutions and the operator labor costs. Table 5.2 also summarizes the probabilities of occurrence of defect in each workstation, obtained by using the novel prediction model developed in Section 3.3 (see Eq. (3.15)).

[6] Part of the research addressed in this section is also present in the paper Verna E., Genta G., Galetto M., and Franceschini F. (2020d). "Inspection planning by defect prediction models and inspection strategy maps for low-volume productions" Submitted to *International Journal of Advanced Manufacturing and Technology*.

Table 5.1 - Current inspection strategy of the pre-stretching device: description of the controls performed in the workstations and the equipment used.

No. workstation	Control type	Control description	Equipment
1	Visual and manual	Cleaning of motor shaft 1, alignment of groups pulley-motor shaft 1 and clamping ring-motor shaft 1	Hands
2	Visual, manual and dimensional	Cleaning of motor shaft 2, correct dimensions of the groups shrink disk-crankshaft 2 and pulley-crankshaft 2	Hands, caliper, bench vice
3	Visual and manual	Surface cleaning of motor support plate 2 and correct assembly of the upper and lower plate	Hands
4	Visual, manual and mechanical	Presence of all the components for the spindle subassembly and spindle spring operation	Hands
5	Visual, manual and mechanical	Cleaning of the wheeled roller shaft and correct rotation of the wheeled roller assembly	Hands
6	Visual, manual and mechanical	Cleaning of idle rolls shaft and correct rotation of idle rollers assembly	Hands
7	Visual and geometric	Correct positioning of the rubber pad assembly 1 and 2 and hexagonal support of the rubber pad assembly 1 and 2	Hands
8	Visual and mechanical	Alignment of the belt tensioning device group and correct rotation of the belt tensioning device roller	Hands
9	Visual and mechanical	Penetration of the protective on the surface of the driven wheels and correct positioning of the clamping rings in the transmission-driven wheels	Hands
10	Visual	Aesthetic appearance of the surface plate of the pre-stretch frame	Hands
11	Mechanical and geometric	Correct rotation of the rubber rolls and alignment of the rubber rollers on the pre-stretch frame plate	Hands
12	Mechanical and geometric	Correct idle roller rotation and alignment of the idle rollers on the pre-stretch frame plate	Hands
13	Mechanical	Correct tightening of the motor bolts 1 on the frame plate	Hands
14	Visual	Correct positioning of the components	Hands
15	Visual and mechanical	Correct tightening of motor bolts 2 on the frame plate	Hands
16	Visual	Correct positioning of components	Hands
17	Visual	Correct positioning of the motor casing 1	Hands
18	Mechanical and geometric	Correct alignment of the belt tensioner assembly and rotation of the belt tensioning device roller	Hands
19	Mechanical and geometric	Movement of the motor drive belt 1	Hands
20	Mechanical and geometric	Movement of the motor drive belt 2	Hands
21	Visual and mechanical	Check the number of screws removed from the component and correct operation of the internal spindle spring	Hands
22	Mechanical and geometric	Correct spindle rotation on the pre-stretch frame plate and alignment of the spindle assembly on the pre-stretch frame plate	Hands
23	Geometric	Correct alignment of the pads on the pre-stretch frame plate	Hands
24	Manual and mechanical	Correct operation of the motor 1, final check of the motor 1 drive belt tension and final alignment check of the motor 1 transmission assembly	Hands
25	Manual and mechanical	Correct operation of the motor 2, final check of the motor 2 drive belt tension and final alignment check of the motor 2 transmission assembly	Hands
26	Visual and mechanical	Alignment and correct movement of spindle release lever assembly	Hands
27	Mechanical and geometric	Correct movement and alignment of the spindle release lever on the pre-stretch frame plate	Hands
28	Visual, geometric, mechanical and dimensional	Correct rotation of the compensation arm roller and alignment of the cam system	Hands, caliper, metallic ruler, Gauge block
29	Visual and mechanical	Correct movement of the compensation arm assembly on the pre-stretch frame plate and correct rotation of the compensation arm roller	Hands

Table 5.2 - Variables related to the inspection strategy IS-0 of the pre-stretching device.

No. workstation	p_i [%]	α_i [%]	β_i [%]	c_i [€]	NRC_i [€]	URC_i [€]	NDC_i [€]
1	4.16	0.5	0.8	0.12	0.37	0.37	1584.00
2	4.34	0.5	0.8	0.32	0.73	0.73	1592.00
3	3.86	0.3	0.5	0.25	0.37	0.37	87.00
4	0.62	0.2	0.5	0.76	0.86	0.86	569.00
5	5.71	0.4	0.8	0.56	2.02	2.02	483.00
6	4.67	0.4	0.8	0.45	2.20	2.20	273.00
7	0.55	0.1	0.1	0.14	0.18	0.18	11.00
8	3.23	0.3	1.0	0.04	0.75	0.75	31.00
9	0.02	0.4	0.6	0.08	0.09	0.09	47.00
10	2.68	0.5	0.3	1.06	1.83	1.83	224.00
11	3.64	0.2	0.2	0.29	0.15	0.15	11.67
12	4.02	0.2	0.2	0.27	0.15	0.15	17.50
13	0.57	0.3	0.3	0.26	0.05	0.05	8.75
14	0.13	0.4	0.8	0.10	0.37	0.37	66.00
15	3.86	0.3	0.3	0.31	0.12	0.12	5.83
16	1.38	0.4	0.8	0.17	0.37	0.37	99.00
17	0.07	0.2	0.2	0.13	0.02	0.02	6.00
18	2.12	0.5	0.9	0.10	0.02	0.02	5.83
19	3.33	0.2	0.2	0.37	0.05	0.05	5.83
20	3.63	0.2	0.2	0.35	0.10	0.10	5.83
21	0.26	0.5	0.7	0.32	0.18	0.18	5.83
22	6.09	0.5	0.7	0.91	0.29	0.29	11.67
23	0.28	0.2	0.2	0.04	0.07	0.07	5.83
24	1.82	0.5	1.2	0.08	0.43	0.43	5.83
25	1.84	0.5	1.2	0.12	0.43	0.43	5.83
26	0.09	0.3	0.3	0.29	0.56	0.56	25.00
27	1.38	0.2	0.2	0.34	0.09	0.09	5.83
28	8.00	0.8	1.2	0.26	0.31	0.31	106.00
29	0.78	0.5	0.5	0.17	0.07	0.07	5.83

Moreover, the estimates of the inspection performances are complemented by an estimation of their uncertainty. To this aim, Table 5.3 reports the estimates of the variances of the probabilities and costs of the model. Specifically, the variance of probabilities p_i is obtained by composing the uncertainties of the two regression models parameters shown in Eq. (3.15) by using the approach proposed in Verna et al. (2020). Besides, the variances of inspection errors (α_i and β_i) and the costs (c_i, NRC_i, URC_i and NDC_i) are estimated by the inspectors based on previous experience.

Table 5.3 - Variances of the variables related to the process and the current inspection strategy of the pre-stretching device (IS-0).

No. workstation	$VAR(p_i)$ ($\times 10^{-4}$)	$VAR(\alpha_i)$ ($\times 10^{-7}$)	$VAR(\beta_i)$ ($\times 10^{-7}$)	$VAR(c_i)$ ($\times 10^{-4}$) [€^{2}]	$VAR(NRC_i)$ ($\times 10^{-4}$) [€^{2}]	$VAR(URC_i)$ ($\times 10^{-4}$) [€^{2}]	$VAR(NDC_i)$ ($\times 10^{1}$) [€^{2}]
1	3.30	0.63	1.60	0.36	3.42	3.42	2.50
2	3.29	0.63	1.60	2.56	13.32	13.32	2.50
3	3.35	0.23	0.63	1.56	3.42	3.42	1.89
4	3.40	0.10	0.63	14.44	18.49	18.49	2.50
5	3.38	0.40	1.60	7.84	102.01	102.01	2.50
6	3.27	0.40	1.60	5.06	121.00	121.00	2.50
7	3.40	0.03	0.03	0.49	0.81	0.81	0.03
8	3.39	0.23	2.50	0.04	14.06	14.06	0.24
9	3.33	0.40	0.90	0.16	0.20	0.20	0.55
10	3.43	0.63	0.23	28.09	83.72	83.72	2.50
11	3.34	0.10	0.10	2.10	0.56	0.56	0.03
12	3.30	0.10	0.10	1.82	0.56	0.56	0.08
13	3.42	0.23	0.23	1.69	0.06	0.06	0.02
14	3.34	0.40	1.60	0.25	3.42	3.42	1.09
15	3.33	0.23	0.23	2.40	0.36	0.36	0.01
16	3.48	0.40	1.60	0.72	3.42	3.42	2.45
17	3.34	0.10	0.10	0.42	0.01	0.01	0.01
18	3.48	0.63	2.03	0.25	0.01	0.01	0.01
19	3.42	0.10	0.10	3.42	0.06	0.06	0.01
20	3.41	0.10	0.10	3.06	0.25	0.25	0.01
21	3.36	0.63	1.23	2.56	0.81	0.81	0.01
22	3.49	0.63	1.23	20.70	2.10	2.10	0.03
23	3.36	0.10	0.10	0.04	0.12	0.12	0.01
24	3.55	0.63	3.60	0.16	4.62	4.62	0.01
25	3.55	0.63	3.60	0.36	4.62	4.62	0.01
26	3.34	0.23	0.23	2.10	7.84	7.84	0.16
27	3.46	0.10	0.10	2.89	0.20	0.20	0.01
28	4.48	1.60	3.60	1.69	2.40	2.40	2.50
29	3.42	0.63	0.63	0.72	0.12	0.12	0.01

Table 5.4 shows the indicators of effectiveness D_{tot} and total cost C_{tot} calculated according to Eqs. (4.4) and (4.5) and variable estimates listed in Table 5.2. Furthermore, the 95% confidence intervals of the indicator estimates are provided in Table 5.4, according to Eqs. (4.52) and (4.53) and variable uncertainties reported in Table 5.3.

Table 5.4 - Mean values and 95% confidence intervals of inspection performance indicators D_{tot} and C_{tot} for inspection strategies IS-0, IS-1 and IS-2.

Inspection strategy	D_{tot} (×10^{-3})	95% confidence interval of D_{tot} (×10^{-3})	C_{tot} [€]	95% confidence interval of C_{tot} [€]
IS-0	4.80	(3.45; 6.15)	10.74	(9.95; 11.53)
IS-1	378.61	(217.32;539.91)	10.13	(7.43;12.83)
IS-2	1.51	(0.64;2.37)	11.41	(11.08;11.75)

As can be observed in Table 5.4, the mean number of defective-workstation-outputs which are not detected by the adopted inspection strategy, is nearly 5 units, considering a production of one thousand pre-stretching devices. As mentioned before, being the production of such devices of only 50 units per year, the number of defective-workstation-outputs that are erroneously not identified by the inspection strategy may be considered very little, i.e. 5 every 20 years. Moreover, by separately comparing the D_i values, the most critical workstations in terms of residual defectiveness may be identified. In particular, the workstations with the highest values of D_i are the number 28, 5 and 24, respectively. For these workstations, the producer could design and adopt more effective inspection activities (see next Section 5.2.1.2).

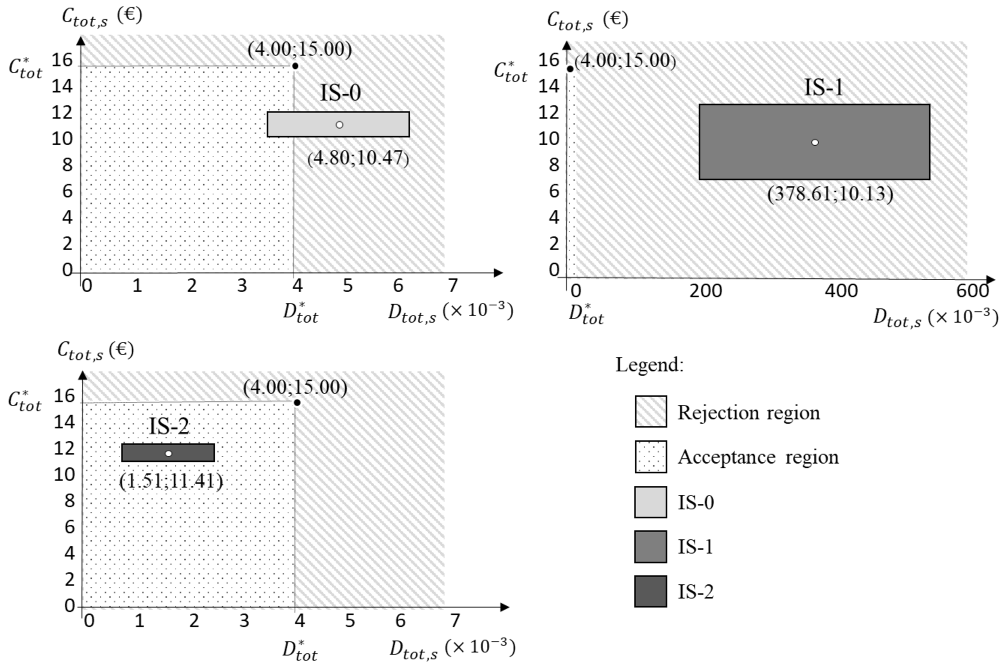


Figure 5.2 - Representation of the ISM for the inspection strategies IS-0, IS-1 and IS-2.

Table 5.5 - Variables related to the inspection strategy IS-1 of the pre-stretching device. Workstations subject to inspection are reported in bold type.

No. workstation	α_i [%]	β_i [%]	c_i [€]	NRC_i [€]	URC_i [€]	NDC_i [€]
1	0.5	0.8	0.12	0.37	0.37	1584.00
2	0.5	0.8	0.32	0.73	0.73	1592.00
3	0.3	0.5	0.25	0.37	0.37	87.00
4	0.2	0.5	0.76	0.86	0.86	569.00
5	0.4	0.8	0.56	2.02	2.02	483.00
6	0.4	0.8	0.45	2.20	2.20	273.00
7	0.0	100.0	0.00	0.00	0.00	11.00
8	0.0	100.0	0.00	0.00	0.00	31.00
9	0.0	100.0	0.00	0.00	0.00	47.00
10	0.5	0.3	1.06	1.83	1.83	224.00
11	0.0	100.0	0.00	0.00	0.00	11.67
12	0.0	100.0	0.00	0.00	0.00	17.50
13	0.0	100.0	0.00	0.00	0.00	8.75
14	0.4	0.8	0.10	0.37	0.37	66.00
15	0.0	100.0	0.00	0.00	0.00	5.83
16	0.4	0.8	0.17	0.37	0.37	99.00
17	0.0	100.0	0.00	0.00	0.00	6.00
18	0.0	100.0	0.00	0.00	0.00	5.83
19	0.0	100.0	0.00	0.00	0.00	5.83
20	0.0	100.0	0.00	0.00	0.00	5.83
21	0.0	100.0	0.00	0.00	0.00	5.83
22	0.0	100.0	0.00	0.00	0.00	11.67
23	0.0	100.0	0.00	0.00	0.00	5.83
24	0.0	100.0	0.00	0.00	0.00	5.83
25	0.0	100.0	0.00	0.00	0.00	5.83
26	0.0	100.0	0.00	0.00	0.00	25.00
27	0.0	100.0	0.00	0.00	0.00	5.83
28	0.8	1.2	0.26	0.31	0.31	106.00
29	0.0	100.0	0.00	0.00	0.00	5.83

Regarding the economic perspective, considering that the total cost of the pre-stretching device, including labor costs and materials, amounts to 3000 €, the cost of the current inspection strategy is less than 1%. Even for this indicator, individual $C_{tot,i}$ values can be compared with each other to identify the most expensive workstations (in this case, numbers 5, 10 and 22 respectively). Therefore, the inspection in the workstation 5 is not only the worst in terms of effectiveness, but it is also the most expensive for the company. It should be noted that such a workstation is also the one with the highest value of p_i. As a consequence, due to the high number of defects, the sum of the cost components related to the repair $(NRC_i \cdot p_i \cdot (1 - \beta_i))$ and to the defects remaining in the pre-stretching device $(NDC_i \cdot p_i \cdot \beta_i)$ are higher than those in the other workstations.

As shown in Figure 5.2, for the pre-stretching device the two thresholds imposed by the company designer are $D^*_{tot} = 4.00 \cdot 10^{-3}$ and $C^*_{tot} = 15$ €. IS-0 is represented in Figure 5.2 as a region delimited by the confidence intervals of both indicators, while the central point of the region corresponds to their average value. It can be noted that IS-0 region belongs only for a small part to the acceptance region and the central point falls in the rejection region. Thus, being this strategy not acceptable by the producer, two alternative strategies are analyzed: IS-1 (Inspection Strategy 1) and IS-2 (Inspection Strategy 2).

Table 5.6 - Variables related to the inspection strategy IS-2 of the pre-stretching device. Workstations accurately inspected by appointed staff through dedicated equipment are reported in bold type.

No. workstation	α_i [%]	β_i [%]	c_i [€]	NRC_i [€]	URC_i [€]	NDC_i [€]
1	0.07	0.10	0.17	0.37	0.37	1584.00
2	0.07	0.10	0.43	0.73	0.73	1592.00
3	0.04	0.07	0.34	0.37	0.37	87.00
4	0.03	0.07	1.03	0.86	0.86	569.00
5	0.04	0.08	0.76	2.02	2.02	483.00
6	0.04	0.08	0.60	2.20	2.20	273.00
7	0.10	0.10	0.14	0.18	0.18	11.00
8	0.30	1.00	0.04	0.75	0.75	31.00
9	0.40	0.60	0.08	0.09	0.09	47.00
10	0.50	0.30	1.06	1.83	1.83	224.00
11	0.03	0.03	0.39	0.15	0.15	11.67
12	0.20	0.20	0.27	0.15	0.15	17.50
13	0.04	0.04	0.35	0.05	0.05	8.75
14	0.05	0.10	0.13	0.37	0.37	66.00
15	0.04	0.04	0.41	0.12	0.12	5.83
16	0.40	0.80	0.17	0.37	0.37	99.00
17	0.20	0.20	0.13	0.02	0.02	6.00
18	0.07	0.12	0.14	0.02	0.02	5.83
19	0.03	0.03	0.50	0.05	0.05	5.83
20	0.03	0.03	0.47	0.10	0.10	5.83
21	0.05	0.07	0.43	0.18	0.18	5.83
22	0.07	0.09	1.23	0.29	0.29	11.67
23	0.20	0.20	0.04	0.07	0.07	5.83
24	0.50	1.20	0.08	0.43	0.43	5.83
25	0.50	1.20	0.12	0.43	0.43	5.83
26	0.30	0.30	0.29	0.56	0.56	25.00
27	0.20	0.20	0.34	0.09	0.09	5.83
28	0.08	0.12	0.35	0.31	0.31	106.00
29	0.07	0.07	0.22	0.07	0.07	5.83

In IS-1, only the workstations whose cost of undetected defects (NDC_i) is considered expensive by the manufacturer (more than 50 €) are reconsidered. In detail, these are the workstations number 1-6, 10, 14, 16 and 28, respectively. Controls performed in such workstations are the same as those adopted in the current strategy IS-0. Accordingly, the inspection variables related to such workstations have the same values of those reported in Table 5.2. For the generic i-th workstation not subject to inspection, the corresponding inspection variables are α_i=0, β_i=1, c_i=0, NRC_i=0 and URC_i=0. The probability p_i and the cost NDC_i do not change compared to IS-0, being not affected by the inspection strategy adopted. Table 5.5 reports the complete list of variables for IS-1.

In IS-2, selected workstations that are critical in terms of defectiveness are accurately inspected through dedicated equipment and carried out by appointed staff. As a result, the cost of inspection activity c_i slightly increases because of an increase in time of 40%, while inspection errors decrease by about 85% with compared to IS-0. The remaining workstations are inspected using the same controls carried out in the current strategy IS-0 and, therefore, the inspection variables for these workstations are set equal to the values of IS-0 shown in Table 5.2. It should be noted that p_i, NRC_i, URC_i and NDC_i remain unchanged from IS-0, being irrespective of the strategy implemented. Table 5.6 provides the complete table of variables for the strategy IS-2.

Table 5.4 shows the mean values of the indicators D_{tot} and C_{tot} of the two alternative inspection strategies IS-1 and IS-2 and their 95% confidence intervals.

5.2.1.2 Comparison and analysis of alternative inspection strategies

Given the results shown in Figure 5.2, the strategy IS-1 is out of the acceptance region. The indicator D_{tot} is about two orders of magnitude higher than the threshold, although C_{tot} is in line with the manufacturer's requirements. Indeed, performing IS-1 leads to a significant increase in the indicator of effectiveness, caused by the non-inspection of selected workstations and, therefore, by leaving defects in the final pre-stretching device. However, the inspection total cost of such a strategy remains affordable and comparable with the cost of the other two strategies because the absence of inspection in the workstations with the lowest values of NDC_i does not entail inspection and repair costs, but only costs of undetected defects, which remain minimal.

Regarding strategies IS-0 and IS-2, the comparison of the corresponding indicators is shown in the ISM illustrated in Figure 5.3.

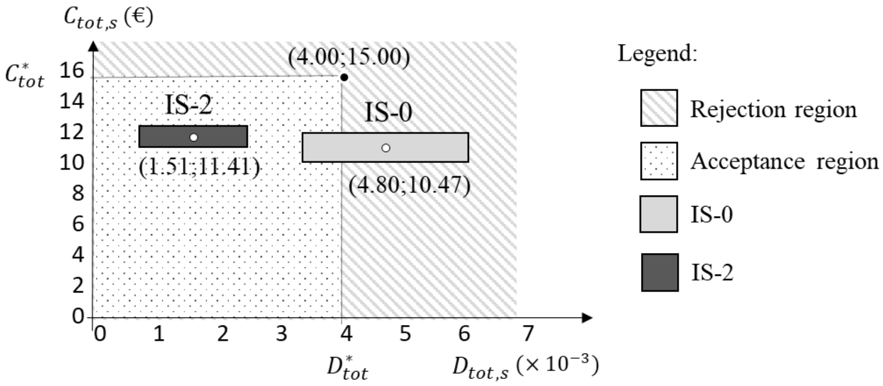


Figure 5.3 – Comparison of the inspection strategies IS-0 and IS-2 using the ISM.

The strategy to be preferred is IS-2. It is the only strategy that allows for a residual defectiveness lower than the threshold D^*_{tot} imposed by the producer. From an economic point of view, both strategies lead to comparable costs, although IS-2 is on average slightly more expensive than IS-0. Besides, as shown in Figure 5.3, inspection indicators D_{tot} and C_{tot} obtained for IS-2 are affected by less uncertainty compared to those obtained for IS-0. Accordingly, the estimates of the two indicators are more accurate for IS-2 than IS-0.

In light of this, since in this case study the higher costs are those of undetected defects, it is advisable choosing an inspection strategy that minimizes them through high-performance inspections, without, however, significantly increasing the costs of inspection activities, as in the case of the strategy IS-2.

5.2.1.3 ISM for designing inspections

ISM can also be used in a reverse way to the approach discussed in Section 5.2.1.2. In other words, when the designer wants to achieve an effectiveness and cost objective, represented by a "target point" on ISM, this tool can guide designer choices. In fact, when the target values of indicators D_{tot} and C_{tot} are known, the conditions for their implementation can be determined. For instance, suppose that the wrapping machines company aims to set as target values of the indicators D_{tot} and C_{tot} respectively $1.00 \cdot 10^{-3}$ and 14 € (IS-3). This situation is represented in Figure 5.4. In order to reach the target point, since probabilities p_i are physiological characteristics of the production process, and being NRC_i, URC_i and NDC_i costs irrespective of the strategy adopted, the sole variables to be addressed are inspection errors α_i and β_i and the costs of inspection activities c_i. A possible strategy involves reducing inspection errors by 80% compared to the strategy IS-0 by improving quality controls in all the workstation (e.g. using dedicated equipment and training inspectors). As a consequence, it is assumed that inspection costs will increase by 50% (see Table 5.7). In this case, the resulting indicators D_{tot} and C_{tot} becomes respectively $0.96 \cdot 10^{-3}$ and 13.76€. It should be noted that, although the cost c_i is increased for all the workstations by 50%, the strategy total cost is approximately 30% higher than that of IS-0 owing to the 80% reduction in both the cost of undetected defects and unnecessary repairs.

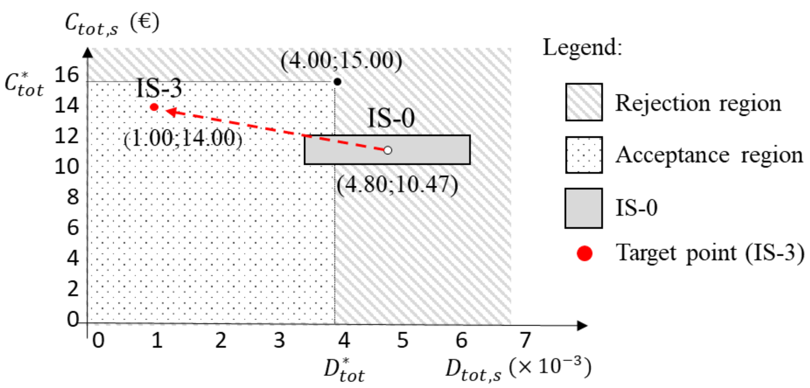


Figure 5.4 - Representation in the ISM of the "target point" (IS-3) to be achieved starting from the condition IS-0.

Table 5.7 - Variables α_i, β_i and c_i related to the inspection strategy IS-3 of the pre-stretching device.

No. workstation	α_i [%]	β_i [%]	c_i [€]
1	0.10	0.16	0.18
2	0.10	0.16	0.48
3	0.06	0.10	0.38
4	0.04	0.10	1.15
5	0.08	0.16	0.84
6	0.08	0.16	0.67
7	0.02	0.02	0.21
8	0.06	0.20	0.06
9	0.08	0.12	0.12
10	0.10	0.06	1.60
11	0.04	0.04	0.43
12	0.04	0.04	0.40
13	0.06	0.06	0.39
14	0.08	0.16	0.15
15	0.06	0.06	0.46
16	0.08	0.16	0.25
17	0.04	0.04	0.20
18	0.10	0.18	0.16
19	0.04	0.04	0.55
20	0.04	0.04	0.52
21	0.10	0.14	0.48
22	0.10	0.14	1.37
23	0.04	0.04	0.06
24	0.10	0.24	0.12
25	0.10	0.24	0.18
26	0.06	0.06	0.44
27	0.04	0.04	0.51
28	0.16	0.24	0.39
29	0.10	0.10	0.25

5.2.2 Offline inspections: Additive Manufacturing[7]

In this section, the case study presented in Section 3.4.2.1 is extended by applying the ISM to select the most suitable inspection strategy among four alternatives.

The AM production of SLM components may be inspected through different offline inspections concerning macro-hardness and roughness evaluations. In this section, four alternative inspection strategies are examined and compared. With respect to hardness, the Brinell Hardness (HB) and Rockwell Hardness (HRB) tests are examined. HB test is a widely used method for characterizing specimens by SLM. The main advantage is the simplicity of implementation, while the main defect is represented by the difficulty (and ambiguity) of the measure (Herrmann, 2011). HRB test is much faster and cheaper than the Brinell test, making this a widely used method of measuring metal hardness in industrial context. However, the considerable practical advantages are accompanied by a loss of metrological

[7] Part of the results discussed in this section are also present in the paper Verna E., Genta G., Galetto M., and Franceschini F. (2020e). "Planning Offline Inspection Strategies in Low-Volume Manufacturing Processes." *Quality Engineering* In press, DOI: 10.1080/08982112.2020.1739309

characteristics (Herrmann, 2011). As far as roughness measurement is concerned, two instruments belonging to two different classes of methods for surface texture measurements, the Line Profiling and the Areal Topography, are considered (Leach, 2011). Specifically, the first instrument is a Contact Stylus (CS) and the second one is a Point Autofocus Instrument (PAI). In CS, the stylus is loaded on the surface to be measured and then moved across the surface at a constant velocity to obtain surface height variation (Leach, 2011). A PAI is a non-contact, optical measuring instrument that automatically focuses a laser beam to a single point on the surface and raster scans an area of interest (Maculotti et al., 2019). Each of the four different methods is characterized by the three probabilities p_{Y_j}, α_{Y_j} and β_{Y_j}, which are reported in Table 5.8.

Table 5.8 - Estimates of defects probabilities, inspection errors, cost parameters and inspection indicators related to each inspection method (HB, HRB, CS and PAI).

Output variable	Inspection method	p_{Y_j} [%]	α_{Y_j} [%]	β_{Y_j} [%]	CF_j [€]	c_j [€]	NRC_j [€]	URC_j [€]	NDC_j [€]	D_{Y_j} (×10^{-5}) [-]	C_{Y_j} [€]
Hardness	HB	0.55	2	1	15	12.5	50	50	100	5.53	28.77
	HRB	0.55	3	2	15	4.2	50	50	100	11.05	20.97
Roughness	CS	0.67	5	4	15	6.3	1.3	1.3	80	26.79	21.39
	PAI	0.67	2	1	15	125	1.3	1.3	80	6.70	140.04

In Table 5.8, hardness defect probabilities (p_{HB} and p_{HRB}) were considered identical and equal to the probability p_{HB} obtained in Eq. (3.36), as well as for roughness defect probabilities (p_{CS} and p_{PAI}), which were set equal to p_{Ra} derived in Eq. (3.37). In fact, as a preliminary approximation, the two different methods for inspecting both hardness and roughness are based on similar technologies with comparable performances in terms of detection of defects. In other words, although p_{HB} and p_{Ra} are strongly dependent on the instrument used, they can be considered good estimates of the actual defectiveness in terms of the order of magnitude. In order to refine the estimates of p_{HRB} and p_{PAI}, future research will be aimed at designing a specific planned experimentation. The inspection errors α_{Y_j} and β_{Y_j} were estimated by the inspectors, for each inspection method, basing on empirical values obtained from similar parts produced with the adopted SLM technique and other manufacturing processes such as casting processes. Table 5.8 also reports the estimates of the cost parameters for each inspection method (HB, HRB, CS and PAI). CF_j was estimated as the cost for calibrating the AM machine carried out by the supplier during the preventive maintenance. The estimates of c_j were calculated considering the time required for the inspection and the labor cost of operators/inspectors. NRC_j and URC_j were estimated starting from the time required for identifying and repairing possible defects (necessary or unnecessary), and the respective labor cost. Finally, NDC_j included external failure costs. According to Eqs. (4.10) and (4.12), the indicators D_{Y_j} and C_{Y_j} were calculated for each inspection method and were reported in Table 5.8. It should be noted that in this case study, the interaction between model variables and costs are, as a first approximation, considered negligible.

By combining the four different inspection methods of Table 5.8, four inspection strategies may be performed (see Table 5.9). The first one, IS-A, includes Brinell hardness test and roughness measurement with the contact stylus CS. The second, IS-B, is performed with a Brinell hardness test and a roughness test using a PAI. ISC requires hardness to be measured with a Rockwell test (HRB) and roughness with the contact stylus CS. Finally, IS-D involves measuring hardness with a Rockwell test (HRB) and roughness using a PAI. Table 5.9 shows the indicators D_{tot} and C_{tot} obtained for the inspection strategies IS-A, IS-B, ISC and IS-D, calculated using respectively Eqs. (4.11) and (4.13). As a first approximation, consider that model variables are not affected by uncertainty and, consequently, the performance indicators are not affected either.

Table 5.9 - Indicators values calculated for IS-A, IS-B, IS-C and IS-D.

Indicator	IS-A	IS-B	IS-C	IS-D
D_{tot} ($\times 10^{-4}$) [-]	3.23	1.22	3.78	1.78
C_{tot} [€]	50.16	168.81	42.36	161.01

The strategy with the lowest value of D_{tot} is IS-B, but it is also the most expensive one. Conversely, ISC has the lowest C_{tot}, but it is characterized by the highest mean total number of undetected defects. IS-A and IS-D are two intermediate strategies between IS-B and IS-C. According to these results, the producer of SLM parts may easily select the best inspection strategy that adequately satisfies its needs by using the ISMs. For example, if the manufacturer is willing to accept on average up to 4 defective output variables undetected every 10000 in order to have a total inspection cost not exceeding 45 €, the best choice is IS-C. This situation is represented in the ISM shown in Figure 5.5.

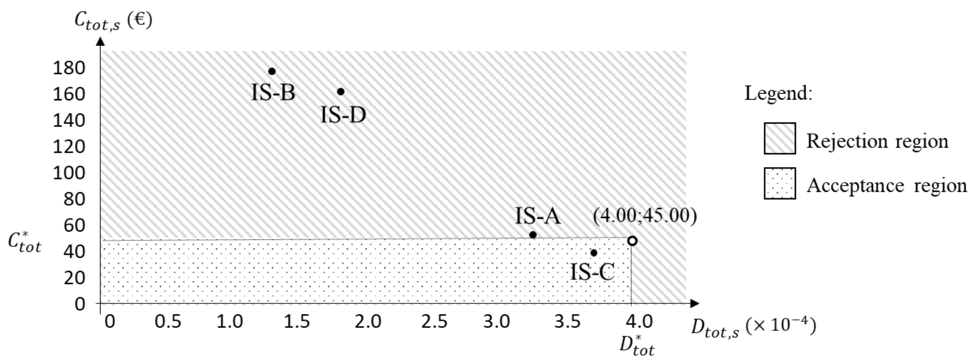


Figure 5.5 - Representation of the ISM for the inspection strategies IS-A, IS-B, IS-C and IS-D, considering the first scenario.

On the contrary, if the objective is the minimization of defects, and in particular the two thresholds imposed by the company designer are $D^*_{tot} = 1.500 \cdot 10^{-4}$ and $C^*_{tot} = 180$ €, the producer will select IS-B, while accepting a quadruple increase in costs with respect to IS-C (see Figure 5.6).

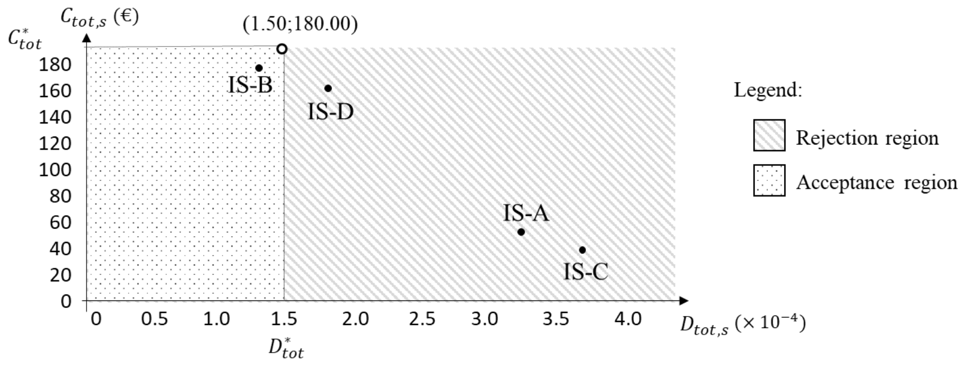


Figure 5.6 - Representation of the ISM for the inspection strategies IS-A, IS-B, IS-C and IS-D, considering the second scenario.

The decision is strictly related to the producer requirements, which are in turn connected with the certification constraints imposed by the product application sectors. For instance, if the component is designed for medical or aerospace sectors, the producer may be more inclined to choose the strategy that minimizes D_{tot}, instead of choosing the most affordable one, because of the considerable consequences that residual defects could have. On the contrary, if the sector requirements are not so stringent, the producer is led to choose the most affordable strategy. However, it should be highlighted that the number of undetected defects in all the four strategies is very small, also considering that it refers to a low-volume production. Indeed, despite in IS-C the indicator D_{tot} is almost three times greater than in IS-B, it means that given a production of 10^4 components, there are nearly 4 defective-output variables which are erroneously not signaled. Since the production of these components can reach a hundred parts per year, the number of defects which are erroneously not signaled is actually very low.

Chapter 6 : Conclusions

The present Doctoral Dissertation was designed to provide new insight into the research field of quality control in low-volume productions for supporting designers during the early phases of the inspection planning. Throughout its chapters, this Dissertation attempted to answer the following three research questions:

> RQ1: Can defects occurring in low-volume production processes be predicted using probabilistic models?
>
> RQ2: How to evaluate the performances of quality inspections in low-volume productions?
>
> RQ3: How to support designers in the early design phases of inspection process planning of low-volume productions?

In this concluding section, the answers to these RQs are provided, summarizing the original contributions of this research, and focusing on the benefits, limitations and possible future developments.

First of all, this Dissertation proposes a detailed analysis of the existing literature on inspection procedures. Starting from the classification proposed in the recent survey of Genta et al. (2020) that subdivided all research studies according to the general characteristics and the modeling structure, this Dissertation moved to describe the two main inspection paradigms that can be identified from the inspection type perspective, i.e., in-process and offline inspections. After having discussed the difference between the two inspection paradigms, a brief review of key research contributions on inspection procedures since the 1960s is proposed, and the emergence and differentiation of the two inspection paradigms are presented. Next, the focus of this Dissertation shifts to recent papers published over the last 20 years, with the purpose of identifying the main research lines that can be distinguished, both addressing in-process and offline inspections. Within this framework, the major reference models identified in the literature for both in-process inspections and offline inspections are then reviewed, highlighting the main advantages and disadvantages of each model. Moreover, an overview of the main research areas covered by the literature on inspection procedures is provided and the major literature gaps are identified. Finally, this Dissertation offers some insight into future research perspectives and challenges that have been identified from the research areas which are not adequately covered by the literature. In particular, the need for accurate defect modeling, as well as the need for greater attention to human skill of inspectors and low-volume productions have been underlined. Accordingly, in the following chapters, this Dissertation has sought to address the issues that have emerged regarding the lack of specific defect generation models for low-volume production and the design of appropriate inspection strategies for this type of production.

After having reviewed the literature on inspection procedures to identify new perspectives, this Dissertation focused on defect generation models in the quality area. In the literature, extensive research has been carried out on the prediction of product defects in the manufacturing field (Antani, 2014; Su et al., 2010; Shibata, 2002; Psarommatis et al., 2020). Furthermore, with the increased digitalization in manufacturing, a huge amount of data can be generated in the overall production process. Accordingly, the generated data sets can now be used by machine learning techniques for analytics of the production process to improve product quality control. However, a review of the main contributions in this field showed that the developed models and approaches had been mostly restricted to mass productions and high-volume production lines. On the contrary, only a limited number of studies was directed to the investigation of defects occurring in low-volume manufacturing processes. In order to address this issue and answer the first research question - RQ1, this Dissertation provided two different defect prediction models suitable for (i) processes decomposable into steps, such as assembly processes, that are inspected through in-process inspections, and (ii) processes in which quality inspections are mainly performed at the end of the production and therefore are mainly offline inspections. The different variables involved in the models have resulted in a different model structure.

Regarding the first category of models, a literature analysis has shown that the most accredited models rely on the close relationship between defects and complexity. Indeed, if assembly complexity is not managed adequately at the early stages of process planning, it can lead to increased assembly time and errors and reduce assembly quality. Following this research line, the first model developed in this Dissertation is based on the novel conceptual paradigm of complexity proposed by Alkan (2019) and Sinha (2014). The predictor of such a model is the structural product complexity formulated by considering both complexities of product elements and effects of product assembly topology. The assembly of wrapping machines was used as a case study for developing and testing this prediction model. This process belongs to the category of low-volume productions (production rate: 50 machines assembled each year). In this situation, identifying an appropriate defect prediction model is essential, being traditional statistical methods not suitable or not applicable. This novel approach was compared with the Shibata-Su model, one of the most accredited in the literature. The comparison between the two models pointed out that, despite the architectural similarities, the novel defect prediction model allows for more accurate and precise estimates of *DPU*. This may depend on the different perspectives used to formulate complexity in the two approaches. In the novel model, product complexity is approached based on objective product characteristics, while an objective perspective is combined with a subjective evaluation provided by experts in the Shibata-Su model. Besides, the objective perspective seems to be preferable as it considers in a combined factor both the complexity due to the process and the design, without separating the two aspects.

Regarding the second category of models, relatively little attention has been paid to the quantification of possible defects occurring in the process when it is optimized. To this aim, the modeling of defects in those processes inspected by offline inspection was proposed by developing a new methodology for estimating the probability of occurrence of defects in the finished product, separately for continuous and discrete input variables. The steps to be followed in the proposed approach for continuous input variables are (i) the definition of input and output variables, (ii) the determination of the mathematical relationship among these variables, (iii) the identification of all the uncertainty contributions, and (iv) the estimation of probabilities of occurrence of defective-output variables. This defect model is applied to an Additive Manufacturing (AM) production in the automotive industry. The selected output variables were macro-hardness and surface roughness. A designed experiment was performed to identify statistically significant process variables and, consequently, the response surface methodology (RSM) provided the mathematical model relating the process variables to the responses. Afterwards, the response surfaces were optimized to obtain the optimal configuration of the process variables. Finally, through the proposed methodology, the probability of occurrence of hardness and roughness defect under optimal working conditions were estimated.

Regarding discrete output variables, the model also relies on the knowledge of the relationships between input and output variables. In detail, the probability of occurrence of defective-output variables can be derived from the probabilities of occurrence of defects in the final product caused by the input variables. An excerpt of application is proposed considering a Selective Laser Melting production again.

By providing a quantitative assessment of output-variables defect probability, the models proposed in this Dissertation can help researchers and practitioners in their understanding of the manufacturing process in terms of defect generation. Furthermore, all the models developed, operatively, have the great potential of supporting inspection designers in the planning of effective quality inspection strategies during the early phases of inspection planning.

The design of quality-inspections for low-volume productions is still a remarkable issue because of the inadequacy of traditional techniques, including cost-benefit models, simulations, optimization models and mathematical programming and optimization models (Neu et al., 2002, 2003; Münch et al., 2002; Hanne and Nickel, 2005; Shiau, 2003; Mohammadi et al., 2015). Accordingly, the second research question - RQ2 - of this Dissertation was addressed by using the aforementioned defect generation models and combine them with inspection variables, including inspection errors and costs, to define two practical performance measures of an inspection strategy. The preliminary study proposed by Franceschini et al. (2018) and Genta et al. (2018) in the field of in-process inspections was extended and adapted to offline inspections. In particular, two practical performance indicators are developed to assist designers in choosing the best compromise between effectiveness and cost of alternative inspection strategies. The method proposed in this Dissertation extends previous studies in the field by considering possible interaction between model variables and costs occurring during the inspection process. A practical application of the method is applied to a real case study in the field of Additive Manufacturing processes. This application highlights the effectiveness of the method in supporting the design team in assessing the effectiveness and cost of an inspection strategy involving a variety of output variables and their interactions.

The method to evaluate inspection performance measures, both for in-process and offline inspections, is complemented with an uncertainty evaluation analysis, by developing a methodology according to the GUM - Guide to the expression of Uncertainty in Measurement - (JCGM 100:2008, 2008).

Finally, this Dissertation presents a novel methodology to support inspection designers in the first stages of inspection planning. Although some preliminary research has been carried out on the design of inspection strategies for low-volume productions, relatively little attention has been paid to the definition of a decision support tool for designers enabling the assessment of the adequacy of alternative inspection strategies. Considering this literature gap, with the purpose to answer the third research question - RQ3, this Dissertation proposes a strategic tool, named Inspection Strategy Map (ISM), able to guide inspection designers in the inspection planning process from the early design phases. The proposed tool relies on defect generation models and uses the pair of practical indicators depicting the effectiveness and total cost of an inspection strategy to map the company's scenario. The ISM represents a powerful tool for (i) enabling positioning assessment and benchmarking of different inspection strategies, and (ii) driving designer choices to achieve desired specification targets.

The proposed tool is very flexible because it is suitable for both in-process and offline inspections. This flexibility allows the ISM to be used in several industrial contexts, making it a very useful tool for inspection designers. To show the validity of the ISM, the methodology is applied to a practical case study concerning the assembly of wrapping machines and an Additive Manufacturing production. In the former, the current inspection strategy performed by the company is compared with potential different inspection alternatives. In the latter, two different scenarios are considered in which four alternative inspection strategies are compared with the aim to show the potential of the ISM tool.

This Dissertation has attempted to provide a deep overview of the quality-inspection strategies and practical tools to support inspection design in low-volume productions. The major limitations of this Dissertation are the following: (i) defect prediction models proposed in Chapter 3 are tested under specific manufacturing field and still require validations on a higher number of different real cases; (ii) performance measures of in-process inspections have not been yet developed considering interactions between variables and costs; (iii) although the tools proposed in Chapter 5 have been tested both in real cases of in-process and offline inspections, further improvements can be made by including variables interactions and uncertainty to enhanced the obtained results.

Although the practical applications proposed in this Dissertation have shown the validity and relevance of the methodologies in different industrial contexts, i.e., in low-volume assembly processes and AM processes, a generalization of the obtained results is still lacking. It is clear that, in the specific case of low volume production systems, the huge variety of possible industrial cases and situations can make the generalization of the proposed approaches a non-trivial problem, also considering that this cannot be achieved within a reasonable time. However, although proof of generalization is missing, the applicability of the proposed models and decision support tools may have general validity. In order to generalize the proposed approaches to different application fields, some modifications might be applied. The defect prediction models developed in Chapter 3 are applicable to any low-volume production, but each model should be tailored to the specific technology, possibly resulting in different model's variables and coefficients. On the other hand, the performance measurements of inspection strategies and the Inspection Strategy Map (ISM) defined in Chapter 4 and 5, respectively, are applicable to any kind of industrial context for which support is required in the quality control planning process. Generally speaking, once the production process and the inspections have been adequately modelled depending on the specific technology and manufacturing field, the proposed approaches for supporting and improving quality control can still be applied without relevant modifications to every industrial application characterized by low-volume production rates.

In light of the results of this Dissertation, several questions can be raised concerning the design of inspections in low-volume productions. In particular, in addition to the issues addressed in the different chapters of this Dissertation, further research is needed to:

(i) examine alternative models involving different predictors both for the approaches developed in the field of in-process and offline inspections. In particular, appropriate machine learning algorithms might be explored for predicting parts quality. In fact, the implementation of these algorithms in the inspection of low volume production systems, as mentioned in Chapter 3, is not yet properly explored, becoming a great opportunity for future research in the field.
(ii) extend the use of the proposed tools and methodologies to real-time monitoring of inspection activities. More in detail, further research should focus on the design and implementation of a general tool, in specific software, to be used in real-time monitoring supervision. Although this tool needs a huge amount of work to be implemented in

each application case, considering the specificities of each of them, the general model could be almost the same.

(iii) expand the research approaches by moving the perspective from product perspective to the overall production process or production system standpoint.

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