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A generic methodology and a digital twin for zero defect manufacturing (ZDM) performance mapping towards design for ZDM

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ABSTRACT

Over recent years, the manufacturing industry has seen constant growth and change. From one side, it has been affected by the fourth industrial revolution (Industry 4.0). From the other side, it has had to enhance its ability to meet higher customer expectations, such as producing more customized products in a shorter time. In the contemporary competitive market of manufacturing, quality is a criterion of primary importance for winning market share. Quality improvement must be coupled with a concern for high performance. One of the most promising concepts for quality control and improvement is called zero defect manufacturing (ZDM), which utilizes the benefits of Industry 4.0 technologies. ZDM imposes the rule that any event in the production process should have a counter-action to mitigate it. In light of this, the current research developed a methodology the manufacturer can use to correctly select or design appropriate ZDM strategies and equipment to implement at each manufacturing stage. This methodology consists of several steps. The first step is to conduct several simulations using a dynamic scheduling tool with specific data sets to develop a digital twin (DT). The data sets are created using the Taguchi design of experiments methodology. The DT model is created for use in predicting the results of the developed scheduling tool without actually using said tool. Using the DT, multiple ZDM parameter-combination sets can be created and plugged into the model. This process generates ZDM performance maps that show the effect of each ZDM strategy at each manufacturing stage under different control parameters. These maps are intended to provide information for comparing different ZDM-oriented equipment to help manufacturers reach a final decision on correct and efficient ZDM implementation or to assist in the design phase of a ZDM strategy implementation.

1. Introduction

Over recent years, the manufacturing industry has seen constant growth and change. On one level, it has been affected by the fourth industrial revolution (Industry 4.0) [1]. On another, it has had to enhance its ability to meet growing customer expectations, such as for more customized products produced at a faster rate [2]. To achieve higher profits, many manufacturing companies have had to produce new products more rapidly than ever. This phenomenon has imposed new rules on product manufacture, such as shorter production time and smaller batch output, making strategies which had been successfully used in the past obsolete or less efficient [3]. Furthermore, the shorter product life cycle has also reduced the life cycle of manufacturing systems. Manufacturers must more frequently reconfigure production systems or design new systems to cope with customer demands [4]. Quality assurance design constitutes a crucial stage of the design phase and can significantly affect the profitability of a company [5]. An efficient quality assurance design allows higher product quality with minimum performance losses and with significantly less waste. The design of a quality assurance plan is a complex task that incorporates multiple factors and heavily affects a manufacturing system. For decades companies have studied the performance optimization and quality assurance of production systems, but most often these were studied separately [6], which was likely to lead to poor solutions [7]. This is due to the influence quality assurance implementations have on manufacturing systems: for example, to avoid potential defects, a quality control system may stop a machine if the machine is out of control, significantly affecting the schedule and by extension the manufacturing system's performance.

Currently there are many quality improvement methods, such as six sigma, lean, theory of constraints, total quality management and their combinations. These methods have a preventive nature, and their goal is to remove defects from items being produced, but importantly, these methods do not involve learning from defects [8]. They improve the

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future by analysing the past without considering information from the present, losing critical information available from the steps between the occurrence of a defect and the solution that eliminates this defect [8]. An emerging concept known as zero defect manufacturing (ZDM) fills the gaps in existing quality improvement methods. ZDM achieves this by using the full potential and capabilities of Industry 4.0 technologies and moving closer to the smart factory concept [9]. In other words ZDM is depending on data-driven technologies because their advance capabilities [10]. ZDM is composed of four main strategies: detect (Dt), predict (Pd), prevent (Pv), and repair (Rp), which are utilized in pairs as described in [11]. The goal of ZDM is to improve the quality by "making it right the first time" rather than trying to mitigate a problem at a later stage. One of the core characteristics of ZDM is the use of prediction technologies, but is not limited to only that technology. The four ZDM strategies cover the all the manufacturing principles for addressing an event, including corrective, preventive, and predictive principles. ZDM strategies can be classified into two categories: the "triggering factors" and the "actions". Detect and predict strategies belong in the triggering factors category, and prevent and repair to the actions category. Fig. 1 illustrates the connections among the ZDM strategies. More specifically, if a defect is detected then it can be repaired (detect – repair), and the data gathered by the defect-detection module can be utilized in two ways. The first is for prompting an alert and thus performing prevention actions to avoid future defects (detect – prevent) and second and more importantly feed them to specifically designed algorithms for predicting when a defect may occur, and can thus be prevented (predict – prevent). The prevention actions can be any action that can have impact on the health of the manufacturing process such as small targeted maintenance or machine tunning for achieving the desired results. The preventive actions are related to the cause of the defect detection or prediction and therefore there is no standard action.

The paper aims on presenting a methodology for designing a manufacturing system for achieving ZDM. The structure of the paper is as follows: in section 2 the key findings from the literature review are presented regarding design of quality assurance strategies and digital twin approaches. Using the information from the literature review the research gaps are identified and the contribution of the current research is summarised in section 2.2. In section 3 the proposed methodology for designing for ZDM is presented, starting with the definition of the ZDM control parameters (section 3.1) and the definition of the KPIs used for the simulations (section 3.2). Section 3.3 presents the methodology for creating the digital twin (DT) model of a manufacturing system, which will be used for achieving the desired goal. The final section of section 3 is the experimental procedure that was followed for implementing the proposed methodology. Section 4 presents a real-life industrial use case, in the semiconductor domain, in which the proposed methodology is applied and the results are presented in section 5. More specifically section 5.1 presents an analysis of how much each ZDM control parameter is affecting the performance of each ZDM strategy. In section 5.2 the DT models for the specific industrial use case are created and their accuracy is validated. Section 5.3 presents the ZDM performance maps which are the goal of the current research. The discussion of the results takes place in section 6.

2. State of the art

The concept of ZDM requires that when a triggering strategy is deployed at a certain manufacturing stage, it examines all the parts produced at that point [12]. In this way, 100 % quality can be ensured, and for all nonconforming parts, mitigation actions must be assigned to correct the defect and maintain quality [9,11]. The process of examining each part can have significant impact on production performance, and the relationship between quality control and production performance cannot be ignored. Despite the existence of this tight relationship, most studies in the literature ignore it [13]. There are numerous research papers on methodologies for designing both production and quality control systems but separately. In each of these studies, one part was kept static and the other was designed. Furthermore, there is research work that stresses the importance of considering quality during the design or redesign phase of manufacturing systems [14–16]. Colledani and Tolio were among the first researchers to incorporate a quality control model into a manufacturing system model, and they extracted useful insights into the connections between quality control and production design [15]. In recent literature there are also a few papers discussing the need of repairing defected product during manufacturing process and also presenting methods for implementing efficiently the reworking process [12], but they focus only to one ZDM pair strategy (detect – repair), which might not be the most efficient approach for a given study.

ZDM is an emerging concept and, as stressed by Psarommatis et al. in [11], most research on this framework focuses on developing and analysing technologies and methodologies for specific ZDM strategies rather than on studying the overall implementation of ZDM. For example there many research papers presenting methodologies for both physical and virtual defects detection [9,17–19]. Furthermore, most of these studies are focusing on specific manufacturing processes, such as additive

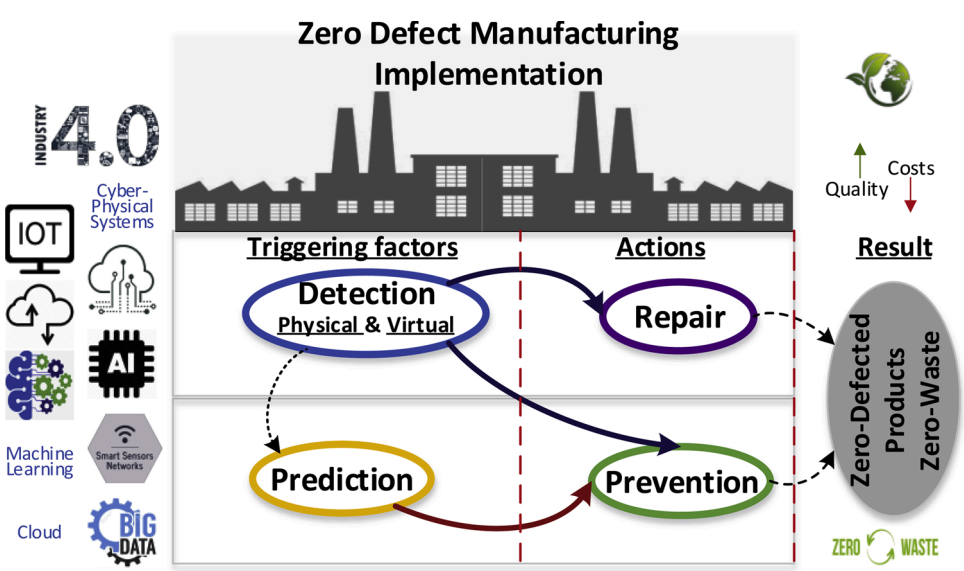

Fig. 1. ZDM implementation strategies and connections [11].

manufacturing [20]. This means there is no literature on how manufacturers can select among the three ZDM pair strategies and implement efficiently ZDM into their production systems. The literature does include methodologies for implementing certain quality improvement methods. One such method is design for six sigma (DFSS), but its approach is to capture customers' needs and satisfy their expectations [21]. DFSS relies on various statistical tools to assist in the process of designing products, processes, and services [22]. However, most research on DFSS has focused on its use for product design rather than process design. One study used DFSS to improve information sharing in a supply chain network [23]. In the pharma domain there is a methodology called quality by design (QbD) which, among other uses, is employed to optimize drug manufacturing processes [24]. In most manufacturing systems, optimization and design are performed under a single or a small number of measured key performance indicators (KPIs). Such approaches can lead to poor solutions because the problems of designing manufacturing systems or quality assurance systems are multi-criteria problem [25]. Discrete event simulation (DES) and design of experiments are methods widely used for simulating and studying the performance of manufacturing systems to extract insights and optimize performance [26,27].

2.1. Digital twins (DTs)

In manufacturing, the digital twin (DT) concept was first presented by Grieves under the topic of product life cycle management, which defines DT as an informational construct about a physical system [28]. The concepts of DTs were initially advanced in the aerospace industry to ensure safer flights through the use of prognostics and diagnostics [29]. However, with the emergence of Industry 4.0, DTs gained great traction in the field of manufacturing, driven by advances in related technologies [30,31].

Despite the numerous research efforts on DTs from both academia and industry, many scholars have expressed the view that no consensus exists on their definition and characteristics [30,32–35]. Therefore, differences exist in the how the DT concept is understood [36–38]. Kritzinger et al. proposed an interesting categorization of DTs based on their level of integration: namely, digital models (DMs), digital shadows (DSs), and DTs. The main element differentiating DMs, DSs, and DTs is data flow: a DT must satisfy the condition of bidirectional automatic data flow between the physical and digital systems. Under this categorization, only 18 % of papers claiming to present DTs are presenting true DTs [35]. Jones et al. conducted a thematic analysis to reach a common understanding of DTs by consolidating the common themes and key concepts.

Simulation is another divisive topic among researchers; some believe that DTs should place emphasis on simulations [39,40], whereas others argue that DTs contain physical, virtual, and connection parts, and virtual space is mapped to physical space through connection parts [41,42]. Tao et al. further proposed a five-dimensional DT model, comprising physical parts, virtual parts, connections, data, and services [43]. In this model, the theoretical foundations of DTs include the following [44]:

- DT modelling, simulation, verification, validation, and accreditation;
- data fusion;
- interaction and collaboration; and
- service.

Under this framework, a number of DT-driven applications have been developed, such as smart product design [45], job-shop scheduling [46], and virtual commissioning [47]. Negri et al. reviewed DT papers by categorizing them into possible uses, which are presented in Table 1 [34].

With rapidly developing technologies to support DTs, semantic technologies have been playing increasingly important roles in ensuring the interoperability of DT systems and extracting full value from DTs across the entire life cycle [31]. Semantic modelling is a promising method for integrating different technologies with different formats, protocols, and standards; such integration is challenging in DT modelling [48]. In response to this challenge, cognitive twins (CTs) have emerged as an enhancement of DTs with the capability of managing model versions across life cycles [49]. Lu et al. developed a knowledge-graph-centric framework to support CT development [50]. As an emerging topic, CTs have much to offer for enhancing DT applications.

Table 1
Digital twin use categories [34].

Support of health analyses for improved maintenance and planning
• Monitoring anomalies, fatigue, and crack paths in physical systems.
• Monitoring geometric and plastic deformation of material in physical systems and reliability of physical systems.
• Modelling reliability of physical systems.
Digital mirroring of the life of a physical entity
• Studying and predicting behaviour and performance by accounting for environmental conditions.
• Providing information continuity across different stages of a life cycle
• Virtual commissioning of a system.
• Managing the life cycle of IoT devices.
Decision support through engineering and statistical analyses
• Optimizing system behaviours during the design phase.
• Optimizing product life cycles using the past and present states to predict future performance.

2.2. Research gaps and contribution

Quality improvement methods focus on improving existing systems by tuning process parameters, but they do not indicate what the best quality control equipment is. Manufacturers are tackling the problem of quality control – assurance equipment independently of quality control methods, which can create knowledge gaps and miscommunication between departments within a company. The quality control – assurance equipment can be any equipment for the physical examination of the manufactured product such as a laser scanner or a vision system or sensors combined specifically designed algorithms for the defect prediction. Furthermore, to the best of the authors' knowledge, the literature offers no study that proposes a methodology for designing quality assurance policies for ZDM.

The goal of the current research work is to present a user friendly and simple but accurate methodology for helping manufacturers design and efficiently implement ZDM into their production lines. The proposed methodology aims to bridge the gap between product designers, production engineers, quality engineers, and management to support quicker and more accurate decision-making. More specifically, this work examines the performance of each pair of ZDM strategies under a large number of control parameter combinations in order to create several ZDM performance maps. These maps then can be utilized by manufacturers both to select the proper quality assurance equipment and to determine the correct parameters for operating the manufacturing system efficiently. Furthermore, the work analyses product characteristics and correlates them with the ZDM performance maps to retrieve deeper insights into the product and process. To achieve this, a custom-made dynamic scheduling tool was utilized as a simulation engine using a set of 17 optimization KPIs, and a tweaked methodology based on the design of experiments was developed for creating a DT of the scheduling tool to minimize simulation time. The developed methodologies were tested and validated through a real industrial use case in the semiconductor domain.

3. Framework and methodology of the proposed solution

In this chapter, the overall framework and the methodologies used

are analysed. The current methodology aims to assist manufacturers in designing, redesigning, or adjusting manufacturing systems for new products to determine the optimal specifications for the equipment in need for quality improvement and assurance. Fig. 2 illustrates the framework that the current study follows; the black boxes mark the main contributions of this research. The framework starts with the definition of the ZDM parameters that will act as control parameters in the scheduling tool, section 3.1. Using the defined ZDM parameters and the design of experiments methodology [51], a detailed set of experiments is produced and conducted using a custom made ZDM-oriented scheduling tool [52–55]. The scheduling tool will be used as a simulation engine, to simulate the production and measure the performance of each ZDM strategy, via specific key performance indicators (KPIs), section 3.2. Then the simulation results are used to create a DT of the specific industrial case, which allows thorough exploration of the performance of each ZDM pair strategy under different ZDM control parameters, while reducing time-consuming computation. This action results in the ZDM strategies performance maps, which can be used in two different ways as explained in section 6.3.

The core of the ZDM-oriented scheduling tool is no different from traditional scheduling tools which is formulated as follows: a set of Orders $R=\{R_k|k=[1,r]\}$, each Order contains products requiring different operations $O_k=\{O_{j,k}|j=[1,n]\}$, which can be manufactured on a set of machines $M=\{M_i|i=[1,m]\}$. $O_{j,k}$ is the jth operations of the order R_k. P_{ij} is the processing time of operation j on machine i. In the same way, the setup time of all operations on each machine is S_{ij}. The setup time for each operation is depending on the previous operation assigned at the same machine. The ZDM oriented scheduling tool used has the following assumptions, such as that once the operation has started the machine cannot be interrupted; that each machine can only handle one job at a time. Each customer order has a due date $D_{k,}$ which should be respected as much as possible. Let $\pi=\{\pi_1,\ldots,\pi_m\}$ represent a schedule and $\pi_i=\{O_{i(1)},\ldots,O_{i(n)}\}$ be the sequence of the operations on the machine M_i. Thus, $O_{i(n)}$ represents the nth job assigned to the ith machine. Operations have precedence constraints, which means that some operations should be done before others for them to be feasible.

The difference from traditional scheduling tools is that the four ZDM strategies are implemented within the scheduling tool. Once a new order or comes or a defect is detected or predicted the corresponding task - actions are created and waiting to be release to the shopfloor according to a specific rescheduling methodology [54], which calculated the most effective time to reschedule the production to include the new tasks. Once a task has finished and the quality is inspected, if the quality is acceptable the task is characterized as finished, if not there are two options, in case the task is repairable the task is repaired and then is characterized as finished or it is sent back as not released because it must be performed from the begging in order to mitigate the defect. Additionally, if a defect is detected or predicted some prevention action might be assigned to the corresponding machine to improve the health of the machine in order to stop producing defects in the future. There are four types of task objects: normal, inspection, repairing and maintenance tasks. The prevention actions are included in the maintenance tasks which can also be machine tuning. Other types of objects are machine objects where we have normal, inspection and repairing machines. The ZDM oriented scheduling tool is be able to handle different orders with different order characteristics, such as order placement day, due date, and quantity. Each order is placed by a "customer" have some parameters to be able to rank them and create a system for serving good, loyal, or customers with high volume orders faster [55].

3.1. ZDM control parameters definition

There are three ZDM strategy pairs: detect–repair, detect–prevent, and predict–prevent, as shown in Fig. 1 [11]. Each ZDM strategy has its own control parameters that affect the effectiveness and performance of the ZDM implementation. For each ZDM strategy in this work, three control parameters were defined, which are presented in Table 2. These parameters were chosen because they are the most important parameters when selecting equipment for ZDM. Because each industrial case is unique and there is no value in generalizing based on data from a specific use case, the following approach was adopted and used for the simulations and the creation of the DT model. Each product has some nominal characteristics, which are calculated if the production was running without any defects or other unexpected events disrupt the normal flow of the production. In this case, the total product production cost and time were calculated and used for converting the absolute use-case specific values to relative values. This was achieved using Eq. (1), which is simply the absolute value of the ZDM parameter divided by the corresponding total estimated product value. The ratio approach selected provided a relative indicator that shows how much extra time or cost is required for the operation of the ZDM strategy. The goal of this simple idea is to unlink the results from a specific case so they can be reused for other cases in which the product is different but the ratios remain the same [56]. Therefore, in Table 2 the parameters marked with an "R" contain relative values and the rest are percentages.

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

The defined ZDM control parameters are depending on each other at some extend but it is not always the case. For example, a laser scanner

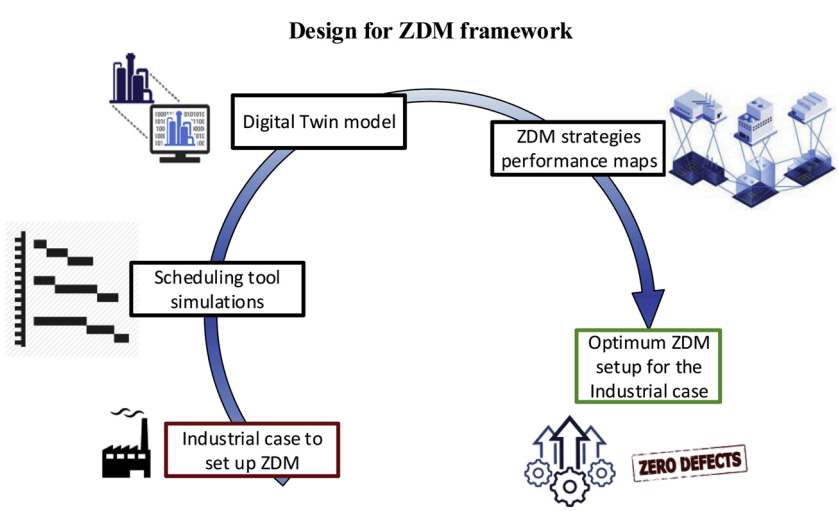

Fig. 2. Framework of the proposed approach and logical steps.

Table 2
ZDM strategies control parameters.

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 labour 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.

might have high operational cost but having very low scanning time. On the other hand, there another laser scanner might have lower operational cost, but requiring more time to scan the same part which might result more a more expensive inspection process compared to the case of the very expensive but very fast equipment. The detection accuracy is also semi-dependent from cost and time. To this said the dependencies of the ZDM control parameters can be quite complex and case specific, therefore in the current research the ZDM control parameters are considered to be independent from each other. This is done in order to capture all the possible configuration even if some of them are practically impossible due to current technological limitations. Currently technological advancements are happening with rapid pace and therefore it would be a mistake and practically impossible to limit the methodology to consider only feasible factor combinations. This is also done in order to explore solutions that previously were unexplored due to their extreme values. For example, if a laser scanner has an extremely high operational cost but offers extremely fast part scanning might be more efficient that others with average values.

3.2. Key performance indicators (KPIs)

The ZDM analysis and simulations were performed using a set of seven main and 10 secondary KPIs; Table 3 and Table 4 present the formulas of the defined KPIs. These KPIs were selected carefully to capture all the aspects that the ZDM concept might require. To combine all the KPIs into a single value in order to compare simulations, a methodology was used for the normalization and weighted sum of all the KPIs presented in [57–59]. The result of this method was one value called the "utility value", which takes values in the [0,1] range, with 1 being the best result.

The implementation of ZDM requires frequent rescheduling of the shop floor to incorporate all mitigation actions into the new schedule [54]. Therefore, the first measured KPI was the rescheduling time, which represents the average interval time for each rescheduling round (Eq. (2)). The second KPI is strongly and directly related to ZDM: namely, the defect ratio of a specific manufacturing stage (MFG) (Eq. (3)). This measure is crucial in the implementation of the ZDM concept because it shows the effect of the implementation.

ZDM is implemented to improve production quality and, by extension, reduce the amount of materials and energy required for manufacturing a specific quantity of products, which leads to more sustainable manufacturing. Therefore, the third KPI was the energy consumption required for the manufacturing of the specific products (Eq. (4)). Meeting due dates is a crucial aspect of staying competitive and reliable. Therefore, total weighted tardiness was used as a KPI [60]. In the current research each individual order was treated as a separate event. This means that the tardiness is calculated for each order, but some orders are more important than others. For this reason, the weighted tardiness was calculated instead of the simple tardiness. The weight in Eq. (5) depicts the importance of an order and was referred to as order criticality (OC). The average order's makespan was the KPI used for evaluating the performance of a simulation run [60] (Eq. (6)). Another important KPI that shows the efficiency of the production and quality of the schedule is the average machine utilization (Eq. (7)).

Table 3
Main KPIs.

$$\boldsymbol{AverageReSchedulingFrequency} = \frac{\sum_{r=1}^{TotalReschedulingTimes}(\boldsymbol{RTime_r} - \boldsymbol{RTime_{r-1}})}{\boldsymbol{TotalReschedulingTimes}} \tag{2}$$

$$\boldsymbol{DefRatio_{MFG}} = \frac{NumberOfDefectedParts_{MFG}}{TotalNumberOfPartsProduced_{MFG}} * 100\% \tag{3}$$

$$\boldsymbol{EnergyConsumption} = \sum_{i=1}^{MFG}(TotalOperationTime_i * EnergyConsumption_i) + \sum_{q=1}^{nRepairTask} TotalRepairOperationTime_q * EnergyConsumption_q + \sum_{f=1}^{inspM}(TotalInspectionTime_f * EnergyConsumption_f \tag{4}$$

$$\boldsymbol{WeightedTotalTardiness} = \sum_{o=1}^{nOrders}(OrderFinishTime_o - DueDate_o) * OC_o \tag{5}$$

$$\boldsymbol{AverageMakespan} = \frac{\sum_{0=1}^{nOrders} OrderFinishTime_o}{nOrders} \tag{6}$$

$$\boldsymbol{AverageMachineUtilization} = \frac{\sum_{i=1}^{MFG}\frac{MachineOperationTime_i}{TotalMachineTime_i}}{MFG} * 100\% \tag{7}$$

$$\boldsymbol{FinalUnitCost} = \frac{\boldsymbol{RSC} + \boldsymbol{IC} + \boldsymbol{RepC} + \boldsymbol{PPC} + \boldsymbol{DPC} + \boldsymbol{PQL} + \boldsymbol{OC} + \boldsymbol{MC} + \boldsymbol{MaintC} + \boldsymbol{DPenC}}{\boldsymbol{OrderSize}} \tag{8}$$

Table 4
Final unit cost sub-KPIs.

$RSC = \boldsymbol{ReschedulingCost} = 2*RMSCF*NT - \frac{RMSCF}{NT_{tot}}*NT^2$	(9)
$\boldsymbol{MC} = \boldsymbol{TotalMaterialCost} = \sum_{r=1}^{NumberOfTasks} RawMatCost_r$	(10)
$\boldsymbol{OpC} = \boldsymbol{TotalOperationalCost} = \sum_{i=1}^{MFG}\left(TotalProcessingTime_i*MachineOpCost_i\right) + \sum_{w=1}^{nOperators}(LabourTime_w*LabourCost_w)$	(11)
$\boldsymbol{PQL} = \boldsymbol{PourQualityLosses} = NumberofDefectedProducts*productTotalCost$	(12)
$\boldsymbol{IC} = \boldsymbol{InspectionCost} = \sum_{i=1}^{MFG}\sum_{f=1}^{nInpsTasks} InspMachineOpCost_i*InspTime_f$	(13)
$\boldsymbol{DPC} = \boldsymbol{DetectionPreventionCost} = \sum_{i=1}^{MFG}\sum_{e=1}^{nPrevActions}\{SparePartsCost_{ie} + PrevTime_{ie}*LabourCost_{ie}\}$	(14)
$\boldsymbol{PPC} = \boldsymbol{PredictionPreventionCost} = \sum_{i=1}^{MFG}\sum_{e=1}^{nPrevActions}\{SparePartsCost_{ie} + PrevTime_{ie}*(LabourCost_{ie} + ProdLosses_{ie})\}$	(15)
$\boldsymbol{RepC} = \boldsymbol{RepairCost} = \sum_{q=1}^{nRepairTask}\left(ManualInspTime_q*labourCost + RawMaterialsCost + ProcessingTime_q*MachineOperationCost + labourTime_q*labourCost\right)$	(16)
$\boldsymbol{MaintC} = \boldsymbol{MaintenanceCost} = \sum_{i=1}^{MFG}\sum_{j=1}^{nMaint}\left\{SparePartsCost_{ij} + MaintTime_{ij}*(LabourCost_{ij} + ProdLosses_{ij})\right\}$	(17)
$\boldsymbol{DPenC} = \boldsymbol{DelayPenaltyCost} = \sum_{o=1}^{nOrders} W_3 ln\ \ (1 + W_8(OrderFinishTime_o - DueDate_o))*OV_o*OC_o$	(18)

The final – and probably the most important – KPI in the current study was the final product cost (PC) (Eq. (8)). The KPI is not an outcome of one equation; it consists of many different factors. Table 4 lists all 10 terms that compose the final unit cost. Briefly, these terms are the rescheduling cost, raw materials cost, operational cost, losses due to poor quality, detection prevention cost, prediction prevention cost, repair cost, maintenance cost, and delay penalty cost.

The first KPI within the final unit cost is the rescheduling cost (RSC) [54], (Eq. (9)). To calculate this KPI an empirical formula was used summarizing the average rescheduling cost per task into the "RMSCF" term. Within this term is included the handling cost of the raw materials if they need to be put back to the inventory. Next, is the materials cost, which includes the cost for all raw materials used during production (Eq. s (10) and (11)). The machine operational cost (OpC) includes the costs for machine setup, operation, and degradation (Eq. (11)). Moving forward, it is inevitable that a defect will occur; therefore, the cost that arises from poor quality (PQL) should also be included in the final PC (Eq. (12)). In the current research in PQL only the costs that are arising inside the factory are considered, because the goal of ZDM is that all of the products are inspected and therefore no defected product is reaching to the customer. More specifically, if a product is defected and is not repairable then it is going to be re-cycled or scraped, the cost that arises from that process is the PQL. In the case of scraping the part the PQL cost is the cost of the raw materials used and the cost that arises from the manufacturing process, because it is also wasted. These two costs are summarised in the "productTotalCost" term in Eq. (12). The next three KPIs refer directly to the ZDM concept and, more specifically, to the three ZDM strategies. Starting with the detection–prevention strategy, the cost of implementing the prevention actions within that ZDM strategy is calculated and is the fourth KPI (DPC, Eq. (14)). The cost of prevention actions within the prediction–prevention strategy is the fifth KPI (PPC, Eq. (15)). The prevention costs are calculated based on the values of the corresponding ZDM control parameters defined in section 3.1. The last ZDM strategy is detect–repair, and the KPI related to it is the total of the cost of manually inspecting the defective part to establish a correct repair procedure, the cost of the raw materials required for performing the repair, the operational cost of the machine to be used for the repair, and the labour costs for the operator of that machine (RepC, Eq. (16)). Moving forward, the maintenance cost is also included in the final PC (MaintC, Eq. (17)). Maintenance is a critical factor for achieving ZDM. Finally, when due dates are not met, manufacturers pay a penalty cost to the customer to compensate for the delay (DPenC, Eq. (18)).

3.3. Digital twin methodology

The current section is devoted on presenting the methodology followed for creating the DT model for analysing the performance of the three ZDM pair strategies for a specific industrial use case. The goal of the DT model is to predict the utility value arising of a given set of ZDM control parameters without the need for running the ZDM oriented scheduling tool. The creation of the DT model is based on a statistical method called Design of Experiments (DoE). More specifically the Taguchi approach was used as the basis of the developed DT method [51,61]. The DoE approach was selected because it provides a methodological approach to capture the individual effects of each of the control parameters. Furthermore, the Taguchi method also provides the methodology for performing the minimum number of experiments that can produce statistically significant results and more importantly defines the experiments that must be performed.

To capture the effect of each control parameter – factor, a high resolution is required for the factor values. To this extend the L_{25} orthogonal array was selected as it fits exactly to the current problem. More specifically L_{25} can host up to six factors with five levels each. Furthermore, L_{25} does not consider interactions between the factors and therefore the results will contain the factors main effects unconfounded. L_{25} orthogonal array imposes that 25 experiments should be performed using the factor levels that are denoted by the experiment line in L_{25}.

Once the experiments denoted by L_{25} are performed, they are analysed using the Analysis of Means (ANOM) method. This method captures the effect of each factor level has to the observed value, in this case the utility value (U). Using Eq. (19) the average S/N ratio of each factor level is calculated. Where R and z are the number of levels and the actual level of factor k. The effect of a factor level is defined as the deviation it causes from the overall mean, Eq. (20). Eq. (21) calculates the overall mean of the results, where Ne is the total number of experiments imposed by L_{25}.

$$M_{k,z} = \frac{1}{R_k} * \sum_{z=1}^{R_k} U_{k,z} \tag{19}$$

$$effect_{k,z} = \left(M_{k,z} - \mu\right) \tag{20}$$

$$\mu = \frac{1}{Ne} * \sum_{z=1}^{Ne} U_z \tag{21}$$

At this point it should be reminded that the goal is to create a mathematical model that when we enter a set of ZDM control parameters, it will give as an output the predicted utility value that would be the outcome of the scheduling tool. So far, the individual effects and average S/N ratios of each factor have been calculated. To integrate all those data together into one equation the method of the additive model was used as described in [51] (Eq. (22)). In short, the additive model considers that the total effect of several factors is equal to the sum of the effect of each individual factor effect [51].

The additive model requires the ANOM results for calculating the corresponding factor coefficients for each level. For the current design of experiments (L_{25}, and six factors), the additive model has the following form (Eq. (22)). The letters A, B, C, D, E, and G represent each factor and the subscripts denote the level of each factor. The observed value is marked with "$\widehat{U}$" and it is the predicted utility value calculated by DT

model. The lowercase letters of the factors represent the coefficients that correspond to each factor level. Furthermore, "μ" represents the overall mean and σ_e the error variance. The error variance contains the error of the additive approximation plus the error in the repeatability of measuring the utility value for a given experiment [51]. Preliminary experimentations showed that the error variance for the problems investigated was near zero therefore in the current research, the error variance was considered zero and therefore it was not taken into account. $M_{k,z}$ represents the ANOM results for each factor for each level. Using Eq. (23), the additive model coefficients could be calculated, considering that $\sigma_e = 0$ [51], which simplifies the Eq. (23) to Eq. (22).

$$\widehat{U}\left(A_i, B_j, C_k, D_l, E_q, G_h\right) = \mu + a_i + b_j + c_k + d_l + e_q + g_h + \sigma_e \tag{22}$$

$$M_{k,z} = \mu + m_{k,z} + \frac{1}{3}\sigma_e^2 \tag{23}$$

The result from the additive model would be a set of five coefficients for each factor, which represent the coefficients for each level. In that way, the observed value can be estimated for all possible combinations of factor levels. This is very helpful because with only 25 experiments that occur from the L_{25} orthogonal array, we can calculate the results of $5^6 = 15{,}625$ combinations without the need for extra simulations, saving valuable time. The prediction model created is capable only of estimating the result for the specific factor levels defined in the L_{25} orthogonal array. This is limiting since the prediction models are not flexible because they cannot estimate the observed value for any value of a factor within the defined range.

Up to this point the methods presented were not new, but taken from the literature. The addition that was made to this method was to convert the discrete coefficient values to a continuous model. The result of the additive model is the matrix presented in Eq. (24), which contains the coefficients for each factor level ($m_{k,z}$, e.g. $m_{1,1}=\alpha_1$, $m_{2,2}=b_2$). Additionally, from the initial data the matrix on Eq. (25) is formed which contains the levels values for each factor.

$$\text{Fcoef} = \begin{bmatrix} a_1 & b_1 & c_1 & d_1 & e_1 & g_1 \\ a_2 & b_2 & c_2 & d_2 & e_2 & g_2 \\ a_3 & b_3 & c_3 & d_3 & e_3 & g_3 \\ a_4 & b_4 & c_4 & d_4 & e_4 & g_4 \\ a_5 & b_5 & c_5 & d_5 & e_5 & g_5 \end{bmatrix} \tag{24}$$

$$\text{Flev} = \begin{bmatrix} A_1 & B_1 & C_1 & D_1 & E & G_1 \\ A_2 & B_2 & C_2 & D_2 & E_2 & G_2 \\ A_3 & B_3 & C_3 & D_3 & E_3 & G_3 \\ A_4 & B_4 & C_4 & D_4 & E_4 & G_4 \\ A_5 & B_5 & C_5 & D_5 & E_5 & G_5 \end{bmatrix} \tag{25}$$

To achieve the conversion from discrete values to continue values the two matrices Fcoef and Flev were combined and formed cartesian points. As x-coordinate was set the Flev value and as y-coordinate the Fcoef value, leading to the set of cartesian points V, equation (26) which is one step before the desired result. As a last step, a piecewise quadratic interpolation is performed for each of the columns of V, leading to the creation of a set of quadratic equations that pass through the defined points. An example of that process is presented in equation (27) where the four quadratic equations for factor 1 are presented. Equation (28) illustrates the generic form of the quadratic equations for describing all the factors. Finally, equation (29) illustrates the final form of the DT which is responsible for estimating the utility value for a given set of parameter values within the specified range. Where K is the number of factors, which in the current case is 6.

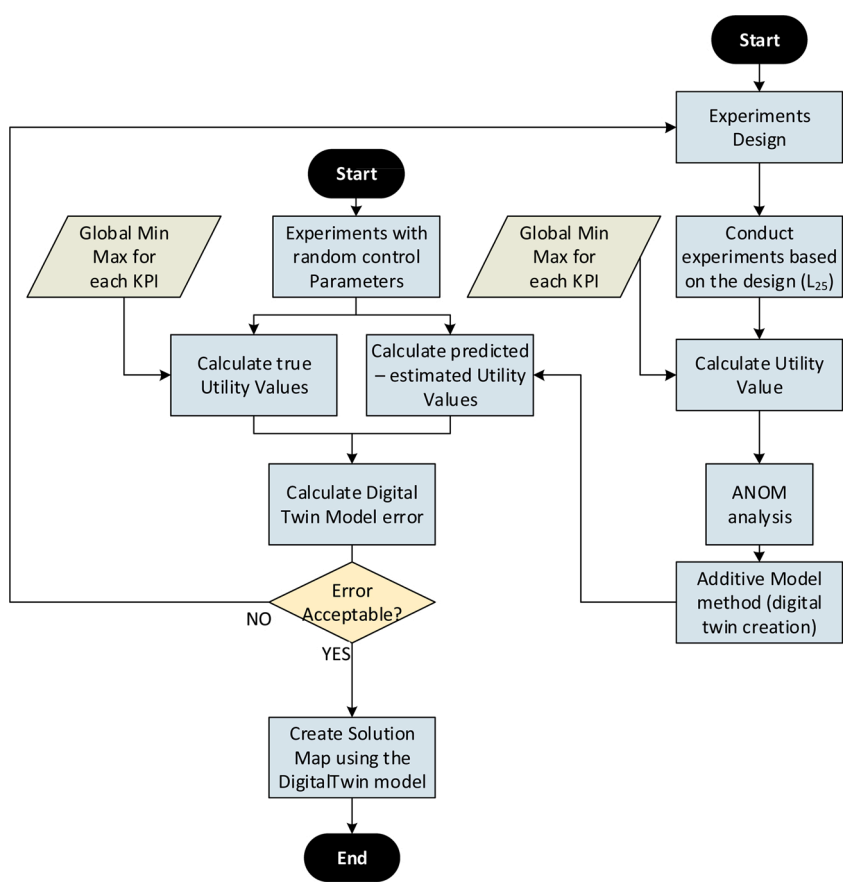

Fig. 3. Experiments and results of the overall procedure for each MFG and each ZDM.

$$V = \begin{bmatrix} (A_1,a_1) & (B_1,b_1) & (C_1,c_1) & (D_1,d_1) & (E_1,e_1) & (G_1,g_1) \\ (A_2,a_2) & (B_2,b_2) & (C_2,c_2) & (D_2,d_2) & (E_2,e_2) & (G_2,g_2) \\ (A_3,a_3) & (B_3,b_3) & (C_3,c_3) & (D_3,d_3) & (E_3,e_3) & (G_3,g_3) \\ (A_4,a_4) & (B_4,b_4) & (C_4,c_4) & (D_4,d_4) & (E_4,e_4) & (G_4,g_4) \\ (A_5,a_5) & (B_5,b_5) & (C_5,c_5) & (D_5,d_5) & (E_5,e_5) & (G_5,g_5) \end{bmatrix} \tag{26}$$

$$\begin{bmatrix} (A_1,a_1) \\ (A_2,a_2) \\ (A_3,a_3) \\ (A_4,a_4) \\ (A_5,a_5) \end{bmatrix} \alpha(x) = \begin{bmatrix} q_{11}{}^*x^2 + s_{11}{}^*x + t_{11} & ,A_1 \le x < A_2 \\ q_{12}{}^*x^2 + s_{12}{}^*x + t_{12} & ,A_2 \le x < A_3 \\ q_{13}{}^*x^2 + s_{13}{}^*x + t_{13} & ,A_3 \le x < A_4 \\ q_{14}{}^*x^2 + s_{14}{}^*x + t_{14} & ,A_4 \le x \le A_5 \end{bmatrix} \tag{27}$$

$$FcoefC(x)_k = \begin{bmatrix} q_{k1}{}^*x^2 + s_{k1}{}^*x + t_{k1} & ,Flev_{1k} \le x < Flev_{2k} \\ q_{k2}{}^*x^2 + s_{k2}{}^*x + t_{k2} & ,Flev_{2k} \le x < Flev_{3k} \\ q_{k3}{}^*x^2 + s_{k3}{}^*x + t_{k3} & ,Flev_{3k} \le x < Flev_{4k} \\ q_{k4}{}^*x^2 + s_{k4}{}^*x + t_{k4} & ,Flev_{4k} \le x < Flev_{5k} \end{bmatrix} \tag{28}$$

$$\widehat{U} = \mu + \sum_{r=1}^{K} FcoefContinues(x)_r \tag{29}$$

3.4. Experimental procedure

This section is devoted to the demonstration of the experimental procedure that was followed (Fig. 3). To use ANOM analysis, the current experimental design requires 25 simulations for each simulation run. The result of each simulation was the utility value, which is the aggregated value of the defined KPIs (section 3.2). Using the ANOM results and the DT model creation methodology (section 3.3), the DT models for each ZDM and each MFG were produced. To validate the proposed method and calculate the error of the produced model, a series of random simulations were conducted. After the completion of the random experiments, the global minimum and maximum KPI values were calculated using the results from the main experiments. Having acquired the global min and max KPI values, the global utility values could be calculated. Using the results from the random experiments, the true utility values were calculated and compared with the predicted estimated utility values, and the developed DT model was used to calculate the error. The final step was to create ZDM performance maps for each MFG for the three ZDM strategies.

4. Industrial use case

For the demonstration and validation of the proposed approach, a real-life industrial use case was studied in the semiconductor domain – specifically in the manufacturing of printed circuit boards for medical equipment. This product is considered expensive, with a manufacturing cost in the range of €3500–6000. Therefore, it is essential that the production system have a correct and balanced quality control system to minimize the incidence of defective parts and keep the organization competitive. Fig. 3 presents the bill of processes (BoP) of the product under investigation. Its manufacture involves a total of 15 tasks. Those tasks represent only the manufacturing operations; no quality control tasks are included. This BoP was modified at each simulation run to add all the ZDM tasks imposed by the corresponding ZDM strategy. A small complication arose in applying the detect–repair strategy, as unlike the other two ZDM strategies, it could not be applied to all of the manufacturing tasks in this use case. This was because, after some processes, repair was not possible and the defective part had to be discarded. The tasks that are repairable are marked in orange Fig. 3. The characteristics of each task and each machine are illustrated in Table 5 and Table 6, respectively.

Table 5
Task characteristics.

Task Name	Raw Materials Cost (€)	Average Processing Time (Mins)
101	77.6261	17.5335
102	75.4928	15.5738
103	55.5688	17.2173
104	77.0744	25.6327
105	40.8960	15.9950
106	58.0152	15.3506
107	44.4479	28.8266
108	30.3497	6.5480
109	98.9972	23.3134
110	82.7139	27.1681
111	81.2628	3.1026
112	92.9253	12.8309
113	206.5667	26.2677
114	218.9517	20.6340
115	158.8546	11.0477

Depending on the ZDM strategy under investigation, extra machines were added to the 15 basic ones responsible for the inspection or repair of products. The additional machines have variable characteristics that are controlled by the control parameters described in Section 3.1, and they are configured as a flow shop [60]. Each machine can perform only one task, but the tasks that are assigned to each machine might be from different orders, and therefore the machine considers them different tasks. When there are repair tasks, the flow-shop configuration is changed to a hybrid layout between a flow shop and open shop.

Based on the industrial data, the nominal production cost is €3760.57, and the nominal manufacturing time is 267.04 min. Once again, those values represent the ideal scenario, in which there are no defects, no delays in production, and no uncertainty. These values were the drivers for the experiments required to develop the DT model and to properly design the production for ZDM

4.1. Product characteristics analysis

Using the industrial data, a preliminary product analysis was performed to decode some key characteristics of the product. Fig. 4 presents the cost and time required for each task (top charts). The bottom illustration in Fig. 4 demonstrates the value of the product in terms of cost and time, taking into consideration the earlier manufacturing steps that were required to make the investigated task possible. Fig. 5 depicts each task's cost and time percentages of the total. These results were generated by dividing the results presented in the top, left, and right portions of Fig. 4 by the total estimated PC and time.

Fig. 7 illustrates an indication factor that shows the magnitude of potential losses from poor quality. The higher the value of the quality control index, the higher the losses due to poor quality. The quality control index is calculated as follows: both the cost and time percentages of each task (Fig. 6) are multiplied by the estimated defect rate, and those two values are summed together. All of these preliminary product results are used for reaching conclusions regarding the various ZDM strategies.

4.2. Demand profile

In this section, the demand profile used for the simulations is presented. The demand profile came from the same industry source as the product and machine data. This demand profile represents the number of orders per month (Fig. 8), and the values are the average order size over a period of 5 years. Based on this demand profile, an average of 337 products are ordered per month, with a minimum monthly order size of 240 and a maximum of 400. More specifically, the current demand profile is composed of 56 orders for a period of 12 months. Furthermore, the average order interval time is 6.49 days, and the average time need to complete an order is 5.54 days.

5. Results

This section presents the results from the simulations. In total 1125 simulation runs were performed – 75 for each MFG (25 per ZDM pair

Table 6
Machine capabilities and characteristics.

Machine Name	Operational Cost Of Machine €/Minute	Estimated Healthy Parts Rate	Mean Time Between Tuning Need (Mins)	Energy Consumption Kw/ Min	Task Capabilities
201	7.5338	0.97	10500.00	0.1815	101
202	7.9520	0.95	13500.00	0.3490	102
203	9.2543	0.94	19500.00	0.3044	103
204	14.2082	0.96	30000.00	0.3256	104
205	6.4285	0.96	14642.85	0.2081	105
206	8.0408	0.97	11388.88	0.3866	106
207	8.7004	0.99	7884.61	0.3754	107
208	12.3080	0.99	5125.00	0.3455	108
209	7.7119	0.99	7875.00	0.2118	109
210	8.1136	0.94	10125.00	0.2415	110
211	8.4941	0.99	14625.00	0.4226	111
212	12.7684	0.99	22500.00	0.2499	112
213	6.3794	0.99	10357.14	0.2387	113
214	7.8707	0.98	8055.55	0.3195	114
215	9.3534	0.95	5576.92	0.3897	115

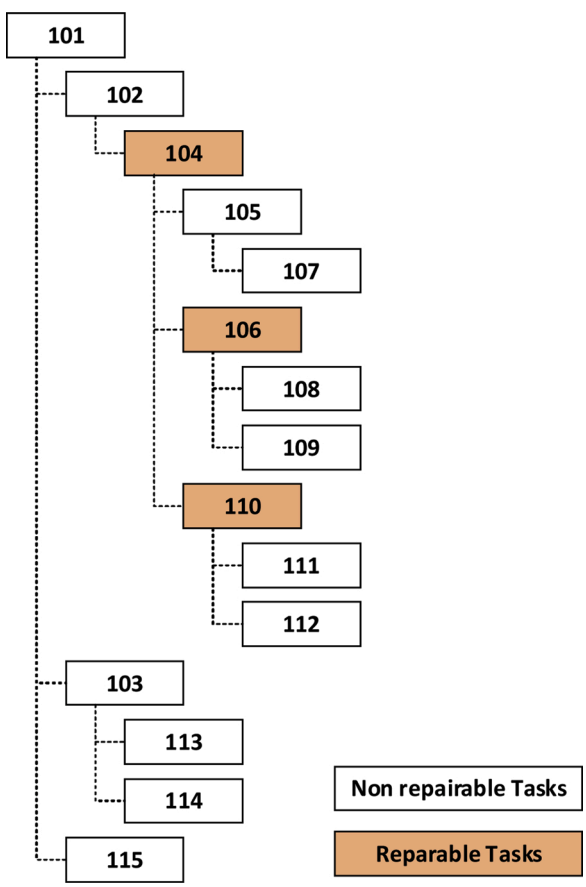

Fig. 4. Product bill of processes (BoP).

strategy). All three ZDM pair strategies were simulated for each of the MFGs using the ZDM – oriented dynamic scheduling tool discussed in section 3 [52–55]. The simulations were performed using the ZDM control parameters presented in Table 7. Each ZDM strategy was modelled into the scheduling tool, and the tool operated with a goal of having 100 % of parts of acceptable quality. Stochasticity was introduced at many levels of the scheduling, with the most important source being the defects generation module. The defects were generated based on an exponential distribution. Furthermore, the current industrial case might examine one product, but tasks that belong to different orders are treated as different tasks [54], and thus the problem is strong NP-hard. To solve the scheduling problem, a set of six heuristic rules were used [53].

5.1. Utility value analysis of means (ANOM)

The utility value ANOM analysis can be performed using the results of the 25 experiments, denoted by L_{25}. Table 8 presents the calculated average effect that each factor at each ZDM strategy had on the final quality of the solution. The factors inspection cost and inspection time had the greatest impact on solution quality, with average effects of 8.91 % and 4.56 % in detect–repair and 9.93 % and 3.28 % in detection–-prevention, respectively. On average, the inspection cost had a greater effect in the detection–prevention and detection–repair strategy. An increase of the inspection cost negatively affected the quality of the solution in all MFGs; this was not the case with an increase of the inspection time. Moreover, the prediction–prevention ZDM strategy seemed to be less influenced by the selected six factors than did the other two ZDM strategies. Furthermore, the detection–repair and detection–-prevention strategies had similar, although not identical, results for the common parameters in most cases. Increased levels of detection accuracy had a positive effect on solution quality in almost all MFGs. The one exception was MFG4 for the detection–repair strategy, where the optimal level for detection accuracy was level 4, and the quality subsequently dropped as the level of this factor increased beyond that.

In the prediction–prevention strategy, some common behaviours were also observed in all of the MFGs. As the prediction horizon increased, the quality of the solution increased, and as indicated before, the higher the defect rate, the more the solution quality improved as the prediction horizon value increased. Prediction accuracy exhibited varied behaviour: it had a bell shape in all MFGs except for MFG15. This means that the optimal solution qualities were observed at the middle levels, and at levels 1 and 5 the solution quality had the lowest values. Prediction reaction time had no uniform impact across the MFGs. In some MFGs, its effect was constant, whereas in others its effect had a bell or "U" shape. The prevention cost and prevention time had almost uniform behaviour across all the MFGs (except for MFG15): namely, the higher the levels of these factors, the higher the quality of the solution. In MFG15, the optimal solution quality was produced by level 1 for both prevention cost and time. The prevention success rate also had non-uniform impact.

5.2. DT models creation and validation

This section describes the creation of a set of DT models. The presented solution is not one DT model, but consists of numerous independent DT models, one for each case. More specifically, one DT model was generated for each ZDM strategy and for each MFG, leading to the generation of 45 individual DT models (3 ZDM x 15 MFG). Each DT

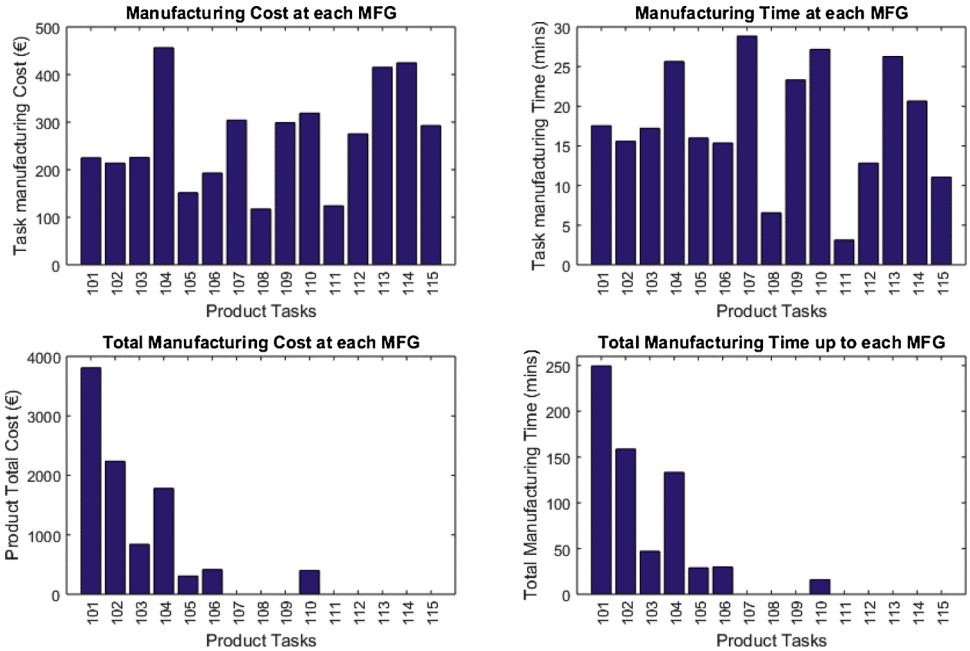

Fig. 5. Product characteristics at each MFG.

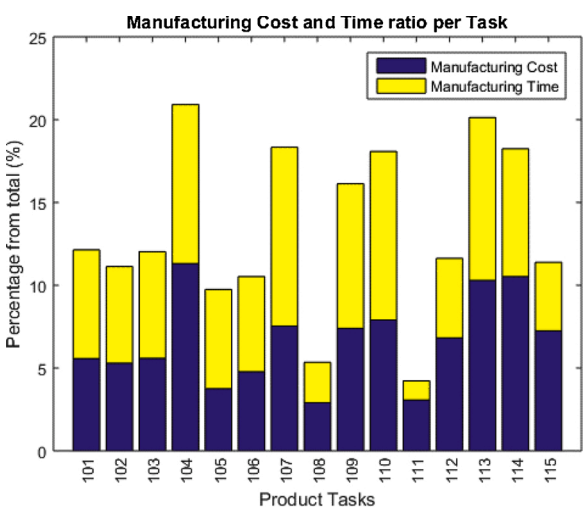

Fig. 6. Cost and time for each task as percentage of the total.

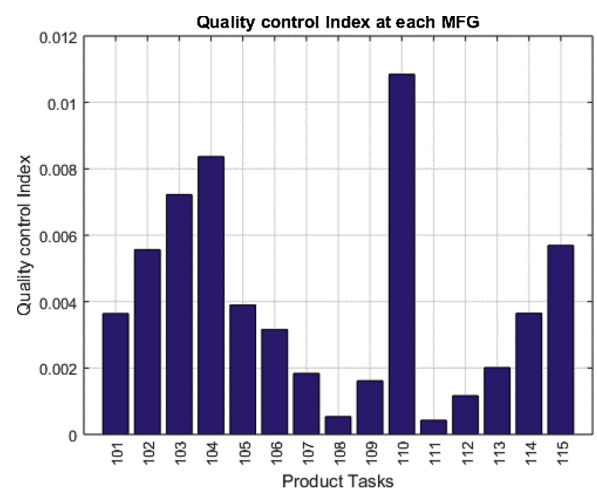

Fig. 7. Quality control index for each task Table 1: Digital twin use categories [34].

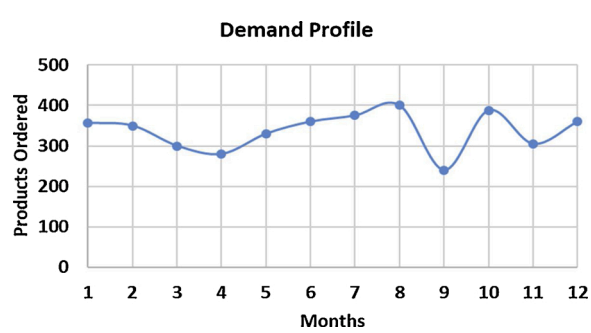

Fig. 8. Overall demand profile for one year.

model is composed of six mathematical models, one for each of the six factors under investigation, in order to capture the behaviour of each factor separately. Each DT model is capable of estimating the utility value that the corresponding simulation run using the same ZDM parameters would produce (Section 3.1), without the need for a vast amount of computation time. The plots of these mathematical models are lengthy, and therefore only one, Fig. 8, is presented as an example.

Before using the developed DT model, the accuracy of the models had to be tested and validated, otherwise the results would not be trustworthy. For the calculation of the accuracy for the developed DT model, the following procedure was followed. For each manufacturing stage, 50 random scenarios were generated and simulated for each ZDM strategy. All the random scenarios had all the same parameters except the six ZDM control parameters under investigation. The values of the six parameters per ZDM strategy took completely random values within the designated range in which the DT models were created. In total, 2250 extra random simulations were performed to test the accuracy of the produced DT model. Using the results from those experiments, all the developed models were validated by comparing the estimated value with the actual value from the scheduling tool.

Using the actual results of the KPIs, taken from simulating the

Table 7
Design of experiments factors levels.

Factors/levels	1	2	3	4	5
Inspection Cost R	0.01	0.1	0.25	0.35	0.5
Inspection Time R	0.01	0.04	0.11	0.18	0.25
Detection Accuracy %	0.7	0.85	0.9	0.93	0.99
Repairing Cost R	0.05	0.3	0.8	1.3	2.5
Repairing Time R	0.05	0.4	0.8	1.3	2
Reparability %	0.1	0.45	0.55	0.75	0.95
Prevention Cost R	0.05	0.4	1.5	3	5
Prevention Time R	0.3	0.8	3	5	7
Prevention success rate %	0.6	0.7	0.8	0.9	0.95
Prediction Horizon (mins)	0.0187	0.0749	0.2247	0.3745	1.1234
Prediction Accuracy %	0.7	0.85	0.9	0.93	0.99
Prevention Reaction Time (mins)	0.1123	0.2247	0.5617	1.3107	2.2468

Table 8
Average (Avg.) effect of factors for all MFGs (ANOM).

Detect - Repair		Detect - Prevent		Predict – Prevent	
Factors	Avg. factor effect	Factors	Avg. factor effect	Factors	Avg. factor effect
IC	8.91 %	**IC**	9.93 %	**PdH**	1.70 %
IT	4.56 %	**IT**	3.28 %	**PdA**	2.04 %
DA	2.91 %	**DA**	2.05 %	**PdReaT**	2.05 %
RC	1.08 %	**PvC**	1.28 %	**PvC**	1.65 %
RT	0.91 %	**PvT**	1.57 %	**PvT**	2.43 %
Rep	0.78 %	**PvSR**	1.01 %	**PvSR**	2.11 %

Table 9
Utility value prediction model error.

	Detect – Repair	Detect – Prevent	Predict – Prevent
MFG1	0.4940 %	0.7841 %	1.6245 %
MFG2	0.5481 %	1.4620 %	2.3254 %
MFG3	0.7320 %	2.0638 %	4.3108 %
MFG4	1.7189 %	3.5686 %	1.9362 %
MFG5	0.5590 %	0.9489 %	3.8798 %
MFG6	0.5675 %	0.9334 %	1.7139 %
MFG7	0.2978 %	0.4543 %	0.3299 %
MFG8	0.3217 %	0.4893 %	0.3746 %
MFG9	0.3883 %	0.3435 %	0.2493 %
MFG10	0.7282 %	2.6136 %	2.0202 %
MFG11	0.3731 %	0.3467 %	1.0939 %
MFG12	0.4077 %	0.6028 %	0.4782 %
MFG13	0.2766 %	0.4004 %	0.4118 %
MFG14	0.3523 %	0.4015 %	0.5683 %
MFG15	0.6931 %	0.8015 %	1.9828 %
Average	0.5639 %	1.0810 %	1.5533 %

random set of experiments with the scheduling tool, the actual utility value was produced for each of the scenarios. At the same time, the exact same ZDM control parameter values for each of the random scenarios were fed into the developed DT model and the estimated utility value was produced ($\widehat{U}$). The next step was to calculate the relative difference between the theoretical and actual utility value. The average relative differences for each MFG and each ZDM are presented in Table 9. The global average relative difference for all the MFGs and ZDM strategies was 1.066 % of the deviation from the actual utility value. In other words, the developed DT model regarding the utility value had an accuracy of 98.934 % on average.

5.3. Manufacturing stages' (MFGs') ZDM performance maps

The final step – and the main contribution of the present research work – was to generate the ZDM performance maps for each ZDM pair strategy for each MFG for various factor combinations. To achieve this, a higher resolution of factor levels was required. Therefore, the upper and lower limits for each factor from Table 7 were used for the creation of Table 10.

In total, 531,441 (9^6) factor combinations were calculated and plugged into the DTs for each ZDM strategy. To assess the predicted utility values, a benchmark scenario representing the ideal scenario without defects was simulated. The utility value for the ideal scenario was 0.6905, which means that the highest possible utility value for the current problem and KPIs is 0.6905. To produce the ZDM performance maps, the relative differences between the predicted and maximum utility values for each of the 531,441 points were required. These differences were sorted from lowest to highest (worst to best) and plotted, creating the ZDM performance maps Fig. 9. Each plot in Fig. 9 illustrates the performance of the three ZDM strategies (detect – repair, detect – prevent and predict – prevent).

The MFGs' ZDM performance maps reveal three patterns in the interaction of the ZDM strategies. In the first behaviour, the ZDM strategy performances are clearly distinguished, and there is a clear indication of the most suitable ZDM for a specific MFG because the ZDM lines do not intersect at any point. In other MFGs, the ZDM lines do intersect, meaning that after the point of intersection the most suitable ZDM strategy changes. A third behaviour is that all three ZDM strategies converge to almost the same point, which applies to both the best and worst points. In the MFGs for which repair of the defective part is not possible, the ZDM strategies of detect–repair and detect–predict have almost equal performance, with some variations. Furthermore, in many cases, when the ZDM factors were becoming more resource-demanding, the dominant and most efficient ZDM strategy was prediction–prevention. This applies to the following MFGs: 1, 4, 7, 8, 9, 11, 12, 13, and 14. Additionally, in the MFGs with a low defect rate, the predict–prevent strategy seemed to have constant performance with little variation. In the MFGs where repair was possible (104, 106, and 110), no strategy clearly prevailed. In MFG 104, the best-performing ZDM strategy was predict–prevent, and the second best-performing was detect–repair. In MFG 106, the detect–repair and predict–prevent strategies had almost the same performance up to a 10 % deviation from

Table 10
Expanded factor levels for all the ZDM strategies.

Levels	1	2	3	4	5	6	7	8	9
IC	0.0100	0.0713	0.1325	0.1938	0.2550	0.3163	0.3775	0.4388	0.5000
IT	0.0100	0.0400	0.0700	0.1000	0.1300	0.1600	0.1900	0.2200	0.2500
DA	0.7000	0.7363	0.7725	0.8088	0.8450	0.8813	0.9175	0.9538	0.9900
RC	0.0500	0.3563	0.6625	0.9688	1.2750	1.5813	1.8875	2.1938	2.5000
RT	0.0500	0.2938	0.5375	0.7813	1.0250	1.2688	1.5125	1.7563	2.0000
Rep	0.1000	0.2063	0.3125	0.4188	0.5250	0.6313	0.7375	0.8438	0.9500
PvC	0.0500	0.6688	1.2875	1.9063	2.5250	3.1438	3.7625	4.3813	5.0000
PvT	0.3000	1.1375	1.9750	2.8125	3.6500	4.4875	5.3250	6.1625	7.0000
PvSR	0.6000	0.6438	0.6875	0.7313	0.7750	0.8188	0.8625	0.9063	0.9500
PdH	0.0187	0.1568	0.2949	0.4330	0.5711	0.7092	0.8472	0.9853	1.1234
PdA	0.7000	0.7363	0.7725	0.8088	0.8450	0.8813	0.9175	0.9538	0.9900
PdReaT	0.1123	0.3792	0.6460	0.9128	1.1796	1.4464	1.7132	1.9800	2.2468

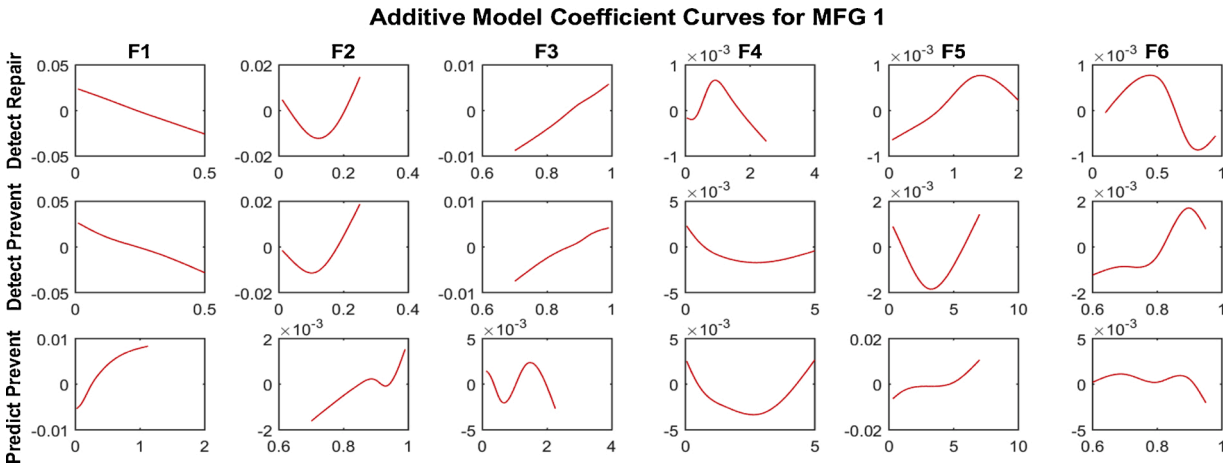

Fig. 9. MFG 1 DT coefficients preview.

the ideal condition. After that point, the predict–prevent strategy performed better, as the factor values increased. In the case of MFG 110, the best-performing ZDM strategy was detect–repair followed by detect–-prevent with an average difference of 6%. Predict–prevent was consistently worse than the other strategies except in the solutions with the highest ZDM factor values, where it performed better than detect–prevent. Moreover, predict–prevent had very small performance variations (Fig. 10).

6. Discussion

6.1. Digital twin methodology and model discussion

The developed methodology for creating a DT model of the developed scheduling tool proved to be lean, efficient, flexible, and highly accurate. The same methodology can be applied in a different case. The only part that must be altered is the definition of control parameters. In the current case, six factors were used. On average, the error of the developed DT models was 1.066 %, which is very low, indicating the model was highly accurate and reliable. Furthermore, for the predict–prevent strategy, the errors for each MFG were slightly higher than those calculated for the other ZDM strategies because a higher level of stochasticity was applied for this strategy. The maximum error observed for the utility value in the DT model was 4.3108 %. A limitation of the method is that the experiments that must be conducted have to be performed based on an orthogonal array. This poses some restrictions because standard orthogonal arrays are limited and may not fit all cases and the construction of an orthogonal array is mandatory, which makes the process more complex. The level of accuracy of the DT model is heavily dependent on the number of levels that each factor has. Five-level factors were selected so the impact of each factor level could be captured. The DT coefficients graphs show that the influence of each factor was not linear but a more complex curve requiring more than three points to be defined.

6.2. ZDM performance maps discussion

The ZDM performance maps revealed that the smaller the defect rate at a station, the greater the advantage of the predict–prevent strategy. This is because in cases where the defect rate is high, the frequent "small" prevention actions that the predict–prevent strategy imposes have a negative impact on the performance of the manufacturing system. Therefore, in cases with a defect rate lower than 3%, predict–prevent is the dominant ZDM strategy and the most efficient.

Furthermore, a pattern was observed between the manufacturing process and ZDM performance. In the current industrial case, three manufacturing process categories were used: assembly, manufacturing of primary components, and processes for adding features to existing components. MFGs 202 and 205 performed the process of adding features to existing components, and both showed a common ZDM behaviour. In both cases, detect–repair was the best-performing ZDM strategy. This was followed by detect–prevent up to a certain point, after which predict–prevent overlapped and became the second-best-performing ZDM strategy. In addition, a crucial point is that all three ZDM strategies in MFGs 202 and 205 where their performance levels were very similar, something not observed in the other MFGs performing different manufacturing processes. Additionally, a common trend in the performance of the ZDM strategies was observed for MFGs that were manufacturing primary components (207, 208, 209, 211, 212, 213, and 214). In all these MFGs, the dominant ZDM strategy was predict–prevent, showing an almost-constant performance drop regardless of the values of the ZDM parameters. In both manufacturing processes, the ZDM behaviour demonstrated similar trends in each case, which is because those manufacturing processes were not dependent on other processes (manufacturing of primary components) or they only depended on the previous process (the addition of features to existing components). On the other hand, for the assembly operation, the results did not follow a common trend as observed with the manufacturing processes. This was because the assembly operation was heavily dependent on the dynamics of the MFGs that provided the components to be assembled. Therefore, the more uncertainty and complexity introduced to an MFG, the more complex the ZDM strategies' behaviour becomes, and the more critical tools such as the proposed one are for the correct design of the implementation of the ZDM concept. MFG 204, where task 104 was performed, exhibited unique characteristics compared with the other MFGs. This is because at that stage an assembly operation was performed joining three subcomponents into one (BoP, Figs. 3 and 4). Such assembly operations make the MFG critical and susceptible to quality issues. Furthermore, the implementation of an unsuitable ZDM strategy with such an MFG may cause great losses and up to a 63 % decrease in performance.

Combining the ZDM performance maps presented in Section 5.3 and the preliminary product analysis presented in Section 4.1, the following can be concluded. In cases with a high defect rate, predict–prevent was not as efficient as detect–repair or detect–prevent. This is because in cases with more defects and higher impact, frequent prevention actions reduced the performance of the system. From the same product analysis, it could also be concluded that when the relative difference in the product utility values with and without the defect rate is positive, then the most effective ZDM strategies are detect–repair and detect–prevent. However, as was mentioned before, if this relative difference is negative, then predict–prevent is the most suitable ZDM approach.

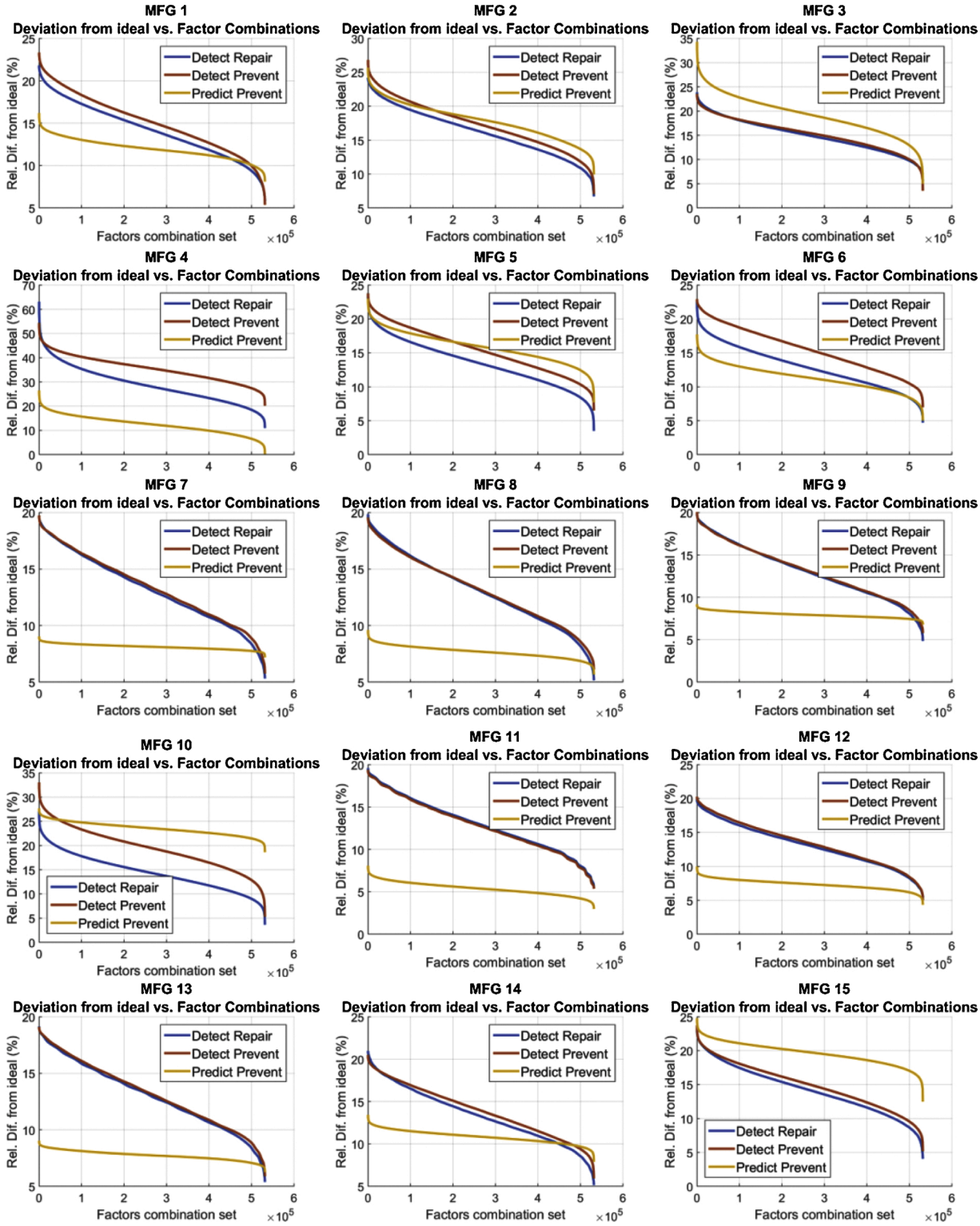

Fig. 10. ZDM performance maps.

6.3. ZDM mapping results utilization

The use of the developed DT model helped in mapping the performance of each ZDM strategy for each of the MFGs. ZDM performance maps are extremely helpful for manufacturers because they can select the best ZDM configuration for their case. At this point, it should be mentioned that some of the factor combination sets may have non-realistic values and it may not be possible to implement them with current technologies. Therefore, the produced graphs should be used in specific ways and not simply by selecting the best-performing set of factors. Instead, there are two ways in which manufacturers can utilize these results. The first can be used when a manufacturer wants to establish a product quality improvement process at certain manufacturing stages and asks several third parties to provide a solution or, if production is at the design stage, when the manufacturer estimates quality issues will arise. When the manufacturer has all potential

solutions, they can evaluate them using the graphs presented in Fig. 9. Simply by using the ZDM parameters of each of the provided solutions as input, the manufacturer will be able to visualize where each solution falls on the ZDM performance map, at which point the best solution can be selected. The second way to use the results works the other way around. Based on the produced graphs, the manufacturer selects a range of ZDM parameter combinations where the performance of the manufacturing systems would be at an acceptable level and then asks a third party to provide a solution with those specifications. This approach entails the danger that the manufacturer might select parameter ranges that are impossible to implement. By using those graphs, manufacturers can easily evaluate and rank alternative solutions for implementing ZDM into their manufacturing systems. Furthermore, the evaluation and decision-making process is significantly faster, and the results are repeatable and are independent of the expertise of a single expert worker.

7. Conclusions and future work

The current research work focused on an emerging concept in quality control and improvement domains named ZDM. The goal of this study was to provide a tool for designing a manufacturing system taking into consideration the principles ZDM imposes. The proposed methodology for creating a DT model to describe the results of the developed scheduling tool without running simulations proved to be easy to use and highly efficient. Each simulation for the creation of the DT model (a total of 1125 simulations were performed), required on average 2.5 h of computation time to solve the given ZDM scenario, which in a real manufacturing environment would be prohibitive. The produced DT models, by contrast, could estimate the output of the scheduling tool for each ZDM parameter value set in less than a second, making it possible to calculate the results that formed the ZDM performance maps. The average calculated accuracy of the DT models was 98.934 %, which was considered very accurate.

Before the creation of the DT model, a preliminary analysis of the product under investigation was performed with the goal of identifying the criticality of each MFG in terms of implementing a ZDM strategy. The results from the preliminary product characteristics analysis indicated the findings are in line with the results produced by the DT model, and some behavioural patterns could be identified.

ZDM performance maps can be helpful to manufacturers when a decision is required for the selection of equipment and strategies for implementing ZDM. Furthermore, such maps are meant to provide repeatable decisions and standardization for quality improvement design. The flexibility of the proposed methodology and tool can also be a benefit in cases where a quick reconfiguration of the production is required to adapt to market needs, as was required during the COVID-19 pandemic. A limitation of the current approach is that the presented methodology is use-case-specific: if the use case changes, the experiments and analysis should be performed again.

Future research steps should focus mainly on the generalization of the developed tools and methodologies. More specifically, the current ZDM analysis was performed based on a specific use case. A detailed study is required to demonstrate whether the concept presented in Section 3.1, with the conversion of the absolute values to relative ones, can be generalized. This is required if the ZDM strategy trends from a given industrial case are to be applied to other cases because the defined ratios are the same or similar. Additionally, a study is required to examine whether the ZDM trends for each MFG can be obtained by simulating only the desired MFG and not the entire production. This approach would save valuable time otherwise spent simulating MFG nodes that are not necessary. Moreover, this will push even further toward the generalization of the method. Finally, the presented methodology for creating the DT method requires some enhancement to make it flexible enough to fit most cases. Currently the presented methodology is limited by the use of standard orthogonal arrays, which are themselves limited. The generalization of the method requires the development of a means for constructing orthogonal arrays to meet requirements and not be limited by the specifications of standard orthogonal arrays.

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