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Optimization of zero defect manufacturing strategies: A comparative study on simplified modeling approaches for enhanced efficiency and accuracy

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ABSTRACT

This paper presents a comparative analysis of three distinct Zero Defect Manufacturing (ZDM) strategies: Detection - Repair (DR), Detection - Prevention (DP), and Prediction - Prevention (PP). We evaluated these strategies based on their effectiveness in optimizing ZDM parameters, considering the specific needs and constraints of various manufacturing setups. Our analysis found that while DR and DP simulation models closely reflected original results, PP models demonstrated lower predictability, underscoring the need for further research and specialized modeling approaches. Nonetheless, the selection of an optimal strategy was determined to be context-dependent, hinging on the characteristics of the manufacturing system. The study also highlights the necessity of validating these strategies across diverse manufacturing setups to assess their performance and suitability. This research augments the existing body of knowledge on ZDM, offering insights to drive future investigations for the development of robust, accurate, and efficient ZDM modeling techniques. The ultimate objective is to move modern manufacturing industries towards a zero-defect environment, thereby enhancing their efficiency, reliability, and overall productivity.

1. Introduction

The industrial revolution, Industry 4.0, is centered on automation, interconnectivity, machine learning, and real-time data, is gradually reshaping the global manufacturing sector (Psarommatis et al., Jun. 2023; Tsaramirsis, Jun. 2022). With these advancements, the bar for quality assurance and production efficiency has been raised. Central to this elevation is the concept of zero-defect manufacturing (ZDM), which aspires for a defect-free production process (Psarommatis et al., 2020; Powell et al., Apr. 2022). In the contemporary industrial environment, achieving operational excellence is a priority, and manufacturing processes are continuously evolving to meet this objective. One of the shifts in recent years that aims at higher manufacturing sustainability is the progression towards the ZDM paradigm (Psarommatis et al., 2020). According to (Caiazzo et al., Jan. 2022), the move towards ZDM not only focuses on the integration of innovative techniques and methodologies but also emphasizes the importance of understanding and addressing the existing challenges in the field. Their comprehensive review highlights the state-of-the-art methods employed in ZDM and underscores the open challenges that researchers and industry professionals should focus on. As the manufacturing landscape becomes increasingly complex with the infusion of Industry 4.0 and now Industry 5.0 principles, understanding and leveraging the potential of ZDM becomes paramount. The numerous benefits, such as improved product quality, reduced production costs, and diminished waste, underscore the significance of ZDM (Psarommatis et al., 2020; Dhingra et al., Aug. 2019). Given this context, the identification of optimal parameters for achieving ZDM becomes crucial and has taken center stage in recent research (Psarommatis and May, Jan. 2023; Psarommatis et al., Jan. 2021).

Complementing this research thrust, modeling and simulation play pivotal roles in the analysis and optimization of complex manufacturing systems (Mourtzis, 2019) and on the creation of digital twins (Psarommatis and May, Jul. 2022; Psarommatis, Apr. 2021). When aiming for ZDM, simulation-based optimization strategies provide a cost-effective means to identify the optimal parameters without the expense and risk of real-world experimentation (Psarommatis and May, Jul. 2022; Psarommatis et al., 2022). While full-scale models provide an accurate representation of the system, their complexity and computational requirements often render them impractical for extensive iterative optimization (Ruiz et al., 2021). This challenge has instigated the

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development of simplified models, which are inherently less accurate but more computationally efficient.

An aspect that adds to this computational challenge is the inherent complexity of scheduling in manufacturing, recognized as NP-hard problems (Pinedo, 2016). Consequently, a significant amount of computational power is required to achieve satisfactory results that align with the desired objective functions. Extensive research, as indicated by the literature review, has been dedicated to developing various heuristic algorithms capable of solving scheduling problems within an acceptable timeframe (Grobler-Dębska et al., Feb. 2022; Psarommatis et al., Jan. 2020; Karimi-Mamaghan et al., Sep. 2020; Zhang and Xing, Aug. 2019). This challenge is further intensified in manufacturing contexts that involve multiple stages, where events at each stage have a direct impact on the scheduling of subsequent stages.

Literature Gap and Study Aim: While numerous studies have investigated ZDM methodologies and their implications, there remains a significant gap in understanding the computational efficiency and time-related challenges associated with ZDM simulations. Moreover, the comparative efficacy of different strategies like Defects Reduction (DR), Defects Prediction (DP), and Predictive Policing (PP) within the ZDM paradigm has not been exhaustively explored. This study seeks to bridge this gap by proposing a simplification process for the original simulation model, aiming to strike a balance between computational time and simulation accuracy. Additionally, this paper conducts an in-depth analysis of the three aforementioned strategies, comparing them in terms of both performance and computational demands.

This paper presents a methodology for simplifying scheduling models, with a goal to significantly reduce the simulation time and provide rapid, yet accurate, results for design towards ZDM. This need was observed during the conduction of this research (Psarommatis, Apr. 2021), where the simulation times for the experiments were in the order of days. More specifically, we developed and compared three different strategies for the simplification of the initial models, not only between each other but also with the initial one. Furthermore, we explored the trade-offs between model accuracy and computational efficiency and evaluated their applicability in various manufacturing scenarios. The insights from this study are expected to guide practitioners, modelers, and researchers in creating fast and accurate simulation models. In this study, the simplified models are intended to be used for selecting an appropriate modeling strategy for specific manufacturing setups, thereby facilitating the identification of optimal ZDM parameters in a computationally efficient manner. By formulating different strategies based on the modeling of tasks, task relationships, and defect rates, this research explores various trade-offs between accuracy and computational efficiency. The work investigates their ability to replicate the dynamics of a complex manufacturing system, emphasizing their effectiveness in identifying optimal ZDM parameters (Psarommatis, Apr. 2021).

The remainder of the paper is organized as follows: Section 2 provides a comprehensive review of the current state of the art in simplified modeling strategies for ZDM, highlighting their strengths and weaknesses. Section 3 details the specific problem statement that the research addresses, emphasizing the significance of the issue in the broader context of ZDM. Section 4 presents the methodology employed in the development and comparison of the three strategies. Section 5 describes the experimental setup used for model evaluation. Section 6 discusses the results, and provides an overall discussion of the findings, comparing the three strategies. Section 7 acknowledges the limitations of the study and proposes areas for future research. The paper concludes with final remarks on the outcomes of the research and their implications for future work. Table 1 presents the abbreviations used in the rest of the paper for the ease of the reader.

Table 1
Abbreviations list.

Term	Description	Term	Desciption
ZDM	Zero-Defect Manufacturing	**$Cmax_j$**	
DM	Defects Management	**$Cmin_j$**	
KPIs	Key Performance Indicators	**C_{ij}**	
T_x	Task x (where "x" is a number representing a specific task)	**T_y**	Task y (where "y" is a number representing a specific simplified task)
MFG	Manufacturing stage	**W_j**	Weight for the j-th KPI

2. State of the art

2.1. Overview of ZDM

The concept of ZDM has evolved into a fundamental pillar within the Industry 4.0 landscape. Numerous methodologies and technologies have emerged to embody this concept, each aiming to eradicate manufacturing defects and thus enhance overall efficiency and product quality. On the technological front, several studies proposed the use of digital tools to enable ZDM. Psarommatis & Kiritsis (2022) put forth a Decision Support System for automated decision-making in response to defects (Psarommatis and Kiritsis, 2021). However, the system's applicability across different production environments remains to be thoroughly investigated. Extending this digital thread, Ruiz et al. (2021) introduced a Smart Digital Twin for ZDM-based job-shop scheduling (Ruiz et al., 2021). Despite the promise, potential hurdles in large-scale integration and widespread adoption cast some shadows. Venanzi et al. (2023) ventured further into the digital realm with a Big Data platform, which enables adaptive analytics for ZDM (Venanzi,May, 2023). Yet, the paper fell short of addressing the inherent challenges in platform implementation.

Several studies focused on methodological advancements in the ZDM context. Psarommatis (2021) devised a novel methodology utilizing a digital twin for ZDM performance mapping. Despite its novelty, the implementation complexity related to digital twin technology might limit its wider adoption across industries (Psarommatis, Apr. 2021). Trebuna et al. (2022) conducted a comparative analysis of modern manufacturing tools and their influence on ZDM strategies. While this study was insightful, it lacked supportive real-world case studies (Trebuna et al., 2022).

Concerning more specific applications, Sousa et al. (2021) deployed data-driven technologies for ZDM within the natural stone industry (Sousa et al., 2021). Although effective within this particular context, the transferability of such solutions to other sectors is not assured. Babalola et al. (2023) underscored the significance of in-situ workpiece perception for achieving ZDM within Industry 4.0 compliant job shops (Babalola et al., Jun. 2023). Yet, the research did not adequately consider potential disruptions and technological demands that might occur during implementation.

Several studies aimed to deal with unpredictability and scheduling within ZDM. Psarommatis et al. (2021) proposed a predictive model for calculating rescheduling time for unexpected events in ZDM (Psarommatis et al., Apr. 2021). However, the model's efficiency hinges on the accurate prediction of such events, which presents a challenge in itself. Building on scheduling methods, Grobler-Dębska et al. (2022) introduced a formal method for ZDM (Grobler-Dębska et al., Feb. 2022), although its inherent complexity could deter wider application. Martinez et al. (2022) attempted to bridge the gap between physical and digital through a cyber-physical system approach to ZDM in light-gauge steel frame assemblies (Martinez et al., Jan. 2022). However, the assumption of high digital maturity in manufacturing companies may not always hold, casting doubts on its universal applicability. Table 2 is a summarizing table of the relevant literature in the relevant field of ZDM:

Table 2
Relevant literature in the relevant field of zdm.

Paper No.	Authors & Year	Key Contributions (+)	Shortcomings (-)
1	Psarommatis & Kiritsis, 2022 (Psarommatis and Kiritsis, 2021)	Automated decision-making for defect management	Unclear efficiency in different production environments
2	Psarommatis, 2021 (Psarommatis, Apr. 2021)	Digital twin for ZDM performance mapping	Complexity of digital twin technology might limit wide implementation
3	Trebuna et al., 2022 (Trebuna et al., 2022)	Comparative study of manufacturing tools' impact on ZDM	Lack of real-world case studies
4	Babalola et al., 2023 (Babalola et al., Jun. 2023)	In-situ workpiece perception for ZDM in job shops	Potential disruptions during implementation not addressed
5	Ruiz et al., 2021 (Ruiz et al., 2021)	Smart Digital Twin for ZDM-based scheduling	Challenges with large scale integration and adoption
6	Sousa et al., 2021 (Sousa et al., 2021)	Application of data-driven technologies for ZDM in the stone industry	Uncertainty in solutions' transferability to other sectors
7	Psarommatis et al., 2021 (Psarommatis et al., Apr. 2021)	Rescheduling model for unexpected events in ZDM	Model's effectiveness relies on accurate prediction of unexpected events
8	Grobler-Dębska et al., 2022 (Grobler-Dębska et al., Feb. 2022)	Formal scheduling method for ZDM	Complexity may hinder wide application
9	Martinez et al., 2022 (Martinez et al., Jan. 2022)	Cyber-physical system approach to ZDM in light-gauge steel assemblies	Assumption of high digital maturity may not be applicable in all scenarios
10	Venanzi et al., 2023 (Venanzi,May, 2023)	Big Data platform for adaptive analytics in ZDM	Insufficient discussion on potential implementation challenges

2.2. Transition from Industry 4.0 to Industry 5.0

While Industry 4.0 marked a significant move towards automation, interconnectivity, and real-time data processing, Industry 5.0 introduces the next phase of manufacturing evolution. Industry 5.0 builds upon the foundational concepts of Industry 4.0 by emphasizing a synergetic collaboration between humans and machines. This collaboration aims to enhance the human touch in manufacturing processes, thereby ensuring products cater more closely to individual needs, preferences, and values.

One of the hallmarks of Industry 5.0 is its focus on enhanced customization. As consumer demand shifts from mass-produced items to more personalized products, the industry needs to pivot its operations to accommodate this demand. Through advanced technologies such as artificial intelligence, augmented reality, and robotics, Industry 5.0 integrates customization right from the design phase to post-production, ensuring a tailored user experience at every stage (Leng, Oct. 2022).

Furthermore, another crucial distinction lies in the integration of sustainability principles. Unlike previous industrial phases, Industry 5.0 not only emphasizes producing more with less but also stresses the importance of sustainable production. The nexus between sustainability and manufacturing has never been more pronounced. This renewed focus entails the utilization of eco-friendly materials, energy-efficient processes, and a comprehensive life-cycle assessment to minimize environmental impacts and ensure the well-being of both consumers and the planet (De Giovanni, Jan. 2023).

Conclusively, while Industry 4.0 laid the groundwork for an interconnected, digitized manufacturing landscape, Industry 5.0 aspires for a holistic approach, harmonizing technology with human values, and underlining the essence of sustainable, customized production.

2.3. Sustainability in the context of ZDM

ZDM not only strives for impeccable product quality but also inadvertently aligns with many sustainability principles. By minimizing waste, rework, and recalls, ZDM practices can reduce the consumption of raw materials, energy, and other resources, leading to both environmental and economic benefits (Lindström, Jan. 2019).

Moreover, the push towards ZDM has broader societal implications. The reduction of defective products means less wastage, which translates into a decrease in landfill contributions. When manufacturing units produce fewer defects, they also decrease emissions and harmful byproducts that can result from re-manufacturing or correcting those defects. This directly aligns with the global pursuit of a more circular economy, where resources are used more efficiently, and waste is minimized at every step of the product lifecycle.

Furthermore, from a consumer perspective, ZDM enhances trust and confidence in products. As manufacturing processes become more transparent and companies emphasize their commitment to ZDM, consumers are more likely to support brands that ensure high-quality, defect-free products. This not only fosters brand loyalty but also encourages sustainable consumer behavior, as fewer replacements and repairs are needed over the product's life span.

2.4. Linking Industry 5.0, sustainability and ZDM

Industry 5.0 offers the technological tools and frameworks that can further enhance the implementation of ZDM. With its emphasis on human–machine collaboration, there is potential for improved defect detection, as humans can provide the intuitive understanding and machines offer precision. Furthermore, the emphasis on sustainability in Industry 5.0 and ZDM means that manufacturers are not just aiming for zero defects but are also considering the environmental and social implications of their manufacturing processes.

2.5. Gap addressed and contribution of our study

Despite the substantial advancements in ZDM strategies, our review of the current state-of-the-art reveals a striking gap: the absence of a balanced approach to model complexity and computational efficiency in simulation-based optimization strategies. This deficiency is particularly apparent considering the scarcity of comparative studies on simplified modeling strategies within the ZDM sphere.

Our study addresses this void by conducting a detailed comparative study of three distinct ZDM strategies: Detection - Repair (DR), Detection - Prevention (DP), and Prediction - Prevention (PP) (Psarommatis et al., 2020; Psarommatis et al., 2022). We evaluated each strategy for their effectiveness in ZDM parameter optimization, considering different manufacturing setups' specific needs and constraints. By probing into the trade-offs between model accuracy and computational efficiency, our study provides valuable insights to guide the selection of the most suitable strategy according to the unique needs of each manufacturing setup.

Our work emphasizes that the optimal strategy selection is contingent on the context, reflecting the dynamism inherent in the manufacturing industry. Our analysis contributes to a broader understanding and future improvement of modeling strategies in ZDM. This research offers valuable insights and is a novel contribution to the ZDM knowledge base, propelling the modern manufacturing industries towards a zero-defect environment. We anticipate a substantial positive impact on the global manufacturing sector through the enhanced efficiency, reliability, and productivity that comes with the optimal selection of ZDM strategies.

3. Problem statement

Designing a manufacturing system for ZDM is a complex task that requires a significant number of simulations to accurately quantify the specifications of the ZDM-related equipment. This is required to ensure that there is minimal or ideally, no performance loss in the manufacturing system. In this study, we utilized a methodology known as “design for ZDM” from the literature (Psarommatis, Apr. 2021). Although in the the simulation method involves utilizes the design of experiments (M. s., 1995), there is still a very high number of required simulations (millions) needed to map a manufacturing system for ZDM strategies. The process is that a set of simulations is performed and then, using the methodology developed in (Psarommatis, Apr. 2021), converting the results into a digital twin of the modeled manufacturing system. Fig. 1 illustrates the simplified steps for the design for ZDM methodology.

This study is centered on the process, indicated in red, of creating simulation models and carrying out simulations. The use of real-life production data is highly promising for creating accurate Digital twins; however, it demands a significant amount of computational time. Within the manufacturing scenario under investigation, the simulation process involves scheduling and executing a full year’s production, with the average simulation time reaching 14 days on an Intel® Core™ i7-8700 K processor with 32 GB of RAM. Consequently, in this paper, we develop simplified models of the same production line setup and assess their impact on the final results using the identical scheduling tool. Our goal is to further diminish the computational time required, making the production design for ZDM even more cost-effective and resource-efficient.

Within the domain of ZDM, several strategies related to defect detect, repair, prevention, and prediction were proposed (Psarommatis et al., 2020; Psarommatis et al., 2022). The introduction of these tasks into the manufacturing stages opens up opportunities for optimization. The key question then becomes: what is the optimal approach for planning these ZDM tasks and incorporating them into the manufacturing processes to deliver zero-defect products while minimizing costs?

In response to this challenge, an innovative scheduling tool and DT methodology, has been developed, aiming at optimizing the ZDM strategy and quality control specifications for a production line (Psarommatis, Apr. 2021; Psarommatis et al., Jan. 2020; Psarommatis et al., Apr. 2021; Psarommatis et al., Jan. 2021; Psarommatis et al., Jan. 2020). This ground-breaking solution enables the identification of the optimal ZDM strategy and parameters without the need to run the scheduling tool itself. Instead, the tool generates a set of graphs that manufacturers can easily use to select the most suitable ZDM strategy and quality control parameters, eliminating the need for time-consuming simulations. This streamlined approach saves manufacturers a significant amount of time in the production design process for ZDM.

Every ZDM approach has unique control parameters that have an impact on the efficacy and functionality of the ZDM implementation. Three control parameters were established for each ZDM technique in this work and are shown in Table 2. These variables were included because they are the most crucial variables to consider while choosing ZDM equipment. The following strategy was developed and used for the simulations and development of the DT model due to the fact that each industrial application is distinct and there is no merit in generalizing based on data from a particular use case. Each product has some nominal properties that are computed assuming that there are no flaws or any unforeseen events that would disrupt the regular flow of production. In this instance, the absolute use-case specific values were converted to relative values by calculating the overall cost and time for producing the product. Equation (1), which is just the absolute value of the ZDM parameter divided by the matching total estimated product value, was used to achieve this. The ratio technique that was chosen gave a relative indication of how much more time or money is needed to operate the ZDM strategy. This straightforward concept seeks to delink results from one situation so that they can be used to other cases where the product is different, but the ratios are the same [55]. As a result, only the parameters denoted by an “R” in Table 3 have relative values; the others only have percentages.

$$\textit{Relative factor Value} = \frac{\textit{Absolute ZDM Value}}{\textit{Estimated Total Value}} \tag{1}$$

4. Model simplification: proposed strategies

In this section, we detail our proposed methodology for simplifying simulation models to minimize computational time, emphasizing its applicability to the ’design for ZDM’ approach. Firstly, the essence of our methodology lies in its focus on single manufacturing stages, capturing KPI effects at each unique stage. We have developed two distinct methods, with the goal to ascertain the most efficient one based on specific use cases. The ’Cycle Time Approach’ serves as our primary simplification strategy, where tasks are consolidated excluding the application of ZDM. This is visually represented in Fig. 2. Depending on the specific scenario—whether the task for ZDM implementation is part of the longest process chain or not—our approach varies, as elaborated in Figs. 3 and 4. Subsequent to this, our study assesses the outcomes

Table 3
ZDM control parameters (Psarommatis, Apr. 2021).

Parameter Name	ZDM strategy	Parameter Description
Inspection Cost (IC), *R*	Dt	The cost related to the operation of the inspection machine per item inspected
Inspection Time (IT), *R*	Dt	The time that the inspection equipment requires in order to inspect one part
Detection Accuracy (DA), %	Dt	The accuracy that the inspection equipment has. Measured in percentage.
Repairing Cost (RC), *R*	Rp	The average repairing cost. This cost includes the extra raw materials needed for the repair and the labor and machine operational cost for performing the repair
Repairing Time (RT), *R*	Rp	The time that is required in order to perform the repair
Reparability (Rep), %	Rp	Reparability represents a percentage that shows how many parts are reparable out of the total.
Prevention Cost (PvC), *R*	Pv	The related cost for the raw materials and operator time cost that are required for the implementation of the prevention actions.
Prevention Time (PvT), *R*	Pv	The time that is required in order for the operator to implement the prevention actions. Those prevention actions could be either small maintenance or machine tuning
Prevention success Rate (PvSR), %	Pv	It is a percentage that indicates the probability of the prevention actions to have real effect to the production line. In other words, if the prevention actions are successful or there was a miss-diagnose.
Prediction Horizon (PdH), *R*	Pd	Is the timeframe that the prediction algorithm looks ahead
Prediction Accuracy (PdA), %	Pd	Is the probability of successfully predicting a defect in the given prediction horizon
Prevention Reaction Time (PdReaT), *R*	Pd	Is the time that is required for implementing the prevention actions.

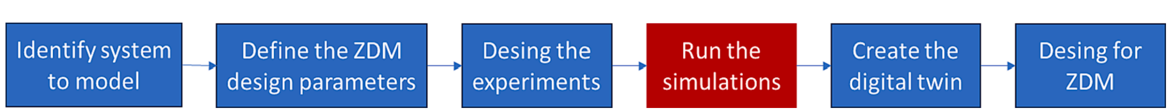


Fig. 1. Desing for ZDM methodology steps.

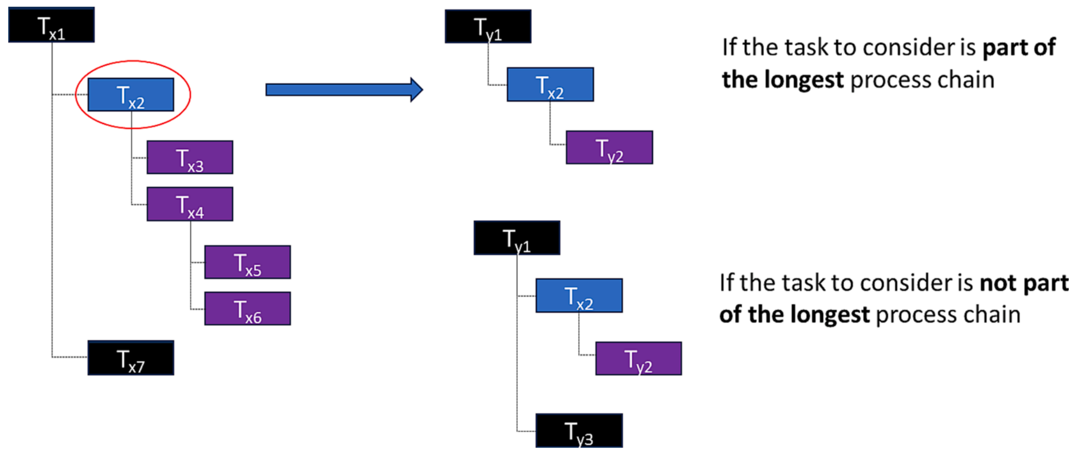


Fig. 2. Simplification strategy overall concept.

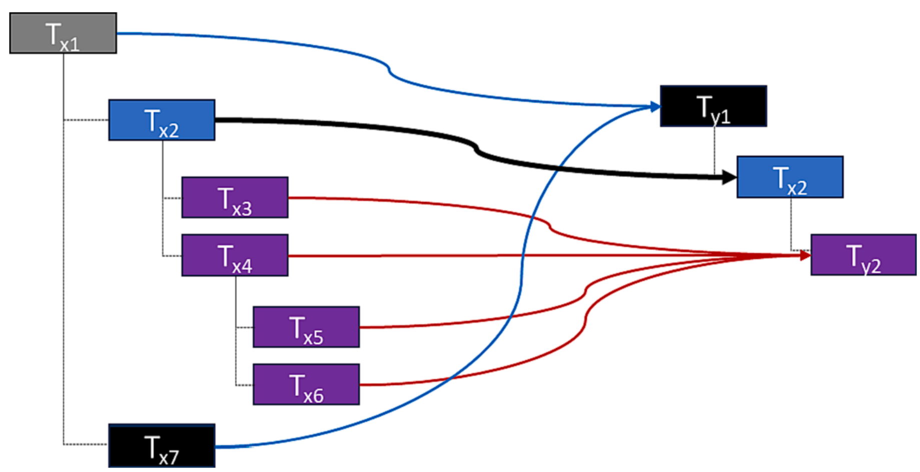


Fig. 3. Task part of the longest process chain simplification process.

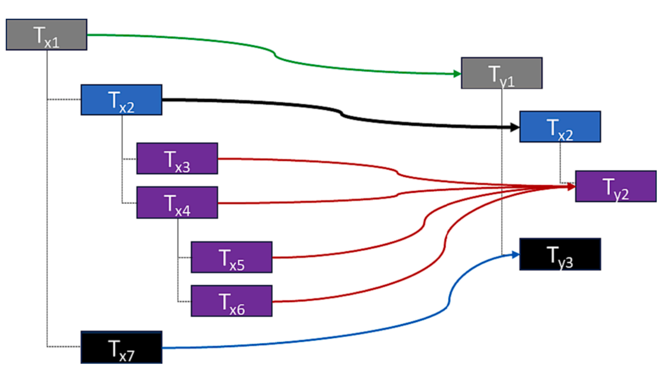


Fig. 4. Task not part of the longest process chain simplification process.

using a set of seven KPIs, as tabulated in Table 2, which consider factors ranging from time and energy consumption to costs associated with defect management.

4.1. *Simplification strategy: the cycle time approach*

The strategy outlined herein is designed to streamline production processes by simplifying tasks excluding the application of ZDM. This is achieved by introducing a new task, which combines all the tasks except the task to apply ZDM. Fig. 2 illustrates the overarching concept of strategy 1′s approach. Specifically, the task earmarked for ZDM implementation is represented in blue. The proposed simplification strategy implies that the cycle time and various machine-oriented parameters (such as machine operational cost, energy consumption) of all remaining tasks are consolidated into a single task, in line with the process branch they belong to. To adhere to this approach, two distinct scenarios must be defined to properly categorize the problem and accommodate different cases.

1. The task to apply ZDM is a component of the longest process chain that determines the cycle time
2. The task to apply ZDM does **not** belong to the longest process chain that determines the cycle time

These two different scenarios bear significance as the combined task will assume a different value depending on the scenario. To calculate and identify the processing time of each process chain, the following steps must be followed: identify the task to analyze and calculate the different process chains. Once the task to analyze is selected, the various process chains are defined by the number of distinct tasks at the same level as the level of the task to analyze. This implies, in Fig. 2, if the task to analyze is T_{x2}, then there are two process chains to be evaluated. The process preceding the selected task (T_{x1}) is common in both scenarios. One branch consists of Tx1, Tx2, Tx3, Tx4, Tx5 and Tx6, while the other includes Tx1 and Tx7.

Table 4
KPIs list.

$\boldsymbol{WeightedTardiness} = \sum_{o=1}^{nOrders}(OrderFinishTime_o - DueDate_o)*OrderCriticality_o$ **(1)**
$\boldsymbol{AvgMakespan} = \frac{\sum_{0=1}^{numberOrders} OrderFinishTime_o}{numberOrders}$ **(2)**
$\boldsymbol{MachineEnergyConsumption} = \sum_{i=1}^{MFG}(TotalProcessTime_i*EnergyConsumption_i) + \sum_{q=1}^{nRepairTask} TotalRepairOperationalTime_q*EnergyConsumption_q + \sum_{f=1}^{inspM}(TotalInspectionTime_f*EnergyConsumption_f$ **(3)**
$\boldsymbol{TotalMachineOperationalCost} = \sum_{i=1}^{MFG}(TotalProcessTime_i*MachineOperationalCost_i) + \sum_{w=1}^{nOperators}(LaborTime_w*LaborCost_w)$ **(4)**
$\boldsymbol{DetectionPreventionCost} = \sum_{i=1}^{MFG}\sum_{e=1}^{numberPrevActions}\{SparePartsCost_{ie} + PreventionTime_{ie}*LaborCost_{ie}\}$ **(5)**
$\boldsymbol{PredictionPreventionCost} = \sum_{i=1}^{MFG}\sum_{e=1}^{numberPrevActions}\{SparePartsCost_{ie} + PreventionTime_{ie}*(LabourCost_{ie} + ProductionLosses_{ie})\}$ **(6)**
$\boldsymbol{RepairCost} = \sum_{q=1}^{nRepairTask}\left(ManualInspectionTime_q*laborCost + RawMaterialsCost + ProcessingTime_q*MachineOperationCost + laborTime_q*laborCost\right)$ **(7)**

4.1.1. *Scenario 1: Task simplification when tasks in the longest process chain*

If the task is part of the longest process chain, then the simplified model is created based on the concept depicted in Fig. 3. In the example presented, the task we want to study for ZDM implementation is T_{x2}. As mentioned before, there are two process branches: one marked in purple and the other in black. Since the task is part of the longest process cycle, task T_{7x} does not influence the overall cycle time. Therefore, in terms of time, task T_{x7} is disregarded, but the remaining characteristics of the task, such as material cost, machine operational cost, machine maintenance cost, and energy consumption are transferred to the immediate parent task - in this case, T_{x1}. Thus, as shown in Fig. 3, the two tasks T_{x1} and T_{x7} are combined to T_{y1}. Following the same principle, all the tasks marked in purple are combined to T_{y2}, as indicated by red arrows. This simplification means that for this example, instead of seven tasks, our simplified model has only three, which will significantly reduce computational time.

4.1.2. *Scenario 2: Task simplification when task NOT in the longest process chain*

Fig. 4 illustrates the procedure to be followed for model simplification, when the task to be simplified is not part of the longest process chain. In this instance, T_{x7} represents the longest process cycle that determines the cycle time, but since T_{x2} is the task of interest, it should not be neglected or combined. The colour-coded arrows in Fig. 4 represent the steps of simplification. The tasks in purple are simplified in exactly the same manner to T_{y2}, but the process branch to which T_{x7} belongs is simplified to T_{y3}. In this example, this process branch consists of only one task, but it could include more. The exact same logic applies to T_{x1} and T_{y1}. In this case, the simplified model is larger - four tasks instead of seven.

4.2. *Key performance indicators (KPIs) for evaluation*

The simulations that are going to be performed will be evaluated using a set of seven KPIs. Table 4 illustrates the various KPIs that will be used for the evaluation of the alternative schedules. The first two KPIs concern time, specifically weighted tardiness and the average makespan of the entire production (as defined in equations 1 and 2 respectively). The third KPI pertains to the energy consumption of production, and equation 4 details the production cost. The remaining KPIs relate to the implementation of the different ZDM strategies. In order to arrive at a single value that encapsulates all the defined KPIs, equations (8) and (9) are utilized. Equation (8) is used for each KPI to normalize its value (this particular equation is used for normalizing KPIs with cost behavior, where smaller values are better). Once all the KPIs are normalized, a weighted sum formula is used (equation (9) to aggregate all the normalized values. The resulting "utility value" lies within the range [0,1], with the best possible value being 1.

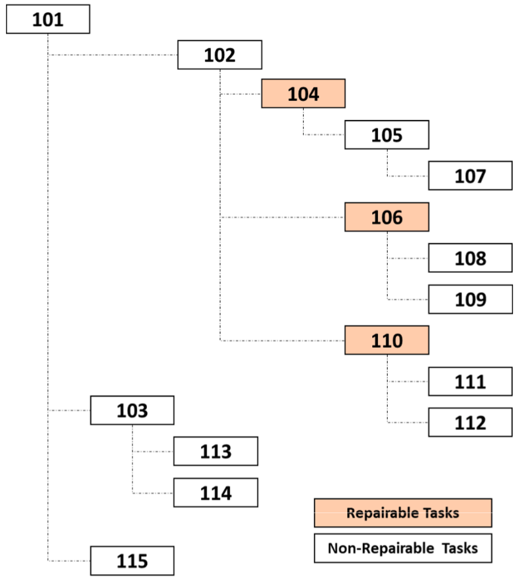
$$\widehat{C}_{ij} = \frac{C_j^{max} - C_{ij}}{C_j^{max} - C_j^{min}} \tag{8}$$

$$U_i = \sum_{j=1}^{m} W_j \widehat{C}_{ij} \tag{9}$$

5. Method validation and performance measurement of simplification

5.1. *Industrial scenario*

Fig. 5 illustrates the Bill of Processes (BoP) for the product under investigation, presenting the sequence of all 15 tasks. These tasks pertain only to the manufacturing tasks and do not include tasks related to the ZDM implementation. The product being investigated is a printed circuit board from the semiconductor domain, intended for use in medical



Task	Task Processing Time (mins)
101	17.533
102	15.574
103	17.217
104	25.633
105	15.995
106	15.351
107	28.827
108	6.548
109	23.313
110	27.168
111	3.1026
112	12.831
113	26.268
114	20.634
115	11.048

Fig. 5. Bill of Process (Left) and Task Processing Time (Right).

devices. Each of these 15 tasks can only be performed by one machine; hence, for 15 manufacturing tasks, there are 15 machines (MFG). The design for the ZDM method suggests that for each MFG, all three ZDM strategies are simulated to quantify the impact each ZDM strategy has on the performance of the manufacturing system.

In essence, the experiments should be performed using a specific methodology known as design of experiments. More specifically, the Taguchi approach is utilized, and due to the involvement of six design parameters in each experiment and the need for high accuracy, the L25 orthogonal array is used. This implies that for analyzing each MFG for each of the ZDM strategies, 25 experiments are required. Consequently, a total of $15 \times 3 \times 25 = 1{,}125$ simulations are needed solely for the simplified scenario presented in Fig. 5. This suggests that if the manufacturing system is larger or there are more design factors, the method's scalability becomes unfeasible. Therefore, the development of the proposed model simplification method is crucial for making the design for ZDM method scalable.

5.2. Simulation results

This section compares the results of the three discussed scenarios with the original results. For each scenario, absolute utility values are calculated for all 531,441 factor combinations, considering 15 manufacturing stages and 3 ZDM strategies. To make comparison with the original results easier, the results obtained are normalized along with the original results.

Table 5 shows a sample of the raw results. As depicted in Table 5, the x-axis represents the 531,441 factor combinations resulting from all possible permutations of the 6 factors, each having 9 levels ($9^6 = 531{,}441$). The y-axis displays the utility values for each factor combination. This arrangement facilitates the selection of optimal factor levels and ZDM strategies based on the utility values.

Upon examining the results, it can be deduced that all strategies exhibit similar trends for DR (Defect Rate) and DP (Delivery Performance). The peaks of Factor 1 and Factor 2 align closely with the corresponding peaks in the original results. However, in the case of PP (Predict Prevent), substantial deviations are observed. These significant variations could be ascribed to the stochastic nature of the PP strategy. These results suggest that relying solely on PP may not offer reliable guidance for selecting the optimal ZDM parameters. To delve deeper into the quality of each strategy, the results will undergo quantitative analysis using various measures in the subsequent sections of this paper. This methodology is intended to offer a more comprehensive evaluation of the effectiveness of the strategies.

5.2.1. Relative difference comparison

By leveraging the calculation of relative difference, the quality of the proposed simplification method can be quantified in terms of the deviation of utility values, as demonstrated in Fig. 6. In general, it is noted that the average relative difference is below 3 %, indicating a good alignment of the simplified model with the original one.

$$RelativeDifference = \frac{|U_o - U_i|}{\left(\frac{U_o + U_i}{2}\right)} \times 100 \quad (10)$$

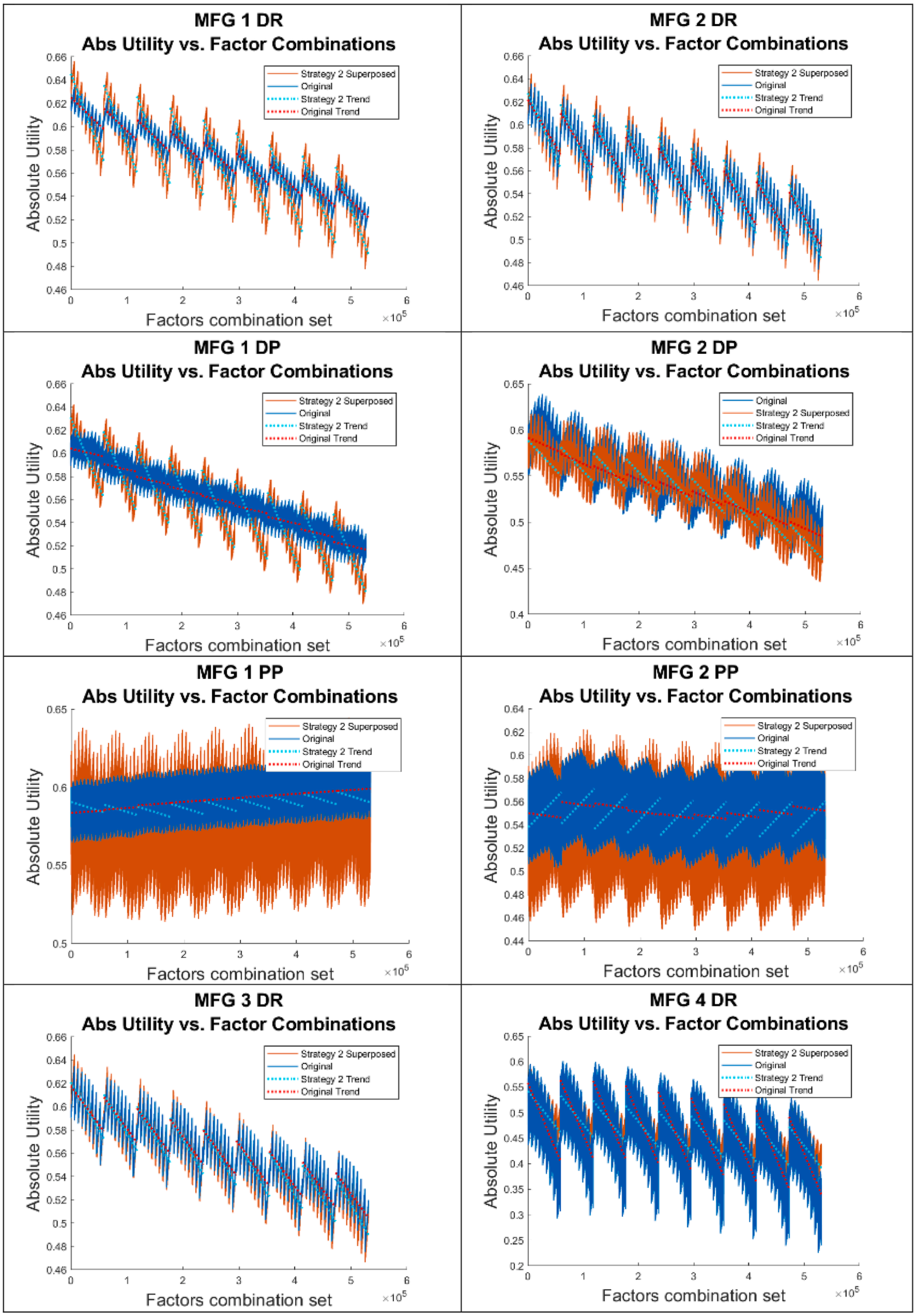
5.2.2. Coefficient of Variation (CV)

CV can act as another tool for quantifying the quality of each strategy in relation to the original results. CV evaluates the dispersion or spread of utility values around the mean values. This analysis provides insights into the stochastic nature of the results, allowing for a more comprehensive understanding of the performance variability in among different strategies.

$$CoefficientofVariation = \frac{\sigma}{\mu}$$

As depicted in Fig. 7, the proposed simplification strategy presents CV values that are closely aligned with the original results, signifying a similar spread of utility values around the mean utility values. Notably, it accomplishes an exceptionally close CV value for PP in comparison to the original results (0.01654 vs. 0.1662). These findings further support the notion that the simplification process effectively maintains the dynamics of the original system, resulting in relatively accurate results.

Table 5
Results from simulation for each mfg of the product under investigation.



DR	DP	PP	Average
2.32%	3.12%	2.34%	**2.60%**
0.98%	2.22%	5.04%	**2.75%**
1.04%	1.66%	5.23%	**2.64%**
6.64%	3.75%	2.38%	**4.26%**
1.68%	2.10%	2.58%	**2.12%**
1.96%	1.90%	1.85%	**1.90%**
1.87%	2.73%	0.91%	**1.84%**
2.16%	3.27%	0.85%	**2.09%**
2.10%	3.02%	0.61%	**1.91%**
2.16%	3.02%	1.23%	**2.14%**
1.69%	1.84%	0.77%	**1.43%**
1.86%	2.74%	1.80%	**2.13%**
1.03%	1.89%	0.91%	**1.28%**
0.72%	1.72%	1.08%	**1.17%**
1.73%	1.80%	0.78%	**1.44%**
2.00%	**2.45%**	**1.89%**	**2.11%**

Fig. 6. Relative Difference of Results.

6. Discussions of results

In this section of the paper, below methods were employed to analyze the results:

- Visual inspection of trends.
- Relative difference of utility values on each factor combination.
- CV calculations.

6.1. Implications of the reduced simulation time

The substantial reduction in computational time is an integral finding in this study. With an average reduction of 90 %, we can conclude that the manufacturing industry stands to benefit from increased efficiency in the optimization process for ZDM. Previously, computations took 14 days using an Intel® Core™ i7-8700 K processor with 32 GB of RAM, which can be considered as a significant resource investment. With the introduction of the simplified models, the same process can be completed on average between [12.4, 260.32] minutes, depending on the size of the model. This drastic reduction in computational time paves the way for faster decision-making processes, leading to quicker optimization of production processes. This efficiency gain can potentially translate into cost savings, making the manufacturing process more economical.

6.2. Analysis of accuracy Trade-Off

Despite the impressive gain in computational efficiency, it is important to address the trade-off involving a slight reduction in accuracy. For the Defects Reduction (DR) and Defects Prediction (DP) strategies, the proposed method exhibited similar trends and absolute utility values when compared to the original results. However, the PP strategy did not fare as well, with the accuracy taking a slight hit. While efficiency is desirable, the accuracy of these models is pivotal to making correct decisions in the manufacturing process. Under what conditions would this trade-off be acceptable? This is a question that future research could focus on, taking into account the nature of the manufacturing process, and the acceptable margin of error.

6.3. Assessment of different strategies (DR, DP, PP)

When analyzing the three strategies, it was found that the DR and DP strategies fared well with the proposed method, both in terms of trends and absolute utility values. However, for the Predictive Policing (PP) strategy, the results were less consistent, hinting at an inherent stochasticity in the strategy. It appears that there is more randomness in the results of the PP strategy, leading to the potential for sub-optimal ZDM parameters being chosen based solely on utility values. This suggests that the choice of strategy should depend on the specific conditions and requirements of the manufacturing process, and a 'one-size-fits-all' approach may not be appropriate.

Original results

DR	DP	PP	Average
0.04468	0.04444	0.01351	**0.03421**
0.05385	0.05720	0.02967	**0.04691**
0.05104	0.05978	0.04295	**0.05125**
0.12412	0.09447	0.04252	**0.08704**
0.05327	0.05462	0.02409	**0.04399**
0.05165	0.05124	0.02079	**0.04123**
0.04886	0.04740	0.00422	**0.03349**
0.04880	0.04774	0.00618	**0.03424**
0.04916	0.04742	0.00379	**0.03345**
0.05808	0.07948	0.01487	**0.05081**
0.04862	0.04876	0.00815	**0.03518**
0.04859	0.04755	0.00893	**0.03502**
0.04555	0.04410	0.00408	**0.03124**
0.04910	0.04669	0.00904	**0.03494**
0.05219	0.05084	0.01643	**0.03982**
0.05517	**0.05478**	**0.01662**	**0.04219**

Results using the simplification process

	DR	DP	PP	Average
MFG 1	0.05467	0.05343	0.03052	**0.04621**
MFG 2	0.05039	0.05185	0.04421	**0.04882**
MFG 3	0.05181	0.04889	0.03859	**0.04643**
MFG 4	0.05310	0.04986	0.04156	**0.04817**
MFG 5	0.05109	0.05015	0.01402	**0.03842**
MFG 6	0.05203	0.04899	0.00635	**0.03579**
MFG 7	0.05684	0.05954	0.00579	**0.04072**
MFG 8	0.05697	0.06101	0.00557	**0.04118**
MFG 9	0.05755	0.06034	0.00473	**0.04087**
MFG 10	0.05666	0.05980	0.01030	**0.04225**
MFG 11	0.05604	0.05720	0.00699	**0.04008**
MFG 12	0.05684	0.06027	0.01294	**0.04335**
MFG 13	0.05047	0.05271	0.00799	**0.03705**
MFG 14	0.04904	0.05062	0.00638	**0.03535**
MFG 15	0.05803	0.05152	0.01212	**0.04056**
Average	**0.05410**	**0.05441**	**0.01654**	**0.04168**

Fig. 7. Coefficient of Variation Comparison.

6.4. Unpredictability of the PP strategy

The unpredictable nature of the PP strategy highlights an area that requires further investigation. Despite the lower relative difference measures compared to DR and DP, the PP strategy produced more random and less consistent results. This inconsistency could potentially lead to the selection of sub-optimal ZDM parameters. These deviations can be attributed to the underlying stochastic nature of the PP strategy. Simplified models were unable to fully replicate these dynamics due to the loss of certain system dynamics in the scheduling process.

6.5. Shortcomings and recommendations for further research

This study provides valuable insights into the benefits and limitations of using simplified models to identify optimal ZDM parameters in production processes. However, more research is needed to fully understand the trade-off between computational efficiency and accuracy, particularly in the context of the PP strategy. Future research could delve deeper into the development of more specialized approaches that can maintain computational efficiency while improving the accuracy of the results for the PP strategy. Additionally, there is room to investigate the application of these methods in different manufacturing contexts, considering the unique requirements and constraints of each context.

Due to the poor accuracy observed in PP, selecting optimal ZDM parameters becomes challenging across the three ZDM strategies. The inherent stochasticity and lack of consistent trends in PP make it difficult to reliably identify the most suitable ZDM parameters based solely on the utility values. Therefore, additional considerations or alternative approaches may be necessary to effectively determine the optimal ZDM parameters in the context of PP.

Fig. 8 provides an example that compares the utility values across all three ZDM strategies for MFG 8. From the graphs, it is evident that DR and DP for the proposed strategy closely resemble the original results in terms of trend. This suggests that using the proposed simplification strategy would likely result in selecting the same ZDM parameters for DR and DP as compared to the original results. However, the situation becomes more complicated when considering PP, as it exhibits lower accuracy. In this specific example, there is a risk of underestimating the utility values of PP, which may lead to the selection of DR or DP instead of PP, even though PP might be more optimal given the available manufacturing setup.

Therefore, further investigation is warranted to improve the modeling strategy specifically for PP. Additional research and development are needed to develop a separate modeling approach that can capture the dynamics and stochasticity of PP accurately. This would enable more precise parameter selection across all three ZDM strategies.

Furthermore, it would be beneficial to validate the established modeling strategies by altering the manufacturing setup. Since the analyses suggest that task processing time correlates with the quality of the results, conducting simulations with both the simplified models and original models while varying the manufacturing setups would provide valuable insights and further validate the findings.

However, like any simulation study, this research is not without limitations. The results obtained through simplified models may not fully replicate the inherent stochastic nature of certain manufacturing strategies, particularly those related to Production Planning (PP). Therefore, the study underscores the need for future work focused on improving the modeling strategy specifically for PP to ensure more precise parameter selection across all ZDM strategies.

7. Concluding remarks

The objective of this paper was to develop a method for reducing the simulation time necessary for performing sustainable deign for ZDM. The approach followed involved the development of a simplification process for the original model. The goal of the utilized Design for ZDM method was to quantify the impact of the ZDM parameters on the selected KPIs. The simulation results showed that the proposed model could significantly reduce the overall computational time by an average of 90 %. This computational time reduction came at the cost of slightly lower accuracy, with an average of 2.11 % relative difference from the full simulation model. However, this level of accuracy is sufficient for designing a system to achieve ZDM.

The paper further evaluated three different strategies, namely Defects Reduction (DR), Defects Prediction (DP), and Predictive Policing (PP), and drew comparative analyses. Comparative analyses performed on these strategies showed that DR and DP strategies demonstrated trends that were similar to the original results. The PP strategy, despite demonstrating lower predictability, might still emerge as an optimal choice under certain manufacturing conditions. Therefore, the choice of an optimal strategy is context-dependent and needs to be guided by the specific needs and constraints of the manufacturing system in question.

In reflecting upon our research methodology and findings, we acknowledge several inherent limitations that merit consideration. Firstly, our simulation model, while comprehensive, may not encapsulate all the nuanced intricacies of a real-world manufacturing environment. This potential discrepancy may give rise to challenges when scaling our findings or applying them in diverse manufacturing contexts. Additionally, while our study integrates principles from both Industry 5.0 and ZDM, it does not exhaustively cover all potential overlaps or conflicting areas between these domains, which may have nuanced effects on certain key performance indicators.

Our research, while offering valuable insights, also illuminates pathways for subsequent studies. A logical progression would be to refine the simulation models by integrating granular real-world data, ensuring they mirror actual manufacturing environments more closely.

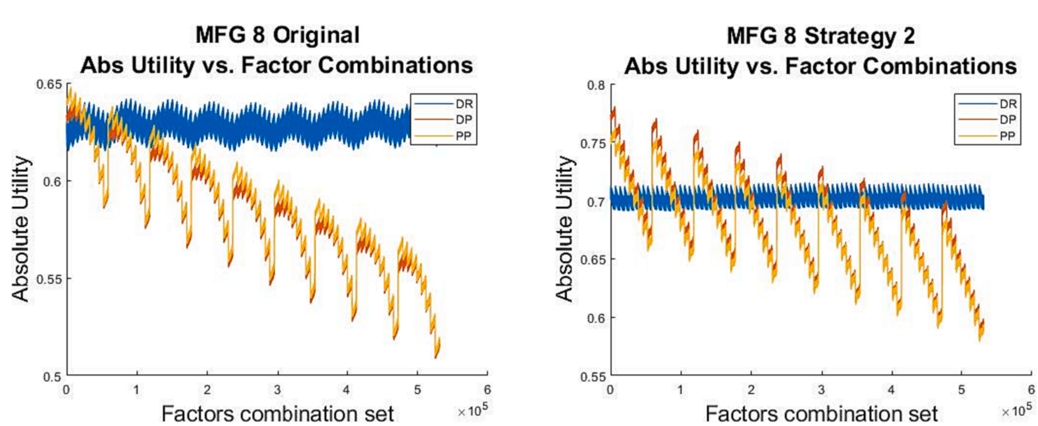


Fig. 8. MFG 8 Strategy 2 Comparison Across All ZDM Strategies.

This would enhance the generalizability and applicability of our results across varied manufacturing contexts. Furthermore, a deeper dive into the relationship between Industry 5.0, ZDM, and sustainability, especially in the context of emerging markets or industries undergoing rapid technological shifts, could unearth critical insights. As Industry 5.0 continues to evolve, a longitudinal study might also be beneficial, tracking its maturation and the implications this has for sustainable manufacturing practices.

Data availability

Data will be made available on request.

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