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Design for Six Sigma Digital Model for Manufacturing Process Design

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Abstract: The transition to digital manufacturing has become more important as the quantity and quality of the use of computer systems in manufacturing companies has increased. It has become necessary to model, simulate and analyse all machines, tools, and raw materials to optimise the manufacturing process. It is even better to determine the best possible solution at the stage of defining the manufacturing process by using technologies that analyse data from simulations to calculate an optimal design before it is even built. In this paper, Design for Six Sigma (DFSS) principles are applied to analyse different scenarios using digital twin models for simulation to determine the best configuration for the manufacturing system. The simulation results were combined with multi-criteria decision-making (MCDM) methods to define a model with the best possible overall equipment effectiveness (OEE). The OEE parameter reliability was identified as the most influential factor in the final determination of the most effective and economical manufacturing process configuration.

Keywords: digital twin model; DFSS; multi-criteria decision-making methods (MCDM); overall equipment effectiveness (OEE); reliability

1 INTRODUCTION

Today, the application of digitalisation is making its way into all areas of our society. On the one hand, the pandemic COVID19 crisis is accelerating the process of digitalisation in education and business through the implementation of distance activities, the development of new digital models, methods, and skills. On the other hand, a significant energy crisis is accelerating electrification processes at a pace that was unimaginable until yesterday. Long-term strategies and plans need to be adapted to the new conditions, as rapid and significant changes occur every year. The biggest challenge in this process is maintaining competitiveness, speed, and quality. The right answer to this challenge can be the combination of known and proven methods and tools adapted to the new conditions in society. It is no longer sufficient to carry out optimisations during the product life cycle (PLC) [1]. It is imperative to look for solutions or partial solutions in the earlier stages of defining the product and its production process. An area that has developed and improved with unprecedented speed in the last decade is also the digitalisation of production processes. There are several tools at our disposal for creating product simulations and the associated production process. A clear methodology describing rules and norms in the form of standards has not yet been developed and defined, but there are numerous studies in the literature on digitalisation, digital twins (DT) and their application [2]. This paper proposes a model for manufacturing process design that combines digital models with Design for Six Sigma (DFSS) principles in studying the effects of different configurations of production equipment [3]. The digital model is validated by simulation in a Tecnomatix software package with analytical calculations on real machine data.

The paper is structured as follows: Chapter 2 contains an analysis of the current literature in the field of DFSS and DT. The aim of the literature review was to search for available tools for manufacturing process design to improve control over the impact of design on the final performance of the manufacturing process. The idea of combining several of the most useful DFSS tools with digital twins is explained in Chapter 3 with a figure of the proposed hybrid model. Chapter 4 presents the research findings resulting from the application of the proposed model to a case study. In the case study, two manufacturing systems with different configurations were analysed in terms of equipment reliability and productivity rate. The last chapter contains an overview, discussion, and conclusions.

2 THEORETICAL BACKGROUNDS

This section is a literature review of the concepts of DFSS, Digital Factory, Digital Twins and OEE from a manufacturing process design perspective.

2.1 Design for Six Sigma in the Life Cycle Environment

The digitalisation process to improve productivity and the economy is unstoppable and irreplaceable. It is a question of strategic level to what extent and when the digitalisation of certain areas and levels in our company or process will take place. One of the best ways is certainly to involve DT as early as possible, i.e., in the design of the product or production system. The desired end state is a digital factory in which all elements are integrated. According to the standard VDI 4499, Part1: 2008-02 of the Association of German Engineers, the digital factory is a generic term for a comprehensive network of digital models, methods, and tools - including simulation and 3D visualisation - that are integrated into an end-to-end data management system [4]. The goal of the digital factory is the holistic planning, evaluation and continuous improvement of all essential structures, processes, and resources of a real factory in connection with the product. In the development of the individual parts of the digital factory, the various digital tools and concepts emerge, the most important of which are: Internet of Things (IoT), Enterprise Resource Planning (ERP), Project Management (PM), Product Lifecycle Management (PLM), Advanced Planning & Scheduling (APS), Manufacturing Execution System (MES). The

Industrial Internet of Things (IIoT) brings together machines, advanced analytics, and people. The networked assets and devices that use communication technologies are creating systems that can monitor, collect, share, analyse and provide valuable new insights like never before [5]. These insights can then contribute to smarter and faster business decisions for manufacturers. According to a Cisco study from 2017, 74% of companies that start an IoT initiative fail because many of these projects were not successful for various reasons. In most cases, projects went over budget, implementation times were too long, there were problems with interoperability between existing platforms or planning, and resources were not allocated appropriately, leading to project abandonment [6]. An IoT platform is a multi-level technology consisting of software and hardware that includes an operating environment, storage, computing resources, security and development tools that support the management of smaller applications and IoT devices. Generic IoT platforms, like AWS, Azure IoT, SaS, Thing-Worx provides technologies and tools that support the management of IoT devices that are not used in an industrial environment. In this context, a home automation platform that manages smart household devices such as refrigerators, smart windows, temperature, etc. can be called a generic IoT platform. IIoT platforms, on the other hand, provide support for machines and smart devices used in an industrial environment. The IIoT platform provides customised software designed for industrial applications and analytics.

Since digitalisation requires significant resources, a certain level of knowledge and achieved the minimum requirement of Industry 4.0 concept, the question arises, especially for medium-sized and small companies, whether there is a simpler, faster, and cheaper solution with which such companies can maintain their competitiveness in the market. The answer lies in the combination of DFSS principles and DT in decision-making. Design for Six Sigma is a well-known element of product development in the Six Sigma quality programme [7]. The goal of DFSS is to prevent defects by integrating quality into the product, process, and system. Unlike other Six Sigma methods, DFSS is product-oriented and not process-oriented. Nevertheless, DFSS should be integrated into a product and manufacturing process development framework, so that it becomes repeatable and optimised to achieve sustainable success for any organisation. DFSS provides a range of techniques that engineers can use to improve their effectiveness in developing systems that reliably meet customer requirements. Talyor et al. [8] have demonstrated the integration of classical techniques to create a highly available system and provided an overview of some of the most useful techniques. Several of these techniques were used in presented case study. There are many available digital tools for product development, but DFSS is not one of them, it represents a cultural change within the various functions and organisations in which it is implemented [9]. It provides strong statistical tools to address weak or new processes and increase customer and employee satisfaction. To successfully implement these continuous methods, the objectives of DFSS and Six Sigma should be linked to the company's goals, vision, and mission. They are powerful tools that support the achievement of leadership in design, customer satisfaction and cultural change.

2.2 Digital Twin in the Life Cycle Environment

Grieves et.al [10], who first introduced the concept DT in 2003, defined DT as "a set of virtual information constructs that fully describe a potential or actual physical product from the microatomic to the macrogeometric level" from which all the required information "could be obtained by inspecting a physical product". DT has developed rapidly over the last few decades, and in recent years have seen an enormous scientific contribution to the exponential growth of scientific papers and patents filed on the subject DT. There are many analyses and attempts to summarise the different views and applications of DT [11]. Of particular interest are the reviews that attempt to define the gradation of seven main areas: Goals, User Focus, Lifecycle Focus, System Focus, Data Sources, Data Integration Level and Authenticity, as in Tab. 1 [12]. In other literature reviews, authors go into detail about the terms digital model, digital shadow and digital twin and the difference between them [13]. The definitions differ in the degree of data integration between the physical and digital parts. Some digital representations are independent models that are not connected to a physical object in real time, while others are fully integrated with real-time data exchange. Most publications are classified as Digital Shadow and Digital Model, only 18% of the papers use the term Digital Twin with bidirectional data transfer [13]. When modelling real-world scenarios in virtual and mathematical environments, it is obvious that the quality of the results depends on the quality of the model. Every production line and every manufacturing plant is different and there are classifications according to parameters and characteristics. Each of these classifications is approached in a particular way when modelling, as each has limitations, and a model is specific to the object of study and cannot be generalised [14].

Table 1 Digital Twin application dimensions [11]

Dimensions	Values			
Goals	Information acquisition	Information analysis	Decision and action selection	Action implementation
User focus	Single		Multiple	
Life cycle focus	One phase		Multiple phases	
System focus	Component	Subsystem	System	System of system
Data sources	Measurements	Virtual data		Knowledge
Data integration level	Manual	Virtual data		Knowledge
Authenticity	Low ⟷ High			

VDI Guideline 3633 defines simulation as the reproduction of a system, including its dynamic processes, in a model with which experiments can be carried out. The aim of simulation is to obtain a result that can be transferred to a system in a real environment. Furthermore, simulation defines the preparation, execution, and evaluation of carefully controlled experiments in a simulation model [15]. Following the same guideline, the basic steps of any process simulation are as follows:

1) Definition of the problem.
2) Examination of the reasonableness: cost-effectiveness of creating a simulation.
3) Definition of the simulation objectives.
4) Verification of the process in a real environment and collection of data needed to create a simulation model.
5) Creation of a simulation model: a twin of the real model in accordance with the desired objectives of the simulation analysis.
6) Verification of the simulation model by comparing the individual results of the model with the actual results of the physical system in production.
7) Conducting experiments, i.e., performing simulations within the simulation model.
8) Analysing the results and interpreting the data - simulation results.
9) Documenting the results, i.e., management decision making based on the simulation results about process improvements in the real environment.

PwC [16] in their quantitative research conducted by 200 industry company in Germany, defines three different types of digital twin for industrial applications in "Digital Factories 2020": the digital twin of the product, the digital twin of the production facility and the digital twin of the factory. This work deals with the digital twin of the factory and is based on a discrete event simulation model representing the machining department in the automotive industry and aims to quantitatively evaluate the impact of different production configurations on lead time, production capacity and number of workers. A digital twin of one or more production lines is used for design, virtual commissioning, and ongoing operation. The focus is on simulating the operation of a plant to adjust and optimise its key parameters and enable concepts such as predictive maintenance or augmented reality. Simulation modelling has become an indispensable tool to analyse expected performance, validate designs, demonstrate, and visualise processes, test hypotheses and perform many other analyses. It is the preferred tool in a wide range of industries, and as mentioned earlier, in some industries it is even required before any major investment. However, there are some cases where simulation is not the best technique to find a suitable solution. Laguna et al. [17] have established 10 rules for when it is not appropriate to simulate.

By applying the basic principles of DFSS with DT in the form of using true-to-life digital models in simulations when designing manufacturing processes, it is possible to investigate most possible scenarios and make the best possible decision when determining the final configuration of the production process quickly and cost-effectively.

3 PROPOSED/NOVEL APROACH IN MANUFACTURING PROCESS DESIGN

Despite numerous articles about tools and models for the product development process, the literature review has not revealed a comprehensive model that proposes the use of methods and tools in the sense of DFSS in the field of manufacturing process design. This chapter presents the author's efforts to propose a hybrid model whose main application is the design of manufacturing systems.

3.1 DFSS and Classical Reliability Techniques

A good explanation of the DFSS tools and methods used to analyse and design highly available systems, with simple examples, is given by the Institute of Electrical and Electronics Engineers [8]. These techniques are listed in Tab. 2.

Table 2 DFSS tools and methods

Abbreviation	Tools / Methods
VOC	Voice of the Customer
KANO	KANO analysis
	Analysis of technical risk
QFD	Quality Function Deployment or House of Quality
CPM	Critical Parameter Management
	First principles modelling
DoE	Design of Experiments
DFMEA	Design Failure Modes and Effects Analysis
FTA	Fault Tree Analysis
	Pugh matrix
	Monte Carlo simulation
	Commercial DFSS tools
	Mathematical prediction of system capability
	Visualizing System Behaviour early in the life cycle
	Critical Parameter Scorecard

3.2 DT terms

As mentioned above, DT has evolved considerably over the past decades without a definitive definition of a standard. Due to the constraints for an adequate implementation of DT (Industry 4.0), it is important to understand the differences in the degree of data integration between physical and digital objects. These crucial differences make it possible to implement DT even without an achieved Industry 4.0 level in the company, at an early stage of the development of the manufacturing process. Uhlenkamp et al. proposes a classification of Digital Twins into three subcategories based on the degree of data integration [12]. The subcategories are shown in Fig. 1 and Fig. 2.

3.2.1 Digital Model (DM)

A DM is a digital representation of an existing or planned physical object that does not use any form of automated data exchange between the physical object and the digital object as shown on Fig. 1, left. Such models include, but are not limited to, simulation models of planned factories, mathematical models of new products, or other models of a physical object that do not use any form of automated data integration. Digital data of existing physical systems can be used to develop such models, but all data exchange is manual.

3.2.2 Digital Shadow (DS)

Based on the definition of DM, if there is also an automated one-way data flow between the existing physical object and a digital object, one can speak of such a combination as DS, as shown on Fig. 1, right.

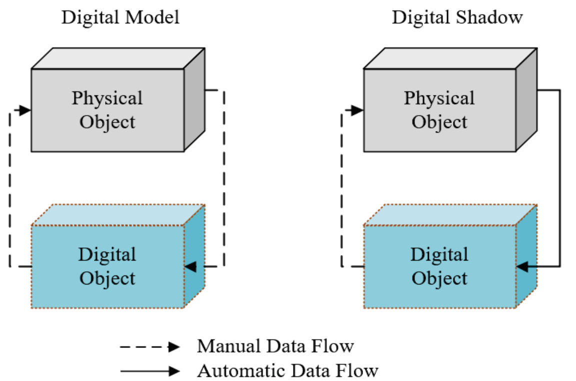

Figure 1 Data flow in a digital model and digital shadow

3.2.3 Digital Twin (DT)

The data flows between an existing physical object and a digital object are fully integrated in both directions, you could call it DT. In this case, the digital object can also act as a control instance of the physical object.

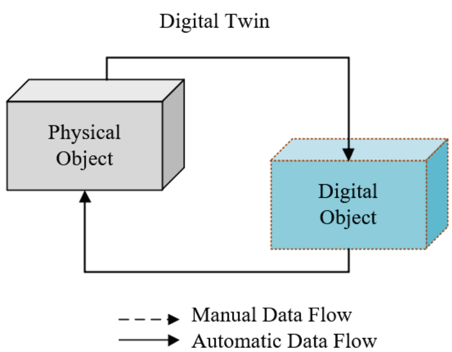

Figure 2 Data flow in a digital twin

3.3 DFSS & DM Novel Hybrid Approach

When developing a new manufacturing process or modifying part of an existing physical object, the authors propose combining some DFSS tools with digital models and MCDM tools. With digital models, it is possible to simulate the model of an existing physical system and analyse or compare alternative solutions for a new complete manufacturing process or part of the system. In manufacturing, it is often the case that several stages of prototypes are produced and tested in the introduction phase of production to improve the product design. Due to limited time and investment, it is not possible to apply the same principle to production facilities. Production optimisation is an ongoing process, both in the start-up phase and during the product life cycle. In some cases, experts have only realised the effects of a non-optimal design of the production process in the late phase of production preparation or later during production operation. The goal of the proposed hybrid Design for Six Sigma Digital Model (DFSSDM) approach is to avoid or significantly reduce these types of costs by using DM together with DFSS techniques. With the proper use of the tools, methods and DM shown in Fig. 3, it is possible to achieve these goals. The structure of the proposed hybrid model consists of using most of the original tools of DFSS and Digital Model in the presented grouped techniques. Certain tools have been replaced by more convenient tools. Design Failure Modes and Effects Analysis (DFMEA) has been replaced by Process Design Failure Modes and Effects Analysis (PFMEA), as the object of analysis is a production system and not a product. Similarly, Voice of Customer (VOC) has been replaced by Voice of Supplier (VOS) as the focus is on the supplier's product, the production system, and not the customer's product. The use of commercial DFSS tools such as Minitab, Matlab and others is complemented by digital twin models. The proposed model recommends the use of Plant Simulation or a similar software package for simulation, as this software offers much richer capabilities for representing the physical system in production and logistics.

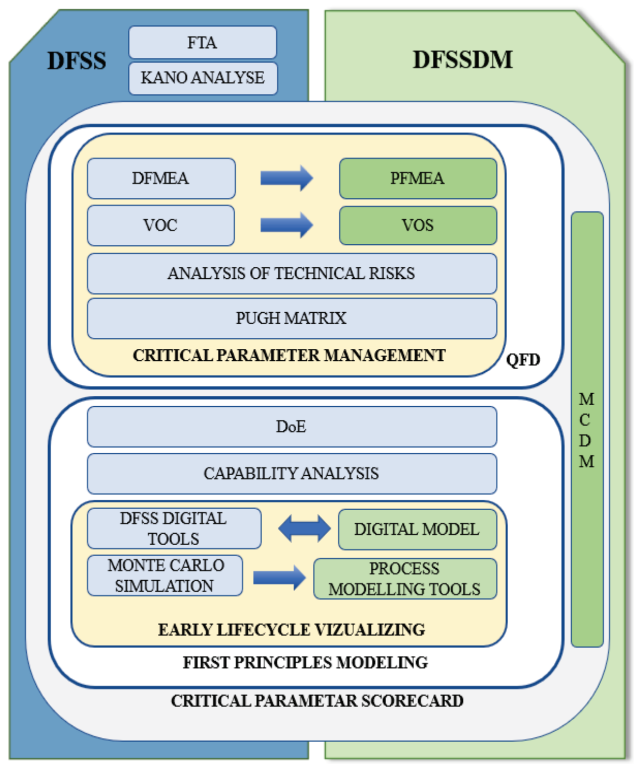

Figure 3 Transition model from DFSS to DFSSDM hybrid model

To properly define the Key Performance Indicators (KPIs) needed to determine the optimal solution for a design or analysis, it is necessary to use one of the many MCDM tools [18]. A model for selecting the most important KPIs and methods for selecting new assets in manufacturing is presented in a paper by the author [19], which can be used in combination with individual DFSSDM tools. Some tools such as the Pugh matrix [20], Design of Experiments (DoE) [8] are combined with other MCDM tools in their original form. Depending on the specificity of the object of analysis, the use of the defined hybrid DFSSDM needs to be adapted, the model can be further extended with individual tools, or the use of the existing tools can be restricted.

3.4 Manufacturing KPI's

The goal of any manufacturing is to achieve all defined KPIs to realise the strategy. The definition of certain KPIs depends on many factors. Without going into the analysis of the KPIs for the design of the manufacturing process, they all have the function of designing an optimal system to ensure the achievement of the planned KPIs in manufacturing. In manufacturing, one of the most important KPIs that shows a real picture of a system's performance is Overall Equipment Effectiveness (OEE) [21]. The OEE value, which is the result of the calculation model that considers process availability, performance and quality, is a good indicator of process performance. The relationship is represented by the following Eq. (1).

$$OEE = Availability \times Performance \times Quality \tag{1}$$

Although all elements of OEE are equally important, practise shows that some companies have more problems with achieving the required quality level, others with the expected performance or plant availability. To improve its performance, each company must identify its weak points. At the stage of defining the manufacturing process, it is very important to know the expected OEE level as well as other KPIs. Since OEE and other KPIs are in a life cycle that is constantly being optimised, it is important to define the best resources in the right configuration to meet the company strategy. In many companies, availability is the most influential element. It depends on many factors, such as the quality of the equipment, the level of knowledge of the user, the quality of maintenance of the equipment, the level of knowledge of the maintenance staff. No less important are the type of maintenance and the organisation at company level. Determining the critical component of the production system is crucial to predicting the occurrence of a bottleneck. Bottleneck characteristics measure the success of the entire production system. This does not necessarily mean that the single most critical and worst element of the system is also the overall outcome of a system. In a production system, it is very important to define the configuration model of the system. However, even if assume that all the above factors are at a very high level, the configuration of the equipment in the production system can significantly affect the overall reliability of the production system. In production system configuration, recognize parallel, serial, and combined configuration models [21, 22]. According to the American Society of Quality [23], the reliability of a production system is defined as the probability that the product will perform its intended function under defined conditions without failure or error during a specified period. The most reliable factories tend to be more productive, have more stable processes that result in high quality and low costs, and have more skilled employees. There is a strong correlation between process KPIs and factory reliability. The reliability of a system can be cascaded to the reliability of its components. Mathematically the reliability of a serial system is expressed by Eq. (2), and for a parallel system by Eq. (3) [24].

$$R(t) = \prod_{i=1}^{n} \left[R_i(t) \right] \tag{2}$$

$$R(t) = 1 - \prod_{i=1}^{n} \left[1 - R_i(t) \right] \tag{3}$$

For simple systems, calculating reliability is straightforward, but often industrial systems involve complex, combined models. In this case, several key parameters need to be considered for a final decision, leading to a rather complex production system analysis, where digital models can be of great help.

4 DIGITAL MODEL VS CONVENTIONAL ANALYSIS – CASE STUDY

4.1 Creation and Validation of a Simulation Model

Prior to the creation of the digital model, the results of the PFMEA, the VOS, the technical risk analysis, and the capability analyses, which are part of the standard procedure of the company concerned regarding the input parameters for the simulation model, were reviewed. Following all the steps presented in chapter 2.2, the PROS1 and PROS2 models were created in the simulation software Siemens Plant Simulation for two production systems with different configurations. Tecnomatix Plant Simulation is a discrete event simulation tool that can be used to create digital models of logistics systems, e.g., in manufacturing, allowing the study of system characteristics and the optimisation of their efficiency. The Tecnomatix Plant Simulation software package can be used to model and simulate production systems and their processes. Material flow, resource utilisation and logistics can be optimised for all planning levels, from global production plants to local plants and specific production lines [25]. The models include CNC equipment for machining, a washing machine, and a leak testing station in various configurations for machining identical aluminium castings. The main difference between the two production systems is the CNC2 equipment (Tab. 3). The PROS1 configuration has four identical units in parallel configuration; PROS2 has one CNC2 unit with 3 serial modules and a robot cell for deburring after machining. The aim of the simulation is to validate the DFSSDM model and define a production system with better OEE performance. The production system PROS1 represents the existing physical equipment, PROS2 is an alternative solution considered to increase capacity. The analytical calculation of the finance department defined PRO2 as the more economical solution to produce a specific product. The purpose of applying the hybrid DFSSDM model is to confirm the hypothesis that the PROS2 system is more productive and economical than the existing PROS1 system. For practical validation of the novel DFSSDM model, the simulation is performed with a minimum number of process inputs. Tab. 3

shows the input data into the PROS1 and PROS2 production model after validation of the model, which was carried out with the same inputs for the same type of plant, and the comparison with the analytical results. The difference between the simulation model and the physical model for PRO1 was less than < 3,7%, so the model passed validation. The main process inputs in the digital model with the biggest difference defined with VOS, CPM and PFMEA are Reliability and Number of employees.

Table 3 Input data in simulation models

		Key process input			
	Assets	*Tc* (min)	*WF*	*R*	*MTTR* (min)
PROS1	CNC1	2,12	0,5	98%	12
	CNC1	2,12	0,5	98%	15
	CNC1	2,02	0,5	85%	11
	CNC1	2,02	0,5	85%	10
	CNC2	4,16	1	90%	5
	CNC2	4,16	1	90%	12
	CNC2	4,16	1	90%	10
	CNC2	4,16	1	90%	10
	WM	0,48	1	90%	20
	LT	0,48	1	98%	14
PROS2	CNC1	2,09	0,5	85%	15
	CNC1	2,09	0,5	85%	17
	CNC2	1,00	0,33	98%	45
	CNC2	1,06	0,33	98%	30
	CNC2	1,05	0,33	99%	33
	RC	0,56	0	90%	5
	WM	0,57	1	90%	20
	LT	0,56	1	98%	10

Work calendar: 24/7, 7,5h/shift, Internal logistic in workforce time
CNC1,2 – CNC machine for different machining operations
WM – washing machine, LT – Leak Test and package station.
RC – robotic cell for deburring
Tc – cycle time, *WF* – number of workers
R – Reliability, *MTTR* – Mean Time to Repair

The data for PROS1 are representative data collected during one production year for all unit types. The data for PROS2 is a combination of collected data for the same type of equipment as in PROS1 and planned data for new equipment provided by the equipment supplier. The system reliability results were calculated using the indirect method based on the results of the processed pieces. For additional validation of the model, the data of the quality level and productivity of the workers were blocked for this analysis, they were set to fixed optimal constant values so that they would not influence the result. The reliability data for the same type of equipment are average values for all equipment of the same type, as only this type of data was available for new equipment, while the mean time to repair (MTTR) values for PROS1 and for PROS2 are real for a similar application. The digital simulation models for production systems are shown in Fig. 4 and Fig. 5.

4.2 Research Results

To investigate the influence of time on the reliability behaviour of the system, simulations were carried out for different production periods, as shown in Tab. 4. From the results presented, for the specified production system with defined input parameters, it is necessary to create a simulation for a longer period, at least for 30 working days, in order to obtain repeatable results. The simulation results for the total produced part for a production period of 1 year and the reliability of the production system are shown in Tab. 4. The results of the resource statistics for PROS1 and PROS2 are shown in Fig. 6 and Fig. 7. These data are used to investigate the potential effects of quality level, workers, and balancing time between system elements on productivity.

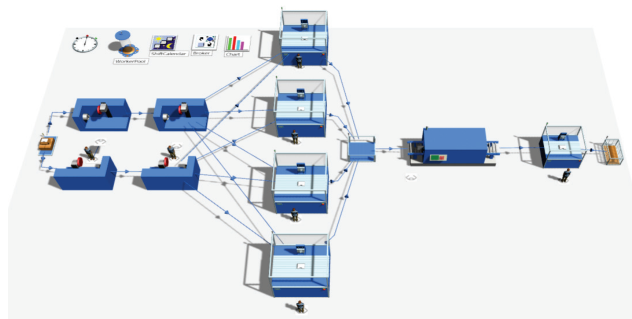

Figure 4 Digital model PROS1

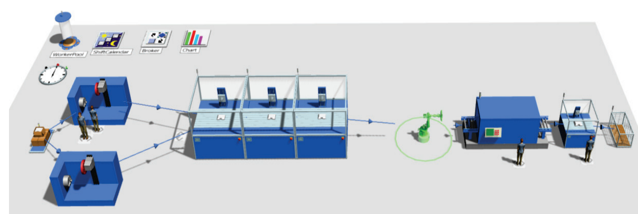

Figure 5 Digital model PROS2

Due to shorter cycle times and significantly higher individual availability in PROS2, the initial performance of PROS2 is better, but the overall result show that the PROS1 system has better reliability and productivity due to the different production configuration.

Table 4 Simulation result for productivity and availability

Production time	8h	1 day	10 days	30 days	330 days
Production (parts) PROS1	325	1045	10533	31605	348331
Production (parts) PROS2	357	1029	9145	27781	307894
Reliability (%) PROS1	93,7	87,8	88,7	88,5	88,7
Reliability (%) PROS2	88,8	84,3	75,0	75,9	76,5

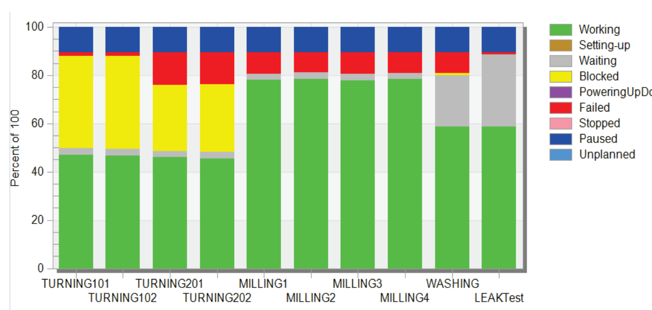

Figure 6 Time ratio of different states of production for PROS1

The PROS1 system can produce 40437 parts or 13% more on an annual basis. Therefore, from the point of view of availability, PROS1 is the better solution than PROS2. For the final decision, the second important factor must also be considered - the number of production workers.

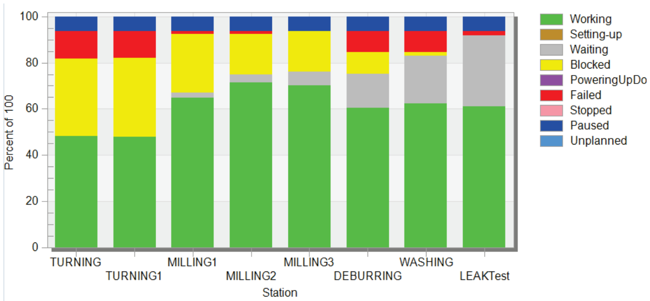

Figure 7 Time ratio of different states of production for PROS2

The initial setting of the number of workers in PROS1 is eight workers required, while PROS2 requires four workers. The results of the simulation models show an average worker utilisation of 94.6% for PROS1 and 72.5% for PROS2. Considering the difference of four workers in terms of number of workers, PROS2 is more favourable. Therefore, for the final decision between the two proposed production systems, additional factors should be considered, which can be done in different ways, e.g., by additionally applying an MCDM method and using the available data and expert groups to make a final decision.

Table 5 Pugh matrix

High Availability & Performance Attributes	Reference	Concept1 PROS1	Concept2 PROS2
Total investments	0	0	0
Maintenance - complexity of activity	0	+	-
Fast repair time	+	0	-
Overload protection	+	0	+
Low downtime	+	+	0
Cost/pcs	-	-	+
Flexibility	+	0	-
Clamping polyvalence	+	0	-
Set-up: complexity and duration	0	-	+
Maintenance - maintainer number	+	0	-
Worker number	-	--	++
Supplier Reference	+	+	-
Additional automatization possibilities	+	+	0
Quality level	0	0	+
OEE	0	0	--
Sum of pluses	8	4	6
Sum of minuses	2	4	7
Total score	6	0	-2

Legend: 0 neutral, + positive, - negative, ++ strong positive, -- strong negative

Another approach may be to define different technical solutions based on the impact of the process configuration on reliability. Alternatively, one can extend the scope of the simulation models to include other data such as quality, energy, logistics, additional analysis of different production configurations, etc. to confirm the analytical calculations of production costs. For the final decision in this study, the MCDM tool Pugh-Matrix was chosen to define the final solution as the period and data needed were limited. Other appropriate MCDM methods such AHP and TOPSIS or PROMETEE can also be used. The results of the Pugh matrix, conducted by a competent team of experts, can be found in Tab. 5. In the final decision based on the Pugh matrix, PROS1 was chosen as the better option for designing the production system for the machining process of the specific product. This means that the original hypothesis that PROS2 is the better solution than PROS1 to produce the identical product can be rejected.

5 DISCUSION AND CONCLUSIONS

This paper presents a model for the design of the manufacturing process that combines digital models with the principles of DFSS and MCDM tools.

Since DT requires significant capital, a certain level of knowledge and the minimum requirement of Industry 4.0 concept, the authors are looking for a solution that combines DFSS principles and DT in the decision-making process. Based on a literature review, good knowledge of DFSS methodology and experience with manufacturing process design, the authors propose a hybrid model for manufacturing process design. The model uses some original DFSS tools, some of them are replaced by more suitable ones, some are slightly adapted, all tools are integrated with digital models and MCDM methods. The use of a digital model is essential for the design of the manufacturing process, as the physical object does not yet exist. The final solution of the digital model is transferred to the digital twin after all networked devices are installed in the production.

The main purpose of the proposed model is to make the design of the manufacturing process professional and relevant by using simulation tools to find an optimal solution that avoids or significantly reduces the cost of starting the production of a new product. The application of the proposed model in a real manufacturing case confirmed the usefulness of using a model in the conditions of real manufacturing processes. The advantage of this model is that companies that are not yet at the level of Industry 4.0 can remain competitiveness on the market and further develop their business processes. With the new technological possibilities, flexibility, agility and lower costs, companies can start their journey to create a digital twin with lower capital investments and shorter time to value than ever before. Another advantage is that the model can be used continuously in optimisation activities in the PLC, so it can be applied to existing manufacturing processes and the development of new manufacturing processes.

In further research, the proposed model can be extended with another existing quality function development (QFD) tool to further define the framework for applying the MCDM method. Simulations with process modelling tools can be integrated with AI, especially in cases where the level of Industry 4.0 has been reached and digital twins are already present in the manufacturing area.

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6 REFERENCES

[1] Semenkov, K., Promyslov, V., Poletykin, A., & Mengazetdinov, N. (2021). Validation of Complex Control Systems with Heterogeneous Digital Models in Industry 4.0 Framework. *Machines, 9*, 62. https://doi.org/10.3390/machines9030062

[2] Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. *White paper*, 1, 1-7.

[3] El-Haik, B. & Roy, D. M. (2005). *Service Design for Six Sigma: A Road Map for Excellence*. Willey-Interscience publication, 33-45. https://doi.org/10.1002/0471744719

[4] VDI 4499 Part 1. (2008-02). Digital Factory – Fundamentals

[5] Lewis, P. T. (1985). Correcting the IoT History. Chetan Sharma, 14 March 2016. Retrieved 1 June 2021.

[6] Wlodarczak, S. (2008). Don't Let Your Industrial Internet of Things Project Fail. *RFID Journal*. https://www.rfidjournal.com/view-from-the-top-5-cios-speak-out-on-rfid?16470%2F2

[7] Pavletić, D., Soković, M., & Krulčić, E. (2006). Six Sigma Process Quality Improvement in Automotive Industry. *Strojarstvo, 48*(3-4), 173-185.

[8] Taylor, Z. & Ranganathan, S. (2014). *Designing High Availability Systems: Design for Six Sigma and Classical Reliability Techniques with Practical Real-Life Examples*. First Edition. The Institute of Electrical and Electronics Engineer. John Wiley & Sons, Inc, 278-302. https://doi.org/10.1002/9781118739853

[9] El-Haik, B. & Shaout, A. (2010). *Software Design for Six Sigma: A Roadmap for Excellence*. John Wiley & Sons, Inc. 21-53. https://doi.org/10.1002/9780470877845

[10] Grieves, M. & Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behaviour in Complex Systems. In: Kahlen, J., Flumerfelt, S., Alves, A. (eds) *Transdisciplinary Perspectives on Complex Systems*. Springer, Cham. 85-113. https://doi.org/10.1007/978-3-319-38756-7_4

[11] Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital Twin in Industry: State-of-the-Art, *IEEE Transactions on Industrial Informatics, 15*(4), 2405-2416. https://doi.org/10.1109/TII.2018.2873186

[12] Uhlenkamp, J. F., Hribernik, K., Wellsandt, S., & Thoben, K. D. (2019). Digital Twin Applications: A first systemization of their dimensions. *IEEE (ICE/ITMC)*, 1-8. https://doi.org/10.1109/ICE.2019.8792579

[13] Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in Manufacturing: A categorical literature review and classification. *IFAC Papers Online*, 51-11.1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

[14] Tao, F., Zhang, M., & Cheng, J. F. (2017) Digital Twin Workshop: A New Paradigm for Future Workshop. *Computer Integrated Manufacturing Systems, 23*, 1-9. https://doi.org/10.13196/j.cims.2017.01.01

[15] VDI 3633 (2018). Simulation of systems in materials handling, logistics and production - Terms and definitions, Verein Deutscher Ingenieure, Association of German Engineers.

[16] Geissbauer, R. Schrauf, S., Berttram, P., & Cheraghi, F. (2017). Digital Factories 2020. PricewaterhouseCoopers GmbH Wirtschaftsprufungggesellschaft (PwC). https://www.pwc.com/ca/en/industries/industrial-manufacturing/digital-factories2020.html

[17] Laguna, M. & Marklund, J. (2019). *Business process modelling, simulation, and design*. CRC Press. 281-287. https://doi.org/10.1201/9781315162119

[18] Zeleny, M. (1982). *Multiple criteria decision making*. New York. McGraw-Hill.

[19] Krulčić, E., Pavletić, D., Dobovičeк, S., & Žic, S. (2022). Multi-Criteria Model for the Selection of New Process Equipment in Casting Manufacturing: A Case Study. *Tehnički glasnik, 16*(2), 170-177. https://doi.org/10.31803/tg-20220407112829

[20] Pugh, S. (1981). Concept selection: a method that works. *Proceedings of the International conference on Engineering Design*, 497-506.

[21] Stamatis, D. H. (2017). *The OEE primer: understanding overall equipment effectiveness, reliability, and maintainability*. CRC Press Taylor & Francis, 19-20. https://doi.org/10.1201/EBK1439814062

[22] Ebeling, C. E. (1997). *An Introduction to Reliability and Maintainability Engineering*. McGraw-Hill, 2, 5, 9.

[23] American Society of Quality. (2022). https://asq.org/quality-resources/reliability (accessed 01.09.2022).

[24] Mangey, R. (2019). *Reliability Engineering – Methods and Application*. CRC Press Taylor & Francis Group. https://doi.org/10.1201/9780429488009

[25] Bigslow, S. (2020). *Tecnomatix Plant Simulation - Modelling and Programming by Means of Examples*. 2nd Ed. Springer. https://doi.org/10.1007/978-3-030-41544-0

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