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Expanding the boundaries of Zero Defect Manufacturing - A systematic literature review

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Abstract

With Industry 5.0 on the horizon, research and innovation is prioritising the transition to sustainable, human-centred and resilient manufacturing. In this context, Zero Defect Manufacturing (ZDM) strategies combine tools, resources and rules with the aim of avoiding defects and increasing the sustainable performance of complex manufacturing systems. Five distinct strategies for ZDM have been identified in the literature: (I) detection, (II) prediction, (III) prevention, (IV) repair, and (V) mitigation or compensation. The main motivation of this paper is to discuss an extension of these five existing dimensions by three more, which will enable the transformation of classical ZDM towards a more sustainable production. The main objective of this paper is to conduct a systematic literature review that covers the state of the art of ZDM and highlights the need to add the three (Zero^3) dimensions: i) Zero Resource Loss (resource and emission improvement) ii) Zero Human Potential Loss (productivity and stability improvement) iii) Zero Data Gap (increase in efficiency of data use).

Keywords: Zero Defect Manufacturing; Sustainable Production, Human Potential Loss, Resource Loss, Data Loss

1. Introduction

The IPCC's 6th Assessment Report clearly shows that humans and the technologies they use have an impact on climate change [1]. In addition, numerous sustainability, circular economy and climate protection studies and strategies highlight the need to respond appropriately to these climate challenges [2]. Meanwhile, industry and business are increasingly competing in a volatile environment with scarce resources, a lack of skilled labour and inefficient use of industrial data [3]. In addition, the shortening of product life cycles has led to more reconfigurations in production systems to adapt to fluctuating customer demands. The increased complexity of modern production systems due to the multitude of production steps leads to an increased susceptibility to errors. These challenges highlight the need to develop advanced quality management strategies to address these issues [4].

One particularly compelling approach is Zero Defect Manufacturing (ZDM), which focuses on reducing defects in a proactive, preventive and reactive manner [5].

There are two approaches to ZDM: product-based ZDM, which evaluates the quality of the product and its relationship to process parameters, and process-based ZDM, which evaluates the condition of the machines and their impact on quality.

How such an extension can be designed for future production is the central motivation of this paper. Furthermore, the research objective of this paper is to discuss a sustainability extension of the traditional ZDM definition by presenting a new

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Characteristics		Categories			
(1)	focus	research outcomes	research methods	theories	applications
(2)	goal	integration	criticism		central issues
(3)	organisation	historical	conceptual		methodological
(4)	perspective	neutral representation		subjective representation	
(5)	audience	specialised scholars	general scholars	practitioners/politicians	general public
(6)	coverage	exhaustive	exhaustive and selective	representative	central/pivotal

Fig. 1: Taxonomy of the conducted literature review following Cooper [7].

approach based on the Zero^3-Dimensions: i) Zero Resource Loss (improving resources and emissions) ii) Zero Human Potential Loss (improving productivity and stability) iii) Zero Data Gap (improving efficiency of data use).

2. Application of the literature analysis

The prevention and repair aspect of ZDM already demonstrates how it contributes to sustainability. On this basis, the concept can be further developed. Therefore, the research methodology of this paper is to identify a representative sample of the literature on ZDM and to analyse this sample in terms of its relation to sustainable development. In particular, the issues of resource loss, human potential loss and data loss in ZDM are highlighted through a targeted selection of keywords.

For this research, a systematic literature search was carried out according to [6]. Vom Brocke et al [6] present a five-phase model for systematic literature searches, which also incorporates applications from Cooper [7]. The phases suggested by [6] can be summarised as follows:

- *Phase 1*: Scope of the literature review: For this phase the taxonomy according to Cooper [7] is applied and presented as a morphological box in figure 1.
- *Phase 2*: Conceptualization: The keywords and its combination for this literature search are: ("Zero Defect Manufacturing" AND "Resource") OR ("Zero Defect Manufacturing" AND "Human") OR ("Zero Defect Manufacturing" AND "Data")
- *Phase 3*: Literature search: For this research the database from www.scopus.com is used, which covers a large amount of research literature. A Total of 278 publication can be found on 18.07.2023 for the keyword "Zero Defect Manufacturing" in which 152 were found with our keyword combination.
- *Phase 4*: Evaluation: After the evaluation of the title and abstract of the 152 publication 21 are found relevant for this review.
- *Phase 5*: Analysis: The relevant literature is analysed in the next phase, which conducts in chapter "3 Results".

3. ZDM in perspective of the Zero^3 Dimensions

To address the current challenges of resource scarcity, skills shortage and efficient use of industry data within ZDM, this section presents 23 scientific publications from the applied systematic literature review [6]. This chapter is structured according to the state of the art of resource loss, human potential loss, data loss within ZDM and the identified research gaps.

3.1 Continuing resource loss reduction in ZDM

In an effort to contribute to more sustainable production, resource efficiency remains a key focus in ZDM, with the aim of moving more towards a circular economy. Furthermore, resource utilisation is closely linked to production costs in the manufacturing industry, as increased human intervention leads to lower optimal resource utilisation costs [8].

Publications have highlighted the importance of quality management in achieving resource efficiency in ZDM [9]. By prioritising quality planning, control and improvement, manufacturers can contribute to the reduction of resource waste, resulting in improved operational, financial and environmental performance [10]. In addition, an emphasis on minimising (reducing) resource use is consistent with the goals of ZDM [11]. Furthermore, green strategies in manufacturing have multiple perspectives, which means that they are highly diversified in terms of resource management [11]. For this reason, it is crucial that future work focuses on defining an approach to describe the relationship between the key performance indicators (KPIs) of different green strategies and to elaborate the impact of this transformation on workflows and in particular on manufacturing processes [12].

When implementing ZDM strategies, it is critical to consider resources such as legacy machinery and technology investment constraints [13]. Recognition of these factors is essential for effective resource management and optimisation.

Research gaps identified in this chapter are still in the transition to a circular economy, the implementation of more than just an r-strategy (repair), and the application of ZDM strategies, methods and tools that significantly increase production performance towards less needed resources [4].

3.2 ZDM as a strategy against planned obsolescence

Brooks Stevens, a prominent American designer in the furniture, automotive and railway industries, introduced the concept of planned obsolescence into business practice. He defined planned obsolescence as business strategies designed to maintain sales in saturated and stagnating markets by stimulating the consumer's desire to buy something slightly newer, better and sooner than strictly necessary [14].

The fixation with maximising sales can be traced back to the 19th century. However, it was not until the advent of the first 'disposable' products that deliberate obsolescence planning began to take shape. It was during this period that the conscious use of techniques to deliberately shorten the life of products became part of the logic of business economics [15].

On the contrary, the idea of ZDM is the prevention of defects in industrial production in order to eliminate avoidable extra costs, including inspection time, rework time, wasted material and labour, lost revenue and the cost of consumer dissatisfaction [15].

However, by extending the boundaries of ZDM, linking planned obsolescence with the new principles of zero resource loss, zero human potential loss and zero data gap could potentially align these seemingly disparate concepts. By minimising waste, optimising human potential and ensuring complete data integrity throughout a product's lifecycle, manufacturers can achieve a balance where product development is sustainable and in line with the principles of ZDM. This can lead to a more responsible approach to manufacturing in the context of global competition.

3.3 Human potential and ZDM

Human potential in manufacturing processes is critical to achieving high quality products due to the high manual content of assembly processes, stress, safety and unique human skills. This comprehensive literature review aims to synthesise findings from a variety of sources to provide insights into the diverse role of humans in the context of ZDM.

Psarommatis et al. [16] highlight the evolving role of humans as strategic decision makers and problem solvers. They emphasise the importance of upskilling, continuous learning and bi-directional relationships with machines to improve performance and efficiency. In line with human-centricity, Caiazzo [8] presents a monitoring platform that integrates human strengths and expertise into anomaly detection algorithms. This approach recognises the importance of human factors in problem solving and decision making, fostering a symbiotic relationship between humans and automation. Schmidbauer et al [17] show how the introduction of cobot technology can disrupt traditional work processes. The study of task allocation also suggests that participants prefer to assign cognitive tasks, such as checking to themselves and manual tasks, such as handling, to the cobot [17].

Silva et al [18] present a human-in-the-loop approach that combines human judgement and artificial intelligence (AI) to improve real-time quality prediction and process improvement. This integration of human expertise increases accuracy, reduces downtime and decreases non-conforming parts.

To achieve ZDM, Wan and Leimo [19] emphasise the collaborative efforts of managers, engineers and operators. Knowledge sharing, assistive technologies and interdisciplinary research are identified as essential to achieve human-centred zero-defect practices. Collaborative robots, software agents and intelligent user interfaces assist workers in complex tasks, enabling better human-machine cooperation, social partnerships and inclusive job creation.

Machine vision systems in the automotive industry are explored by Serrano-Ruiz et al. [20], highlighting their application in quality related tasks and automation. The integration of AI techniques and the development of self-adaptive capabilities are identified as future directions to improve vision systems and achieve zero-defect manufacturing.

Konstantinidis et al. [21], Fragapane et al. [4] and Psarommatis et al. [5] address the challenges of inspection cost and process optimisation. They propose the use of machine learning techniques and decision support systems to reduce pseudo defects, improve inspection efficiency and enhance data-driven optimisation strategies.

Future research that relies on human potential within ZDM should further investigate augmented worker support systems to prevent production defects and take more into account human factors such as safety, stress and skill development [8].

3.4 Data gap and ZDM

The presence of a data gap in ZDM can significantly hinder the ability to identify and address potential defects, leading to compromised product quality and increased risk of customer dissatisfaction. A comprehensive and accurate data collection system is essential in ZDM to bridge the data gap and enable effective monitoring, analysis and quality control measures that ultimately contribute to achieving defect-free products and operational excellence. The collection and automatic analysis of data in a multi-stage manufacturing process was investigated in Lughofer et al. [23], where a whole range of topics related to machine learning were explored, including the interpretability of adaptive structures [23], the detection of anomalies in production processes [24], and online learning methods [25] for automatic model fitting.

The state of the art (SOTA) also includes research on data retrieval through the development of digital twins of products [26], computational methods for optimising the flow of parts in a ZDM manufacturing environment [27], and sensor data analysis methods based on deep learning and neural networks for managing large data sets [28].

The development of robust situation awareness systems requires the availability of high quality and structured data. This often leads to a reluctance to share sensitive data.

Furthermore, Isaja et al. [29] introduce the Product-Process -Data trusted framework, which uses distributed ledger technology to enable the exchange of trusted and traceable quality data between factories in a product supply chain. Research gaps covering data-related issues in ZDM should be investigated in deep learning-based anomaly detection and reduction of unnecessary data collection for overall more efficient data processing.

3.4 Environmental impact of ZDM

The application of the ZDM strategy approach offers several benefits. These include lower costs, shorter lead times, improved planning and a reduced environmental impact of industrial production, resulting in less energy consumption and waste of resources [30].

Reducing the number of defective products in a manufacturing process leads to less scrap, which has an impact on the amount of waste generated. It also reduces the amount of emissions and possible harmful by-products from unnecessary rework. In the context of zero resource loss and zero loss of human potential, there is potential for improved defect detection and therefore improved sustainability in manufacturing due to the availability of the technological tools of Industry 5.0 [31].

In a broader context, if durable and high-quality products are prioritised to reach the consumer, this will also reduce the return rate, leading to a reduction in transport emissions and resource waste.

3.5 Zero³-Dimensions

Structured in the state of the art of Resource Loss, Human Potential Loss and Data Loss within ZDM, this chapter concludes with Table 1 and an approach to extend the traditional ZDM definition to include the Zero3 dimensions of

Table 1 Extended approach for ZDM to meet current research gaps.

		Identified SOTA and ZDM research gaps categorised within Zero3-Dimensions
Sustainable ZDM Extension Dimensions (Zero3-Dimensions)	Zero Resource Loss	ZDM aims to reduce waste caused by imperfect production processes, resulting in environmental benefits [8] as well as financial and operational improvements [10]. Both academics and practitioners need to increase their focus on all R-strategies (reduce, reuse, recover, etc.). In the transition from a linear to a circular economy, this strategy can strongly support the move towards a zero-defect, zero-waste paradigm. Therefore, future research should investigate repair and remanufacturing methods [9]. Many of the respondents experienced a neutral impact on production performance after applying ZDM strategies and methods. The use of ZDM strategies, methods and tools should significantly improve production performance in the future and lead to a shift towards the efficient use of resources [4].
	Zero Human Potential Loss	Human-centred approaches are still lacking in ZDM. Future research should therefore investigate how to further support and augment the operator in working towards zero defects [9]. It has been shown that humans are still responsible for a significant amount of product rework [16]. It has also been shown that humans prefer to delegate cognitive tasks to cobots [17], which in combination with human skills contribute to quality and process optimisation in production. This effect can be further enhanced by the addition of AI technologies [18]. However, the influence of human skills is a relevant issue, as the results of automated technologies still depend on the cognitive inputs of the operators [4]. According to our comprehensive analysis, human factors such as safety, stress and skill development should be considered when developing maintenance plans and decision-making procedures. This may involve the development of human-centred models and tools that take into account the health and job satisfaction of workers, as well as the impact of human factors on the effectiveness of maintenance operations and the reliability of systems [10].
	Zero Data Loss	Many studies have introduced AI methods for ZDM, but these methods are still less applied in practice. Future research should further invest in prediction methods that adapt to the different sudden events that can occur in an industrial process, especially in the presence of anomalies [11]. Recent studies show that data generation and the use of digital twins [26] for the optimisation of intralogistics processes in production [27] and the use of incomplete data sets by AI technologies [28] make a comprehensive contribution to a ZDM. The identification of anomalies, supported by the application of online learning methods [23] and predictive models for quality detection [25], makes it possible to identify and sort out parts at an early stage in the production process, thus avoiding the waste of resources and time in subsequent processes [23]. Companies need support to increase the use of data to gain more insight and reduce defects at a larger scale [9]. Companies need to reduce not only physical waste, but also digital waste. Future research must provide methods to move from inefficient 'offline' rework to efficient 'online' defect prevention [9]. The challenges associated with limited data availability and big data analytics in Industry 4.0 maintenance should be addressed. This may involve innovative thinking on how to collect, store and process data, as well as improving methods for using data-driven modelling to make diagnoses, predictions and decisions [11].

Zero Resource Loss, Zero Human Potential Loss and Zero Data Loss to address the currently identified research gaps.

4. Conclusions

This publication examines ZDM from a sustainability perspective, with a particular focus on current developments in resource loss, human potential loss and data loss. For this purpose, 152 scientific publications were searched and analysed using the systematic literature analysis method of vom Brocke et al [6]. The main claim that the traditional definition of ZDM needs to be reconsidered results from the current research gaps highlighted in Table 1.

This research is limited to the methodology applied by vom Brocke [6]. Another limitation is the database scopus.com, where the literature search was carried out, and the literature available on the database until July 2023, when the search was applied.

Furthermore, this research includes the different methods of the searched articles themselves. The results of the searched articels are generated by methods of systematic literature analysis, expert interviews, mathematical models and industrial use cases. This study only considers the results from the articles and does not differentiate how they were obtained.

This study is also limited by the filtering process of the articles in the literature search. For this purpose, the scientific articles found are subjectively categorised by the researchers as relevant or irrelevant according to their title and abstract. The articles are then searched for keywords from the three Zero^3 dimensions (resource loss, human potential loss, data loss). If the corresponding text passages are recognised as relevant, the article is considered relevant overall and included in this study. As a result, this publication approaches an extension of the traditional ZDM definition to include the Zero^3 dimensions of "Zero Resource Loss", "Zero Human Potential Loss" and "Zero Data Loss".

Zero Resource Loss continues to ensure the success of ZDM, with quality management playing a key role in reducing waste and improving overall performance. Using tools such as those proposed by Psarommatis et al [5], stakeholders can identify reusable, adaptable and combinable resources, ultimately optimising the ZDM approach.

Zero Human Potential Loss emphasises the multiple roles of human potential in manufacturing and production processes. It highlights the evolving responsibilities of humans as decision makers, problem solvers and operators. It concludes that the integration of human expertise, continuous learning and collaboration with technology is essential to achieve zero defect manufacturing and avoid any loss of human potential.

Zero Data Loss integrates the challenges associated with limited data availability and big data analytics, which still require innovative thinking on how to collect, store and process data, as well as improving methods for diagnosis, prognosis and decision making in ZDM.

For the future, ZDM platforms that integrate more than one company could accelerate the implementation of sustainable dimensions. Sharing best practices on these platforms would help to minimise implementation errors. In addition, integrated decision support systems could be installed and trained on such platforms to further develop existing ZDM systems.

All in all, this publication contributes to the current challenges of resource scarcity, lack of skilled labour and efficient use of industry data within ZDM by systematically analysing the state of the art and arguing for maintaining and developing ZDM for more sustainable production.

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