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A cost model for the investment feasibility of quality inspection technologies in the Zero Defect Manufacturing era

Joan Lario [a,b], Javier Mateos [a], Foivos Psarommatis [a,c] and Ángel Ortiz [a]

[a]Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València, València, Spain; [b]Departamento de Organización de Empresas, Universitat Politècnica de València (UPV), Valencia, Spain; [c]SIRIUS Labs, University of Oslo, Oslo, Norway

ABSTRACT
The current global market forces companies to focus on suitable manufacturing based on zero defect and zero waste strategies. Higher energy prices and critical raw material supply disruptions stimulate the implementation of non destructive inspection technologies for real-time quality assurance, which aims to increase high-quality products and lower production costs via better materials and energy uses. By embracing these advancements, businesses address market dynamics and strategically position themselves for sustained success in a competitive and resource-conscious world. Traditionally, in small and medium enterprises, new manufacturing or inspection equipment is acquired based on a management decision that is, in turn, based in quality purposes and does not focus deeply on the impact on the final factory cost reduction. This research focuses on developing a costing procedure to incorporate the impact of Non Destructive Inspection Technologies into the multistage cost structure for investment decisions. A case study is presented to demonstrate the applicability of the cost breakdown and return on investment for justifying the investment of the Non Destructive Inspection Technology in additive manufacturing machinery. The proposed cost model provides a framework to preliminary assess the viability of Non Destructive Inspection Technologies investments.

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Non destructive technologies; cost estimation; investment decision; zero defects; zero waste; ZDM

1. Introduction

Economical efforts made to help industries in transitioning toward non destructive testing and zero waste have become a pressing challenge, but a mandatory one when discussing solutions to minimise the impact on the environment in circular economy initiatives (Psarommatis and Kiritsis 2022). Zero Defect Manufacturing (ZDM) is the latest approach for quality assurance and by extent waste minimisation (Psarommatis et al. 2022; Wang et al., 2020). ZDM is composed of four main strategies detect, predict, prevent and repair. The current paper is focusing on the first ZDM strategy the detect, which in other words is the inspection. The inspection can be classified into the physical and virtual detection, the physical detection is the inspection with direct physical access to the product and the virtual is using data from the production to estimate the produced quality without physical access to the part, this approach is communing from the virtual metrology domain (Dreyfus et al. 2022). In this study, the focus is on the physical inspection where the integration of Non Destructive Inspection (NDI) Technologies will optimise production, and reduce energy use and material consumption, by decreasing the amount of destructive testing for quality assurance purposes, while keeping companies on the technological edge (Psarommatis and Bravos 2022). NDI solutions (NDISs) may represent a change in the quality assurance approach, which could have a direct impact on the company´s business economic sustainability. Ideally, implementing NDI systems should result in reduced waste and defects, which are key business objectives for an industrial company. The integration of NDISs is a promising path to achieve European manufacturing excellence (Lindström et al. 2020).

Zero Defect Zero Waste (ZDZW) strategies aim to minimise the number of items that require rework because this does not meet quality standards or must be scrapped given that an inline or in-process inspection is performed during manufacturing (Psarommatis et al. 2020b). ZDZW strategies represent a crucial approach in manufacturing by focusing on the reduction of the items that require rework or face being scrapped because they fail to meet stringent quality standards.

CONTACT Joan Lario jlario@cigip.upv.es Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València, Camino de Vera S/N, 46022, València, Spain; Departamento de Organización de Empresas, Universitat Politècnica de València (UPV), 46022, Valencia, Spain

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This is achieved by implementing inline or in-process inspections throughout the manufacturing process, as highlighted by Psarommatis et al. (2020a) (Psarommatis et al. 2024). The incidence of non conformance items is intricately linked with material consumption and energy use, and is a crucial aspect of operational process sustainability. An inherent goal of NDISs is to reduce the downstream flow of non conformance items during subsequent operations. To effectively achieve this, NDISs must seamlessly be integrated into the manufacturing process by providing robust in-process quality assurance mechanisms, as emphasised by Powell et al. (2022). This integration ensures a comprehensive strategy that identifies and addresses defects promptly and contributes to reducing material and energy waste.

Quality control allows companies to verify products' conformance to requirements and specifications and to, thus, build customer satisfaction and the brand's reputation (Rožanec et al. 2022). Every decade, the burden of products must fulfil customer requirements regarding quality increase, which leads to high personnel costs for making inspections, and no value-adding activity is performed (Tirkel et al. 2016; De Ruyter, Cardew-Hall, and Hodgson 2002). Convention quality inspection policies rely on manual inspections that are made by operators who carry out repetitive tasks, which may lead to errors caused by lack of concentration or fatigue (Connor 1986; SAgnisarman et al. 2019; Nikolaos and Mousavi 2023). The new development of information technologies (IT) and sensors allows manual inspections to be replaced with automatic in-line or in-process NDIs (Psarommatis et al. 2024). These new quality inspection policies aim to reduce personal costs, improve reliability and standardise quality inspection procedures (Reichenstein et al. 2022). Product quality and reliability are important metrics for any manufacturer to consider, such as cost of quality (CoQ), to identify, measure and improve their industrial process to seek to minimise costs and to maximise profits (Farooq et al. 2017; Wudhikarn 2012). The detection of a defective part may occur during manufacturing processes for several reasons, where the process randomly shifts from an in-control state to an out-of-control one (Abdul-Kader, Ganjavi, and Solaiman 2010; Sarkar and Saren 2016; Wan, Chen, and Zhu 2023). For this reason, quality inspection policies are deployed in industry to detect defective parts before being sent to customers. Early defect detection avoids defective items from passing to the next manufacturing steps, which may result in significant losses of time, materials and money (Hauck, Rabta, and Reiner 2022; Rezaei-Malek et al. 2019). Depending on the type of inspection policies, sampling and the customer service level, different costs can be incurred. On a quality inspection based on an acceptance sampling, two types of error can occur: the batch is considered unacceptable while it is acceptable, or the batch is judged acceptable while it is unacceptable. The net profits are reduced when larger samples are employed, employing destructive and non-destructive testing (Al-Salamah 2016; Guha and Bose 2020). The cost of inspection policies is directly related to five main factors: typology of inspection (on-machine, in-process, in-line or off-line), type of inspection (non destructive or destructive), inspected quantity (entire batch or sampling), cycle time and nature of inspection (manual or automatic) (Bose and Guha 2021; Psarommatis et al. 2024).

Industrial companies need to assess the impact of integrating NDI technologies (NDIT) on the manufacturing environment, where topics like payback, first-time right and cost related to labour, material consumption and energy use should be considered (Abdul-Kader, Ganjavi, and Solaiman 2010; Asiedu and Gu 1998). The economic evaluation needs to address the entire potential savings and benefits of NDIT integration for real-time inspections. The present article aims to create the cost model for managers or engineers to quantify savings/costs and quality improvements of the NDIT in the manufacturing environment. It should be noted that top management support involvement is critical for removing barriers by playing a critical role in ensuring that all the information (material and energy consumptions, costs, amortisation, labour, etc.) is available to deploy the cost model.

For the defective parts at upstream manufacturing process levels, the problem posed in the present article is relevant for many companies with several production steps, such as electronics, energy production equipment, or even commodity products. Several studies demonstrated that company profitability can be improved with the integration of a production control model based on quality control, economic production quantity and maintenance policy (Al-Salamah 2016; Guha and Bose 2020; Shojaee et al. 2024). This study investigates the economic impact of a scenario in which the NDIT is integrated into an in-process inspection production process compared to a scenario where inspection is made at End-Of-Line (EOL) by means of an NDIT. The impact on savings that can be achieved through in-process NDISs on the manufacturing job shop is represented in the additive manufacturing of ceramic parts. In the use case, two scenarios (with and without NDIT) are presented to compare the impact of operating costs, where two types of machines and raw materials are employed. Manufacturers should attempt to identify the critical parameters or properties to which NDITs should be implemented for in-process inspections. In the earliest stage, when the NDIT can be implemented, more cost savings can be made by using less material, energy and labour.

An accurate product cost estimation is a multifaceted process that draws on a wide range of resources, such as historical data and qualitative and quantitative models, as explained by Niazi et al. (2006) and Psarommatis et al. (2024). An invaluable tool in this estimation is the cost breakdown evaluation method, which is particularly useful for assessing the transformative effects induced by applying NDITs in manufacturing processes. Product cost intricacies are closely linked with the consumption of various productive resources, which range from labour and machinery to facilities, materials and energy, in the manufacturing life cycle (Shehab and Abdalla 2001a; Heilala, Helin, and Montonen 2006). To broaden the true impact of NDIT solutions on operational performance, it is imperative to comprehensively estimate the product's cost by taking into account the contributions of all these components. This holistic approach not only improves the accuracy of cost projections, but also provides an understanding of how NDIT implementations influence the overall efficiency and economic viability of manufacturing operations (Psarommatis 2021).

This article makes three significant contributions to the NDI for in-process quality assurance in industrial production scenarios. First, the article addresses the economic importance of ZDZW strategies based on NDITs. Second, a manufacturing cost estimation model is defined by considering the final factory cost to assess the return on investment related to the acquisition of NDIT based on the improvement in the first-time-right rate thanks to the deployment of real-time in-process quality assurance. The scope of the current paper is to provide all the necessary tools, methodologies and information for industries to used for improving their systems. The current paper can act as a step-by-step method for accurately and efficiently invest and deploy NDIT techniques.

In this paper, the cost estimation, which is based on a cost breakdown methodology, is introduced to evaluate the impact of integrating NDISs on the manufacturing shop floor. Third, the use case is employed to estimate the rate of return on investment (ROI) of Mid-Infrared Optical Coherence Tomography (MIR-OCT) when it is integrated into lithography equipment employed to manufacture ceramic antennas. The present use case enables the proposed cost model to be deployed and evaluates the impact of the cost related to reducing material, energy and other productive resources when an NDIT is applied. The model proposed in this study is applied for parts manufactured by the additive manufacturing process, which are later subjected to several heat treatments to consolidate parts and to achieve desirable properties. However, by means of the present methodology, an extension of the proposed model can be employed for other industries or parts beyond that proposed in the case of study. The paper´s novelty lies in the proposed cost breakdown model, which enables the evaluation of the impact on the final factory costs (labour, energy, materials, capitalised, etc.) when the first-time ratio is modified thanks to deploying an in-process NDIT for inspection quality assurance.

The paper is structured as follows, section 2 presents the evaluation of different solutions for ZDZW and their economic impact, section 3 presents the manufacturing cost estimation model and section 4 presents the return of investment model. The final section 5 is the conclusions summarising all the findings of the current paper.

2. Evaluating the economic impact of ZDZW solutions

This section addresses a fundamental challenge faced by the NDI system for justifying the high investment required for its integration into the manufacturing flow shop (EMAT sensor, MIR-OCT, Acoustic emission, GPU hardware, etc.) that is required to promote more advance quality inspection methodologies (in-process, on-machine or in-line). One barrier that significantly hinders the widespread adoption of NDISs lies in the complexities associated with accurately defining initial assumptions and making precise cost analysis estimates and impact on production profitability. These critical aspects are indispensable for calculating the expected value and variance of cash flows attributed to the deployment of automated inspection equipment. The inherent complexity in these preliminary steps is a significant barrier, and overcoming it which requires careful consideration and strategic planning (Dietrich and Cudney 2011). Successfully overcoming this challenge is imperative for organisations to search to acquire the benefits of NDISs, which underlines the importance of a thorough comprehensive approach to justify investments in advanced inspection technologies in manufacturing.

Today's current economic status remains very volatile due to geopolitical tensions between the main industrial nations (USA, China, Russian Federation and European Union), which have ended in rising inflation, interest rates and global trade sanctions (European Central Bank, 2023). After the COVID-19 pandemic, as European countries have become aware of the marked level of their dependency from the industrial point of view (European Commission 2021), one of the main goals for forthcoming decades is to regain their industrial competitiveness on the world market. Once clear example of an economic long-term strategy is visible in the EU Chip

Act, where more than €57 billion will be invested in production capabilities and infrastructure until 2035 (Ciani and Nardo 2022).

In some specific cases, investment in automatic inspection systems tends to be capital intensive with a payoff over a longer period, but the focus should be placed on long-term results, such as product recall, non conformities or a manufactured product's reliability (Pan et al. 2022). Depending on the industrial sector or type of products (aerospace, energy production, medical, etc.), these benefits can be considered to be competitive advantages. In some industries, the established payback period is 2 years, and an investment that presents higher values would require more work to justify investment. Implementing automatic NDITs enables companies to cut operational costs, which consequently lowers its selling prices. As customer goods are or outsourcing production is price-sensitive, they can gain market shares, increase their volumes and benefit from supplier's discounts or large production batches. However, if companies do not focus their efforts on manufacturing excellence and zero defect strategies, they will gradually have less competitive prices, which will narrow their market share, and they will be forced out of business sooner or later (Cochran, Foley, and Bi 2017).

The economics of quality inspection equipment does not differ from manufacturing systems. The main goal of any investment is to acquire an economical rate of ROI. This economic rate depends on the added value of the manufactured item and the industrial sector in which NDI equipment is installed. Investment in NDI equipment should consider the cost of acquiring and operating equipment, and labour and management costs in the manufacturing facility. ROI should be calculated by considering the added value obtained by installing NDI equipment.

Investing in quality assurance equipment is represented by the capital needed to integrate all the sensors and software to be feasible to inspect parts. This investment may be influenced by several factors: automatisation level, integration IT infrastructure, inspection accuracy, inspection velocity, and flexibility of the products to be inspected. Elevated automation requires a higher investment because several sensors and control systems are needed to provide feedback to inspection equipment, and also to the manufacturing system where it is installed. The economic evaluation of NDI equipment requires identifying the production equipment, material waste, energy use and inspection labour which, can be realistically reduced in the ROI window.

The benefits of NDI systems include the capability to detect, quantify and respond to changes in the production environment. These abilities provide the capability to adapt the manufacturing process to the changes that might occur during production. All industrial investments always involve some risk. The risk in automatic NDISs is the chance that the system will not achieve the planned accuracy level, the reliability of quality inspection, inspection velocity is slower than planned or the cost will be higher than estimated. ROI declines when one or more of these possibilities occur, which makes the solution less interesting from an economical point of view.

3. Manufacturing cost estimation model

Manufacturing environments are complex scenarios in which several operations, raw materials and productive resources are consumed to manufacture a product. Capturing this complexity is essential to accurately estimate the manufacturing cost, a task that can be addressed by applying various models (Asiedu and Gu 1998). All cost models rely on a central pillar: the definition and estimation of the parameters, coefficients or constants employed in the different equations proposed for a specific model (Niazi et al. 2006; Shehab and Abdalla 2001a).

This complexity can be translated to estimate the manufacturing cost; the current task can be performed by several models. For this reason, an accurate, reliable and updated database to estimate the manufacturing cost should be employed in cost simulation models.

The cost estimation model allocates the different consumed productive resources (machines, labour, raw materials, energy, infrastructure, etc.) based on the routes and bill of materials (BOM) for the specific manufactured part, and on a specific direct or no-direct cost. The cost breakdown approach proposed in this paper can consider increased product structure complexity. Traditional quantitative cost estimation methods are arranged in three main families: operation-based (Niazi et al. 2006), feature-based (Shehab and Abdalla 2001b; Mörtl and Schmied 2015; Jung 2002) and breakdown approaches (Mahadik and Masel 2018). The operation-based approach focuses on a very detailed estimation of manufacturing processes, but needs to improve the definition of the indirect cost (capitalise, allocate or administration cost). The feature-based cost estimation approach identifies the cost related to product features and estimates their costs based on historical data. The breakdown approach divides the part manufacturing cost into different elements (Mahadik and Masel 2018; Mörtl and Schmied 2015; Park and Kim 1995). The estimated part cost is given per the total contribution of all the direct and indirect cost elements incurred during manufacturing. The present research work focuses on the Final

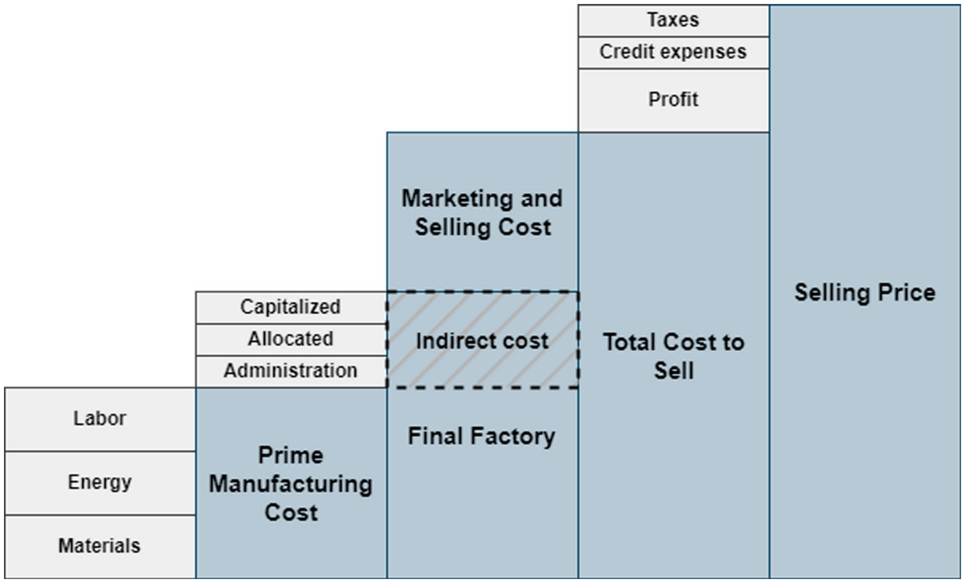


Figure 1. Cost element diagram.

Factory Cost, which considers the prime manufacturing cost and indirect expenses in a proposed breakdown model approach. To obtain the final selling price, the selling and marketing costs and the company profit margin should be considered, but this analysis is beyond the scope of this work (Figure 1). The proposed cost model extends the literature on investment feasibility for new technologies based on ZDM strategies since it integrates the impact of NDIT technologies in advanced quality inspection methodologies (in-process or in-line). For these purposes, the variable of FTR is considered in the direct labour costs, energy use costs, material costs, and capitalised costs to quantify the impact in the final factory cost where NDIT is implemented in-process or on-machine quality inspection.

In order for companies to stay competitive they need to develop new cost estimation models that adapt to the flexibility of their manufacturing process, and to consider the impact of integrating NDISs for in-process quality assurance, while being accurate and reliable (Park and Kim 1995). For this reason, the Zero Defect Manufacturing approach is utilised, as it is the latest approach for quality assurance (Powell et al., 2022). This requires fully contemplating the potential savings and benefits of the investment projects or inspection equipment based on ZDZW strategies (Azamfirei, Psarommatis, and Lagrosen 2023).

They should also allow managers or engineers to quantify indirect savings/costs and intangible benefits, such as improved quality linked with manufacturing flexibility and the first-time-right rate (Psarommatis and Kiritsis 2019). To provide a detailed ROI calculation to implement NDITs, manufacturing costs were analysed by following a breakdown approach that aims to provide accurate insights into how NDIT helps to minimise the costs associated with the process. The breakdown approach is a proven accurate cost estimation model when it comes to analysing all the resources consumed in the production cycle of an industrial product (Niazi et al. 2006). Figure 2 shows the hierarchy cost breakdown structure proposed to assess the impact of NDIT implemented for in-process quality assurance purposes based on ZDZW strategies.

In this section, the basic formulas proposed in this paper for all the considered cost elements are introduced and their essential aspects are discussed. The presented formulas can be adapted for different product structures and each cost element is estimated per part.

The Direct Cost component is composed of four cost components that are calculated by adding the Direct Labour Cost (C_{DL}), Direct Labour Cost Benefits (C_{DLB}), Energy Cost (C_{EC}) and Material Cost (C_{MAT}), as shown in Equation (1). Some of the aforementioned costs are related to the First-Time-Right Ratio (FTR_i), and the building ratio per process (BR_i). These two variables are intrinsically related to the use of NDITs in the manufacturing process.

$$Direct\ Costs \left(\frac{\text{e}}{unit}\right),$$

$$C_D = C_{DL} + C_{DLB} + C_{EC} + C_{MAT} \tag{1}$$

The direct labour costs consider the building rate and the FTR rate that depends on the processing parameters employed during each specific operation according to the manufacturing bill of materials, and the feedback collected from NDIT solutions to make decisions that

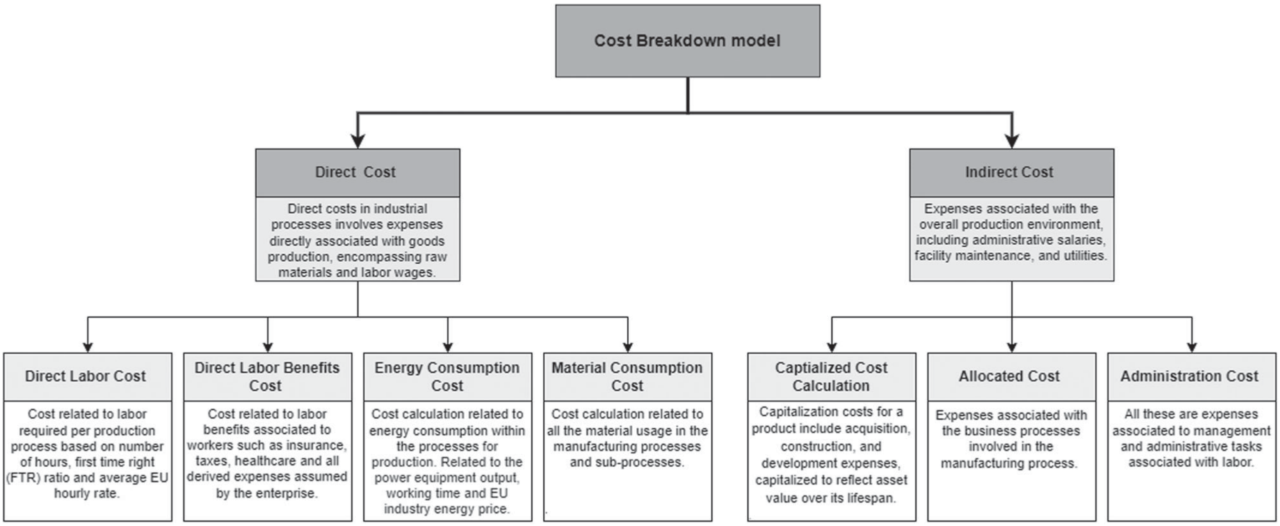


Figure 2. Tree diagram for cost estimation.

modify the FTR rate. The direct labour cost is obtained by dividing the average labour hourly cost by the building ratio and the FTR rate, and multiplying the coefficient based on the process labour needs for each process considered to manufacture the part. In the equation of the direct labour costs (Equation 1.1), a variable (K_{PLn}) to indicate the labour required per process or operation step is added. The Average Hourly Cost (AVG_{HC}) concept emerges, which indicates the average price per hour of a worker operating a machine in an industrial environment, or the building ratio (BR_n), which is defined as the units produced in an hour for a given process.

$$\textit{Direct Labor Costs}\left(\frac{e}{unit}\right),$$

$$C_{DL} = AVG_{HC} \times \sum_{n=1}^{N} \frac{K_{PLn}}{BR_n \times FTR_n} \tag{1.1}$$

where n refers to the process and N denotes the total amount of subjected processes.

$$\text{Average Hourly Cost}, AVG_{HC}\left(\frac{e}{\text{hour}}\right)$$

$$\text{Building Ratio per process}, BR_n\left(\frac{\text{unit}}{\text{hour}}\right)$$

$$\text{First} - \text{Time} - \text{Right ratio per process}, FTR_n(\%)$$

$$\text{Coefficient based on the process labor needs}, K_{PL,n}(\%)$$

The Direct Labour Benefit Cost (C_{DLB}) calculation relates the labour benefits associated with workers, such as insurance expenses, taxes, healthcare, and all the social expenses related to EU standards paid by enterprises. According to EUROSTAT, this cost estimation accounts for 21% of the direct labour expenses incurred on average, as seen in the following equation.

$$\text{Direct Labor Costs Benefits}\left(\frac{e}{unit}\right),$$

$$C_{DLB} = K_{LBE} \times C_{DL} \tag{1.2}$$

$$\text{Coefficient based on the labor benefits expenses}, K_{LBE}(\%)$$

The energy use costs ($C_{EC\,n,j}$) are composed of the energy use of all the manufacturing operations 'n' to manufacture one item, as well as the subtasks 'j' or operation performed during one manufacturing operation. Therefore, the first term of the equation defines the energy use for industrial equipment based on its nominal power ($P_{n,j}$) and operating time ($WH_{n,j}$), while the second term focuses on the energy use that takes place during heat transfer processes, by taking into account the material-specific heat ($c_{n,j,k}$), temperature increase ($\Delta T^{a}_{n,j}$), material ($RM_{n,j}$) used, among others. Working hours have a direct influence on both terms for the unit energy, which is why they have been broken down into an hourly rate per day (D_{WH}) and the days that the process took to be completed (D_{WH}).

$$\textit{Energy Use Costs}\left(\frac{e}{unit}\right), C_{EC} = C_{MEC} + C_{HTEC} \tag{1.3}$$

$$\textit{Machine energy use costs}\left(\frac{e}{unit}\right),$$

$$C_{MEC} = \sum_{n=1}^{N}\left(\sum_{j=1}^{J} P_{n,j} \times WH_{n,j} \times E_P\right) \quad (1.3.1)$$

where, j refers to the subtask and J refers to the total amount of subjected subtasks.

Working hours operating time in operation n and subtask j (hours), $WH_{n,j} = D_{WH} \times N_{WH\,n,j}$ (1.3.1.1)

Output nominal power per manufactured unit during operation i and subtask j, $P_{n,j}$ $\left(\frac{kW}{unit}\right)$

Hourly rate per day $\left(\frac{h}{day}\right)$, D_{WH}

Operating process phase days per subtask j performed during operation i (days), $N_{WH\,n,j}$

EU Average energy industrial price $\left(\frac{e}{kW \times h}\right)$, E_P

Heat Treatment energy use costs $\left(\frac{e}{unit}\right)$,

$$C_{HTEC} = \sum_{h=1}^{H}\left(\sum_{k=1}^{K} \Delta T_h \times c_{p_k} \times \omega \times \frac{RMC_k}{FTR_i} \times WH_h \times \eta_o \times E_{P_2}\right) \quad (1.3.2)$$

where k is the material identifier and K refers to the total number of material used during heat treatment.

where h is the heat treatment step and H refers to the total number of steps used during heat treatment.

Subtask heat treatment temperature(K), ΔT_h

Specific heat value for material$k$ $\left(\frac{KJ}{kg \times K}\right)$, c_{p_k}

Heat transfer coefficient $\left(\frac{kW \cdot h}{KJ}\right)$, ω

Raw Material Consumption for material k $\left(\frac{kg}{unit}\right)$, RMC_k

Oven efficiency(%), η_o

EU Average energy industrial price for heat treatment $\times \left(\frac{e}{W \times s}\right)$, E_P

Lastly, to summarise all the direct costs, the material costs of the process at the raw material level, also known as Material Cost (C_{MAT}), are included. The material cost includes manufacturing material losses, scrap and administration charges, which have to be considered to obtain the final product. All these costs are assigned to parts based on the amount of consumed material; NDIT integration will increase the FTR rate and decrease the consumed amount.

Material Cost $\left(\frac{\text{e}}{\text{unit}}\right)$,

$$C_{MAT} = \sum_{n=1}^{N}\left(\sum_{k=1}^{K} \frac{RMC_k \times RMP_k}{FTR_n}\right) \quad (1.4)$$

Raw Material Price $\left(\frac{e}{kg}\right)$, RMP_k

The Indirect Costs are regarded as overhead expenses associated with the overall production environment, administration personnel salaries, facility maintenance, utilities, among others. These costs are crucial for determining the comprehensive unitary production cost and are defined in the equations below. The Indirect Costs contemplate the capitalise, allocation and general/administration costs. The capitalised costs are defined as the equipment costs/ expenses imputable for each process that consume resources to manufacture a part. The equipment cost expenses per unit consider the overall equipment costs for a specific operation, available on working days, and the number of years to be contemplated for depreciation and the building ratio. The depreciation period is selected by considering the product manufacture type, the employed technology and finance company policies. The capitalised cost is calculated based on the overall equipment cost allocated for a specific process, working hours per year and the amortisation period.

$$\text{Indirect cost } \left(\frac{\text{e}}{\text{unit}}\right),\ C_{IC} = C_{CAP} + C_{AC} + C_{G\&A} \tag{2}$$

$$\text{Capitalized Costs } \left(\frac{\text{e}}{\text{unit}}\right),\ C_{CAP} = \sum_{n=1}^{N} CEQ_n \times K_n \tag{2.1}$$

$$\text{Equipment Costs expenses per unit } \left(\frac{\text{e}}{\text{Unit}}\right),$$
$$CEQ_n = \frac{OEC_n}{WD_n \times WH_n \times BR_n \times FTR_n \times NY_n} \tag{2.1.1}$$

$$\text{Overall equipment cost}(e), OEC_n$$

$$\text{Working days per year } \left(\frac{\text{day}}{\text{year}}\right), WD_n$$

$$\text{Working Hours operating time during operation} \times n \text{ (hours)}, WH_n$$

$$\text{Number of Years for Technological Depreciation} \times \text{(years)}, NY_n$$

$$\text{Operating expenses coefficient (\%)}, K_n$$

The allocation cost includes the cost of maintenance, services and infrastructure to support the equipment or machine. It is also necessary to bear in mind that the Capitalised Cost (C_{CAP}) will depend on the accuracy and resolution required during the process, which is subject to tolerances and the integration of NDIT for in-process quality inspection purposes. The Overall Equipment Cost for NDI (OEC_{NDI}) is based on several factors: working hours per day (WD_i), number of years for technological depreciation ($N_{y,i}$) and the building ratio per process (BR_i). Finally, in relation to equipment, the costs associated with the allocated cost (C_{AC}) in relation to the equipment maintenance and installation associated cost are both merged in an allocation cost coefficient and linked with the equipment cost expenses per unit ($C_{EQ,i}$).

$$\text{Allocated Cost of process } n \left(\frac{\text{e}}{\text{Unit}}\right),$$
$$C_{AC} = \sum_{n=1}^{N} CEQ_n \times K_{ACn} \tag{2.2}$$

$$\text{Allocated cost coefficient per process } i \text{ (\%)}, K_{ACn}$$

Management and administration costs are a percentage of the direct labour (D_L) and labour benefits (D_{LB}) imputable on general and administration costs. A company's policies normally balance the direct labour with the personnel assigned to general and administration costs. For this reason, the coefficient ($K_{G\&AC}$) multiples the costs associated with direct labour and benefits.

$$\text{General and Administration Cost } \left(\frac{\text{e}}{\text{unit}}\right),$$
$$C_{G\&A} = K_{G\&AC} \times (C_{DL} + C_{DLB}) \tag{2.3}$$

$$\text{General and Administration Cost coefficient (\%)}, K_{G\&AC}$$

The net revenue is the difference between the operational cost without NDI equipment and the estimated operational cost with the integration of NDI equipment, multiplied by the real production. Finally, ROI is obtained by dividing the net revenue by the total NDI investment. Once all the costs are adequately defined, the cost variation from the As-Is scenario to the potential To-Be scenario in which NDIT is deployed is carried out based on the following equation.

$$\text{Return of Investment (\%)},$$
$$\text{ROI} = \frac{\text{Net Revenue}}{\text{NDIT Overall Equipment Cost}} = \frac{\Delta OPR \times \Delta C_w}{OEC_{NDIT}} \tag{3}$$

$$\text{Overall Production Rate variation } \left(\frac{\text{unit}}{\text{year}}\right), \Delta OPR$$

$$\text{Unitary Cost variation } \left(\frac{e}{\text{unit}}\right), \Delta C_w$$

The proposed cost model to evaluate the investment viability of NDIT for on-machine, in-process, and in-line allows manufacturing companies to quantify the potential financial performance outcomes. Since these NDIT presents the capability to detect defects in real-time, and potentially adapt the manufacturing process to disturbances the FTR rate is improved, reducing the materials consumption, increasing the energy efficiency, and decreasing the environmental impact of the manufacturing process.

4. Industrial use case for return of investment for NDIT applied in AM ceramic antennas

The analysed use case evaluates the economic feasibility of integrating MIR-OCT for the real-time inspection of high-value ceramic parts manufactured by lithography additive manufacturing equipment. This model serves as a basis for the quantification of the actual financial influence of MIR-OCT as an NDIS applied for high-value ceramic parts manufactured by AM technology.

A short description of the lithography additive manufacturing technology is described in this paragraph. This manufacturing process consists of fabricating ceramic parts from photocurable ceramic suspension. The stereolithographic technology employs LEDs as a light source and a Digital Mirror Device (DMD) chip as a dynamic masking to create the 3D ceramic part (Baino et al. 2022). Once the green part is obtained, the ceramic parts should follow several heat treatments to eliminate the organic matrix and to consolidate the ceramic powders through sintering. The heat treatment is composed of four steps: the first one is the debinding step, in which the green parts are heated to 200°C for 2–3 days to eliminate photocurable resins. The second heat treatment is the degassing step, in which the ceramic parts are heated to 400°C to remove the gasses trapped in the ceramic powders, which lasts around 12–24 h on average. During the third heat treatment, temperature is raised to 1100°C to perform pyrolysis and to remove any remaining organic compounds. It lasts around 18–24 h. During the last heat treatment, the sintering temperature is achieved (around 1700°C), at which the ceramic particles are consolidated and porosity is reduced or removed, depending on the cycle time employed, which usually lasts 2 or 4 days (Baino et al. 2022).

4.1. Cost breakdown for the economic feasibility of non-destructive inspection solutions

The printing system selected for the economic analysis is CeraFab 8500 from Lithos GmBh, with a working area of 115 × 64 mm and a building speed of 80 layer per hour (116.7 unit/hour), with resolution on the x-y plane and 25 µm deposition thickness layer. The additive machine cost is considered to range from 300,000 to 569,000 euros, with an amortisation horizon of 4 years (Ozog et al. 2019; Romanov and Zhuravleva 2020; Romero 2018). The integration of MIR-OCT technology for real-time inspection and control purposes has an estimated cost of 120,000 euros. The equipment with no in-process control solution presents an F-T-R ratio of 50%, and this value increases to 66% when the MIR-OCT technology is integrated into the lithography equipment, complemented by AI-driven image recognition capabilities to enhance the analytical potential of the data acquired by the MIR-OCT system. The lithography equipment operates 254 days per year at a rate of 16 h per day. The furnaces operates 24 h per day. The present case focuses on specific parts that employ micrometric or submicrometric powder, whose price can range from 300 to 2200 euros per kilogram depending on powder size and purity, and with an average weight per part of 5 grams (Romanov and Zhuravleva 2020; Romero 2018). The higher cost related to the raw material is related to current suspension, which is composed of 97.4–99.99% ceramic material with particle sizes between 10 and 0.1 μm (Sobhani et al. 2020). Based on the literature review, the electric furnace selected to perform the economic analysis is Nabertherm (Baino et al. 2022).

4.2. Non-destructive inspection technology economic analysis

The cost of the ceramic parts manufactured by the lithography additive manufacturing technology was broken down into direct labour (labour, benefit, energy, materials) and indirect (capitalised, allocated and administration). Economic analysis performance relies on the operating cost related to the lithography machine and the electric furnaces employed to consolidate parts. The cost to manufacture high-value ceramic parts though Digital Light Processing (DLP) consider five main elements: direct costs; material cost, allocated cost, capitalised costs, general/administration cost (Dossett 2014). Direct costs are related to the equipment cost per operation hour, which are composed of direct labour, benefits and energy costs. Direct labour considers the hourly rate that would be charged for each part for the involved lithography and heat treatment processes. The hourly labour costs are estimated as €30.5, which is the current average in the EU (Eurostat, 2023). The direct labour benefits cost is estimated by multiplying a social benefit coefficient by the direct labour cost. Benefits include health and life insurance, compensation, state unemployment tax, holidays and employer social security contributions that the company pays. The energy use cost considers two main inputs: the first cost comes from machine energy use and the second from heat treatment, which generally represents high energy use. The electricity prices selected for this study were obtained from the Eurostat Database as 0.1886 €/kilowatt-hour for industrial consumers (Eurostat, 2023). Table 1 summarises the parameters employed to calculate the manufacturing cost in the present use case of ceramic parts.

The material cost is defined by multiplying the material consumption per the raw material cost and the

Table 1. Use case parameters for the cost breakdown estimation.

Description	*Value*	*Units*
Average Hourly Cost, AVG_{HC}	30.5	(€/hour)
Building Ratio per process, BR_1	116.7	(unit/hour)
First-Time-Right ratio per process without NDIT, FTR_1	50.0	%
First-Time-Right ratio per process with NDIT, FTR_2	66.0	%
Coefficient based on the process labour needs, $K_{PL,i}$	50.0	%
Coefficient based on the benefits labor expenses, K_{LBE}	21.0	%
Specific heat value for material k, c_{p_k}	0.955	(KJ/(kg × K))
Heat transfer coefficient, ω	2.778 x10^{-4}	((kW × h)/KJ)
Raw Material Consumption for material k, RMC_k	5×10^{-3}	(kg/unit)
Oven efficiency, η_o	240	%
EU Average energy industrial price for heat treatment, E_P	0.1886	(€/(KW × h))
Raw Material Price, RMP_k	300–2200	(€/kg)
Overall equipment cost without NDIT, $OEC_{Lithography}$	300,000–569,000	(€)
Overall equipment cost with NDIT, $OEC_{Lithography\ NDIT}$	420,000–689,000	(€)
Overall equipment cost, OEC_{Ovens}	25,000	(€)
Working days per year, WD_i	254	(day/year)
Working Hours operating time in Lithography, $WH_{Lithography}$	16	(hours/day)
Working Hours operating time in Sintering, $WH_{Sintering}$	24	(hours/day)
Number of Years for Technological Depreciation, $N_{y,\ i}$	4	(years)
Operating expenses coefficient, K_i	100	%
Allocated cost coefficient per process i, $K_{AC\,i}$	20	%
General and Administration Cost coefficient, $K_{G\&AC}$	45	%

Table 2. Detailed cost breakdown for high-value AM ceramic parts.

	AM Lithography ceramicwithout MIR-OCT	*AM Lithography ceramicwith MIR-OCT*
Direct costs (€/unit)	**[3.577–22.577]**	**[2.709–17.103]**
Direct *labour* (€/unit)	0.261	0.198
Direct labour benefits (€/unit)	0.055	0.042
Energy (€/unit)	0.260	0.197
Debinding heat treatment (€/unit)	0.016	0.012
Degassing heat treatment (€/unit)	0.011	0.009
Pyrolysis heat treatment (€/unit)	0.032	0.024
Sintering heat treatment (€/unit)	0.201	0.152
Material costs (€/unit)	[3000–22,000]	[2273–16,667]
Indirect costs (€/unit)	**[0.557–0.897]**	**[0.535–0.792]**
Capital*ised* costs (€/unit)	[0.345–0.629]	[0.356–0.570]
Lithography operating costs (€/unit)	[0.316–0.600]	[0.334–0.548]
Furnaces operating costs (€/unit)	0.029	0.022
Installation operating costs (€/unit)	[0.086–0.157]	[0.089–0.142]
Allocated cost (€/unit)	[0.069–0.126]	[0.071–0.114]
Lithography equipment costs (€/unit)	[0.063–0.120]	[0.067–0.110]
Furnaces equipment costs (€/unit)	0.006	0.004
General and Administration costs (€/unit)	0.142	0.108
Total (€/unit)	**[4.133–23.473]**	**[3.244–17.895]**
Total production (Unit/year)	**237,134**	**313,017**
ROI (%)	-	**56–353**
Payback period (months)		**4–21**

first-time-right rate for each raw material during every manufacturing process that consumes materials according to the bill of materials. For the capitalised cost, in the present study it includes the depreciation of the main equipment (lithography, furnaces, installations) employed while producing AM ceramic antennae. As part of the allocated costs, repairs and maintenance cost, fixture or tooling costs and process control are considered. The administration costs and indirect personnel cost, infrastructure and general utilities cost are included in the General and Administration costs.

The main results from the ROI of the MIR-OCT technology applied as NDI on lithography machines are summarised in Table 2. This table shows that integrating the MIR-OCT NDIT reduces the Direct Costs from 3.577–22.577 €/unit to 2.709–17.103 €/unit. The improvement in the FTR ratio improves productivity, reduces energy use and also lowers the material costs by around 24%. Nevertheless, integrating MIR-OCT into the AM lithography machine increases the capitalised costs by about 24%, and also the allocation costs, because purchasing the lithography equipment and its related costs increase. It is necessary to consider that the capitalised costs depend on the precision and technology employed with the lithography equipment. Depending on the cost of the selected machine, and the employed raw material, the ROI windows range from 56-353%, and the payback period can range from 4 months (for expensive machine and raw material) to 21 months (more economical machine and raw material).

Table 2 presents the ratios of different costs considered to calculate both ROI and payback period (PBP) of implementing MIR-OCT. Figure 3 presents a detailed investment feasibility calculation flow, outlining the step-by-step calculation and financial metrics for investment decision-making in non-destructive inspection technologies. These results clearly evidence that implementing MIR-OCT as an NDIT in the lithography additive manufacturing technology considerably lowers both energy use and material waste. The manufacturing cost heavily depends on the size and composition of the employed powder (material selection), and on powder characteristics because powder is the main element that allows high-value ceramic parts to be produced. When a high-investment lithography machine and expensive

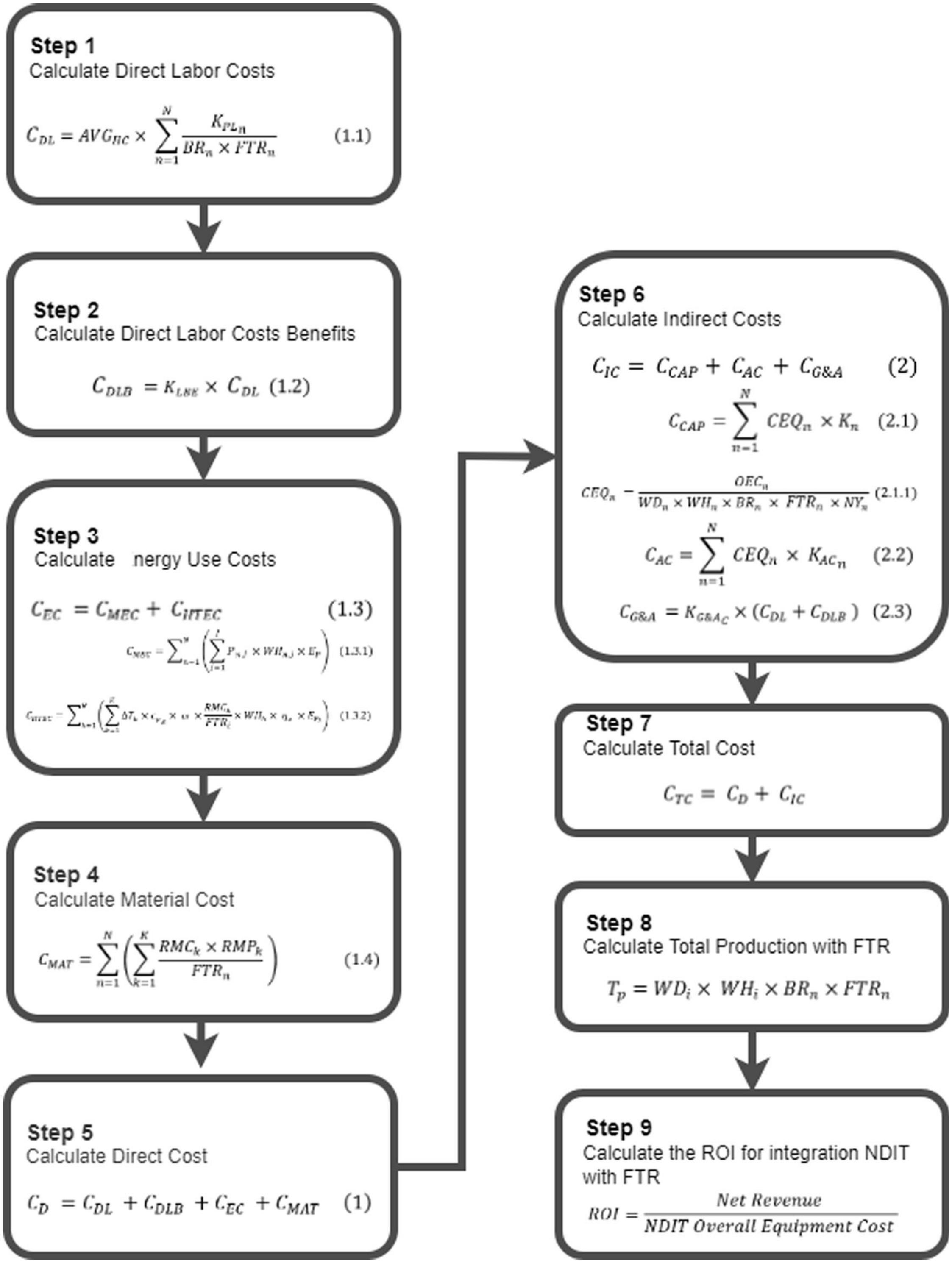


Figure 3. Flow diagram for investment feasibility.

powder are employed, the improved FTR by integrating MIR-OCT in-process inspection allows four months of PBP, which is considerably lower than the other scenario where less expensive raw material and lithography equipment are employed. The scenario in which MIR-OCT is implemented as in-process quality inspection technologies can reduce the total manufacturing cost by around 1–6 euros/part, which gives an estimated saving of 30% for material waste and energy use.

The economic analysis indicates that integrating the NDIT based on MIR-OCT into a manufacturing process that employs lithography machines with a higher investment and higher cost of raw materials presents shorter payback periods compared to more economical approaches. Moreover, integrating NDIT for in-process inspections may increase the FTR ratio and lower the prime manufacturing costs (labour, energy, materials), which improves the final factory profitability. Finally, to evaluate the productivity improvement of NDIT deployment, organisations should ensure it through equipment validation and employ performance metrics, such as OEE, as indicators and drivers of performance improvements (Binti et al. 2016; Cochran, Foley, and Bi 2017; Huang et al. 2003; Wudhikarn 2012). Integrating an NDIT will modify machine availability, production and the quality rate. Therefore, these three elements form part of the OEE and evaluation of metric performance, and will be required after NDIT integration.

The deployment of MIR-OCT or other non-destructive inspection technology on machine for in-process quality inspection methodology decrease the probability of failure in the manufacturing processes, increase the first-time right rate and improve the production sustainability. Psarommatis et al. (2024) demonstrated that advancing to in-process inspection methodologies in machining aluminium parts for the aeronautical industry reduced material handling by $>30\%$, delays by 10%, and production costs $>45\%$. The current study is aligned with Psarommatis et al. (2024) since the improvement in FTR, after MIROCT integration for in-process quality assurance, may reduce the final factory cost by around 35%, depending on the operational conditions selected.

In the current ceramic use case, deploying MIR-OCT and artificial intelligence algorithms for defect detection will allow for advancement in a quality inspection-based in-process approach. The new capabilities will allow to quantify the internal defects, such as inclusion, porous, aggregates, or others that may make the part manufactured by lithography out of specifications. In this new scenario, based on the inspection data acquired during production, a digital twin can be created to estimate the final material properties; this can be employed on a reactive approach to adapt the process parameters to the subsequent manufacturing operations (Azamfirei, Psarommatis, and Lagrosen 2023; Catalano et al. 2022; Psarommatis and May, 2023; Rožanec et al. 2023). For example, MIR-OCT with AI algorithms can quantify the porosity on the green part; this information can be used to set up the sintering temperatures and process heat treatment cycle-time. Another example of using the digital twin, created with the data gathered with NDIT, is the prediction of mechanical properties of the manufactured part, which can be employed to select optimal machining parameters (feeding rate, revolution, tool geometry, etc.). This reactive approach based on deploying NDIT for in-process inspection can be employed to reduce the defect probability in machining (cracks, fissures, burrs, and others). This digital twin could also select part handling parameters, such as gripping forces, geometries or tightening torques.

5. Conclusion

The current paper provides a toolbox for efficiently evaluating the manufacturing cost and the KPIs for investing in an NDI. This is very important for the industries as it offers a complete and practical tool for using. A lot of focus was paid for making the proposed method practical to have real application to the industrial domain. More specifically, this work contributes to develop a cost estimation breakdown model that evaluates the ROI and payback period of a quality inspection policy based on in-process inspection by an NDIT. Innovation is accomplished by developing a model that considers the FTR ratio in the prime manufacturing cost and the indirect cost, which can be modified by integrating an NDIT. In this work, a general overview of NDITs is presented, which plays a crucial role in the in-process inspection of defects that occur during industrial processes. Automatic NDI systems deployed on the manufacturing shop floor can reduce energy use and materials consumption by optimising the production rate, and decreasing the amount of destructive testing for quality assurance purposes. The proposed economic cost model relies on the definition of the production equipment cost, labour, material consumption/energy use and infrastructure that influence the ROI value of automatic inspection systems based on the ZDZW paradigm. The proposed cost model can be applied in any manufacturing production scenario in which several production steps are carried out, and where material, energy and labour are consumed, and scrap is produced. The primary contribution of the proposed cost model based on the ZDZW strategy is that managers can employ it to evaluate the economic feasibility of an investment based on NDITs. Different scenarios can be established to evaluate the expected final factory cost before and after an NDIT is integrated into production with different FTR production rates. In the future, the proposed model can be extended by considering quality inspection costs based on the inspection type, the required inventory levels, tooling cost and setup time for machining, and the employed workforce.

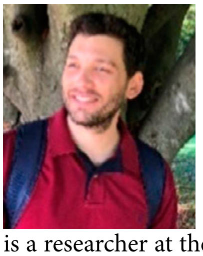
Disclosure statement

No potential conflict of interest was reported by the author(s).

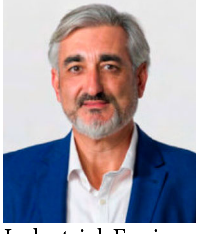
Notes on contributors

Doctor Joan Lario is associate professor at the Department of Business Organization at the Universitat Politècnica de València (UPV) and researcher at the UPV's Centre for Research in Management and Production Engineering (CIGIP). He has taught in the Degree in Industrial Organization Engineering and different master's degrees at the UPV. He has worked in several multinationals companies in the automotive and biomedical sectors as a process and industrialisation engineer for over ten years. His research activities are related to developing metallic materials using powder metallurgy techniques, specifically in manufacturing beta-titanium alloys and using surface treatments to improve biocompatibility, and the integration of non-destructive inspection technologies for quality assurance purposes. He is a co-author of several articles published in international indexed scientific journals, as well as contributions to international conferences, and a reviewer of materials sciences journals.

Javier Mateos Luengo is a Junior Research and Development Engineer with an MSc in Industrial Engineering, specialised in industrial tool equipment development, vision-systems and cyber-physical systems. Javier's professional career has allowed him to work in the New York (USA) as an Electrical Engineer in the energy sector, where he became interested in the use of robotics and drones with non-destructive inspection tools. Javier is currently working in Valencia (Spain) as a R&D Engineer at the UPV's Centre for Research in Management and Production Engineering (CIGIP), where he has developed research work in 4 European projects. In addition, he is Head of Engineering of STR Drones, a drone operator company that develops industrial solutions for the automation of inspection processes using non-destructive technologies. He is a member of the European Union aviation Safety Agency (EASA) and a member of Official College of Industrial Engineers of the Valencian Community (COIICV).



Foivos Psarommatis is a passionate engineer and a highly active researcher in the area of quality management in manufacturing systems. Currently, he is the founder and CEO of Zerofect, a company based in Switzerland and focusing on providing digital technologies for sustainable manufacturing. Additionally, he is a researcher at the University of Oslo (UiO) and Universitat Politècnica de València (UPV). More specifically is a pioneer in the area of Zero Defect Manufacturing (ZDM), as is the first who modernised and set the foundation of modern ZDM. His scientific interests, motivation and vision are around Industry 4.0 and on how ZDM can be applied efficiently to production systems, focusing on the decision making, scheduling and design of a system or a product, with ultimate goal to achieve true sustainable manufacturing. Regardless the young if his age he was listed in world's top 2% of Scientists for 2022. He is actively involved in EU research programmes in the area of Factories of the Future and Enabling ICT for Sustainable Manufacturing. Foivos holds a BSc and an MSc in Mechanical engineering with specialisation on design and manufacturing engineering from the University of Patras. He has also a second MSc from National University of Athens in Automation systems with specialisation on manufacturing and production systems. He did his PhD around the topic of Zero Defect Manufacturing École polytechnique fédérale de Lausanne - EPFL. Foivos is the chair on a CEN/CENELEC working group responsible for standardising ZDM.



Ángel Ortiz Bas studied Industrial Engineering at the ETSII of the UPV (Polytechnic University of Valencia), where he later completed his PhD. He is currently a University Professor in the Department of Business Organization (DOE). He has been Deputy Director of Planning at the Higher Technical School of Industrial Engineering, Academic Director of the University master's degree in advanced production, Logistics and Supply Chain Engineering (MUIAPLCS) and Deputy Director of the Research Center in Management and Production Engineering. Previously, he held the positions of Director of the Strategic Planning Area at the UPV and Secretary of the Department of Business Organization. Affiliated with the ETSII since 1995, he has taught first-cycle, second-cycle, degree, master's and doctoral degrees in areas related to strategy, business processes and logistics. He is President of the Engineering and Architecture Commission of the Agency for the Quality of the University System of Catalonia. He has led or participated in 18 European projects and in more than 40 contracts with companies and institutions.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

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ORCID

Joan Lario http://orcid.org/0000-0003-4843-3334
Javier Mateos http://orcid.org/0009-0003-8007-1545
Foivos Psarommatis http://orcid.org/0000-0002-2731-8727
Ángel Ortiz http://orcid.org/0000-0001-5690-0807

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