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Optimizing smart manufacturing systems using digital twin

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ABSTRACT

Presented paper investigates the application of digital twins for the optimisation of intelligent manufacturing systems and focuses on the comparison between simulation modelling results and real-world production conditions. A digital twin was created in the Simio software environment using a data-driven simulation model derived from a real-world production system. Running the digital twin in real time, which was displayed graphically, facilitated the analysis of key parameters, including the number of finished products, average flow time, workstation utilization and product quality. The discrepancies were attributed to the use of random distributions of input data in the dynamic digital twin, as opposed to the long-term measurements and averages in the real-world system. Despite the limitations in the case study, the results underline the financial justification and predictive capabilities of digital twins for optimising production systems. Real-time operation enables continuous evaluation and tracking of parameters and offers high benefits for intelligent production systems. The study emphasises the importance of accurate selection of input data and warns that even small deviations can lead to inaccurate results. Finally, the paper highlights the role of digital twins in optimising production systems and argues for careful consideration of input data. It highlights the importance of analysing real-world production systems and creating efficient simulation models as a basis for digital twin solutions. The results encourage extending the research to different types of production, from job shop to mass production, in order to obtain a comprehensive optimisation perspective.

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1. Introduction

With the transition to Industry 4.0, digitization brings special challenges and concerns for production. One way to deal with these challenges is to use a digital twin. Digital Twin has emerged as a central paradigm in the field of smart manufacturing and Industry 4.0, with profound implications for production management, control frameworks and the broader landscape of modern manufacturing. The digital twin is not just a technological artefact, but also a multi-layered construct that connects physical entities with their virtual counterparts. It encompasses various dimensions, including its connotation, its reference model, its applications, and the associated research questions [1]. In the context of complex product assembly shop floors, a digital twin-based smart production management and control is emerging. This framework uses the concept of the digital twin to improve the agility and responsiveness of manufacturing processes. It provides a dynamic, real-time representation of the physical system that enables predictive maintenance, optimized resource allocation and adaptive production scheduling [2]. The interplay between digital twin and smart manufacturing are explored and their importance for transforming traditional manufacturing processes is highlighted [3]. This approach enables real-time monitoring, data-driven decision-making and improved operational efficiency [4]. The study focuses on optimising manufacturing takt time within a supply chain, with an emphasis on the strategic placement of a decoupling point. While the study provides a basis for improved operational efficiency, it is important to discuss the assumptions and generalisability to different production environments. Applications range from predictive maintenance to quality control, highlighting the versatility and transformative potential of digital twin-driven smart manufacturing [5]. The correlation and comparison between digital twins and cyber–physical systems (CPS) form a critical discourse. Both concepts have similarities in bridging the physical and digital worlds. While CPS emphasizes the integration of computational algorithms with physical processes, digital twins extend this integration to a comprehensive virtual representation [6]. This study looks at the central role of planning algorithms in smart manufacturing and addresses the associated challenges. The study not only highlights the advances in algorithms, but also emphasises the need for adaptive algorithms that can cope with dynamic production environments. Understanding their correlation helps to refine the conceptual framework for smart manufacturing [7]. The fusion of digital twin and big data [8] is explored in a 360-degree comparison. Big data analyses enrich the concept of the digital twin by incorporating extensive data sets into the virtual representation, thus enabling improved analyses and well-founded decisions. The synergy between the digital twin and big data serves as a cornerstone in the evolution towards smarter manufacturing processes [9]. In exploring the practical applications of digital twins in production logistics, this study presents a testbed that uses real-time location data [10]. Although the study is promising, it provides ideas for thought on the challenges of scalability and the need for further validation in complex production ecosystems [11]. By examining the enabling technologies, challenges and open research areas related to digital twins, a comprehensive understanding of the current landscape is achieved. From advanced sensor technologies to the intricacies of data interoperability, the path to realizing the full potential of digital twins is fraught with challenges. However, these challenges also present opportunities for further exploration and innovation that push the field into uncharted territories [12]. The focus on dynamics in manufacturing presents a new paradigm [13]. This reference highlights the transformative potential of the digital twin in redefining shop-floor operations by providing real-time insights and adaptive capabilities critical to managing the complexity of modern manufacturing [13]. By integrating the digital twin and improved bacterial foraging, job scheduling becomes more adaptable in dynamic production environments [14]. However, the limits of algorithmic scalability and generalisability of the proposed approach underline the need for further investigation [15]. Researchers look at the values digital twin brings to the modelling landscape, navigates the challenges faced in implementation, and identifies enablers that are critical to successful modelling [16]. Anticipating future developments broadens the discourse. This study [17] examines the enabling technologies and potential applications and provides a forward-looking perspective on industrial development beyond Industry 4.0. The comprehensive review provides an examination of the concepts, technologies, and industrial applications of the digital twin [18]. This synthesis enriches our understanding by providing a panoramic view of the historical development, current technological landscape, and practical applications of the digital twin in various industry sectors. By integrating the digital twin and improved bacterial foraging, job scheduling becomes more adaptable in dynamic production environments.

The digital twin plays a central role in the vision of the smart factory. It enables the transition from analysing the past to predicting the future. The concept of the digital twin represents a transformative force in the landscape of smart manufacturing and Industry 4.0. Its multidimensional nature, as explored through the systematic literature review and research, highlights its versatility and the need for further exploration. The intersection of digital twins with smart manufacturing frameworks, cyber-physical systems, big data, and their associated challenges points to a promising path for the future of manufacturing paradigms.

2. Methods

2.1 Digital twin

In the rapidly evolving landscape of modern manufacturing, the integration of digital technologies has revolutionised traditional approaches, giving rise to the concept of digital twins and paving the way for the era of smart manufacturing. At the centre of this transformative paradigm is the seamless connection between the physical system and its virtual counterpart, creating a symbiotic relationship that increases operational efficiency, productivity, and overall manufacturing system performance. The physical system, as the cornerstone of the production environment, embodies the tangible entities and processes that are essential to production. In parallel, sensing devices, consisting of sensors, internet of things devices and other data sources, play a central role by actively collecting real-time data from the physical system. This data, which is often voluminous and diverse, serves as the lifeblood of the digital twin ecosystem and requires a robust communication infrastructure for its transmission to the data processing unit. The communication infrastructure is an important link in the data flow chain that enables the transmission of the collected data to the data processing unit. This unit, which is responsible for pre-processing and organising the incoming data, plays a crucial role in ensuring data quality and relevance. The importance of this step cannot be overestimated, as the effectiveness of subsequent analyses and decision-making processes is highly dependent on the integrity and accuracy of the processed data. Subsequently, the focus is on data collection, in which the processed data is recorded and stored for further analysis. This stock of information forms the basis for the creation of the digital twin model. The digital twin, a virtual representation of the physical system, contains current states, behaviours and other relevant attributes derived from the collected data. In the field of intelligent manufacturing, the digital twin model goes beyond mere simulation and becomes an intelligent entity capable of making informed decisions [19]. Control systems capitalise on the insights offered by the digital twin by using it as a virtual mirror of the physical system, enabling precise decision-making and issuing commands to the control units [20]. This synergy between the digital and physical worlds creates a closed loop in which the digital twin continuously refines its understanding and responses based on feedback from the real world. As we delve into the scientific study of digital twins in smart manufacturing, the intricate interplay between the physical system, sensing devices, communication infrastructure, data processing, data acquisition, modelling of the digital twin and control systems underpinning this transformative paradigm becomes apparent. By deciphering the complexity and dynamics within this interconnected framework, we can unlock unimagined potential for efficiency, adaptability, and innovation in the manufacturing landscape, as shown in Fig. 1.

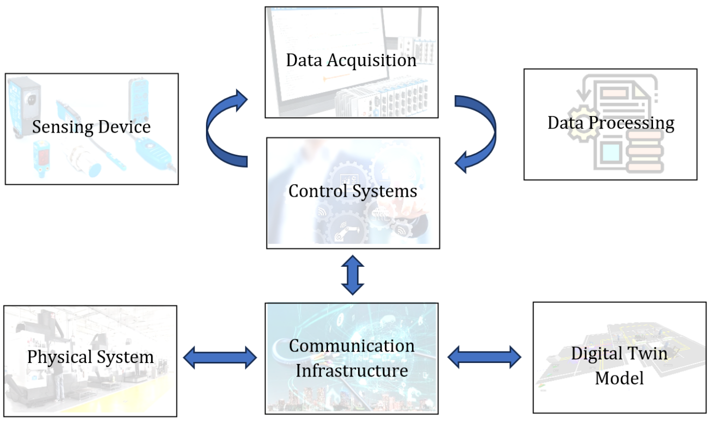

Fig. 1 Digital twin proposed block diagram structure

- Physical system: Represents the actual physical entity or process in the manufacturing environment.
- Sensing Devices: Collect data from the physical system. These can be sensors, IoT devices or other data sources.
- Communication infrastructure: Transmits the collected data to the data processing unit.

- Data processing: Includes the pre-processing and organisation of the data. This step is crucial to ensure the quality and relevance of the data.
- Data acquisition: Captures and stores the processed data for further analysis.
- Digital twin model: Uses the captured data to create a virtual representation of the physical system. This representation includes the current state, behaviour and other relevant attributes.
- Control systems: Use the digital twin model to make decisions and send commands to the control units.

2.2 Simio

Simulation modelling is a central aspect of decision-making processes that relies on simulation languages with different prerequisites for the programming language. This paper describes the Simio programming environment, which is characterised by its simulation language SIMIO, developed in the last decade. This language is characterised by the integration of 3D animations and graphical representations, which increase the visual appeal. The Simio software environment facilitates the creation and use of dynamic 3D animation models and offers a comprehensive library of standard elements. This library includes elements such as sources, sinks, servers, combiners, separators, resources, vehicles, workers, basic nodes, transfer nodes, connectors, paths, time paths and conveyors.

- Source: Serves as the entry point for new workpieces/orders and creates entities with specific types and arrival patterns.
- Sink: Represents the ending point for workpieces and is responsible for terminating entities that have completed processing.
- Server: Represents a workstation where processes are executed on workpieces.
- Combiner: Integrates individual entities, e.g. by assembling a product from different components.
- Separator: Works in the opposite way to a combiner by splitting one entity into several or creating several copies.
- Resource: Represents any intermittent resource that is required for a job and then returns to its intended location.
- Vehicle: Represents a transport mechanism that either has a predetermined route or is executed in response to specific requests.
- Worker: A mobile resource that is activated for specific tasks or to facilitate entity transfers between node locations.
- Basic node: Represents a connection point with no special functions, typically used upon arrival at the workstation.
- Transfer node: A dedicated node that is used to implement transport logic and is primarily used when leaving the workstation.
- Connector: Establishes connections between individual nodes; it is characterised by negligible time expenditure and is suitable for cases in which travel time is irrelevant.
- Path: Represents a classic transport path in which the user specifies both the distance and the speed of the element being traversed, thereby influencing the travel times.
- Time path: A special path in which the user specifies the duration of time that the element travels through.
- Conveyor: Represents a perpetual transport system, e.g. a constantly moving belt.

Each element is characterised by properties, states, events, appearance, and logic. Properties include user-defined input values, while states represent dynamic values that can change during the simulation. Events are temporal triggers that notify other elements of subsequent events. The appearance is displayed as a 3D graphical representation of the element within the model. Logic encapsulates a model within a model by prescribing the element's reactions to certain events and thus specifying its behavioural dynamics. Once the model is finalised, the Simio software environment offers the possibility to define different scenarios. These scenarios allow different parameters to be analysed simultaneously and their combined effects on the system to be observed. Individual scenarios facilitate the modification of model properties and provide insights into their isolated effects on the dynamics of the system in general.

2.3 Case study description

In the first phase of creating the simulation model, which was based on the architectural layout of the company's production facility in the Simio software environment, we meticulously described the spatial allocation of the machine installations while maintaining realistic dimensions. The existing transport and transit routes, warehouses and ancillary rooms were fully taken into account. It was decided to start the simulation model with an authentic workplace layout. The specific locations of the operational workstations were determined from the floor plan of the production hall and then integrated into our model using the dimensions initially determined. This preparatory step simplifies the positioning of the subsequent simulation elements, where several constraints were identified and carefully considered when creating the model:

- Element constraint: the specification that the model must not contain more than 30 elements required a pragmatic solution for the source and sink of entities, so these components had to be merged into a single source and sink.
- Time specification: The time frame of the simulation was limited to 10 working days. In order to adapt to this time parameter, the processing and setup / tear-down times were divided proportionally by 10 to ensure the temporal congruence of the simulation.

Before the actual construction of the model, overarching goals were defined to capture the planned attributes of the simulation:

- Different attributes: Different sequences of orders, processing times and setup and tear-down times depending on the type of entity created.
- Variable entity frequency: Entities of different types are generated with different frequencies.
- Type-dependent entity generation: The number of entities generated simultaneously depends on the type of entity generated.
- Trigger mechanism: The generation of new entities is triggered by the release of product A.
- Operational monitoring: The simulation interface provides a continuous overview of the length of the queues at the individual work centres.

In line with these constraints and the formulated objectives, three different entities were defined in the model, using the Model Entity element and symbolising the workpieces with the designation's product A, product B and product C. To increase the clarity of the model, each entity was clearly colour-coded. In addition, a travelling speed of 2 m/s was defined between the individual workstations, which represents product transport with forklift trucks. Assuming that an entity corresponds to a product batch, the intrinsic value of the entity was determined by multiplying the product cost and the batch size.

2.4 Digital twin model in Simio

The Simio simulation environment not only facilitates the creation of digital twins, but also offers a significant advantage when utilising input data from real-world production systems. The data-driven simulation model, complemented by a user-friendly graphical interface, not only enables efficient and robust numerical calculations, but also ensures a fast response time. This fast calculation capability is crucial for the successful implementation of a digital twin. In addition, the short calculation times in Simio enable the development of a digital twin where the numerical results can be seamlessly integrated into the real-time simulation within a visual virtual reality (VR) interface. This integration improves the overall experience of the simulation and provides a dynamic and interactive representation of the system behaviour. The use of a visual VR interface contributes to a deeper understanding of the simulated processes and facilitates in-depth analysis and decision making to optimise the real production system. The input data comes from a real-world production system consisting of seven workstations. Table 1 shows the main input data that drives the data-driven simulation model and describes the financial, time, energy, location, and efficiency parameters of the real-world production system.

In the production system shown in Fig. 2, our analysis revolves around the dynamic flow of three different products that pass through a series of seven strategically positioned workstations. Each workstation is supervised by a dedicated employee who ensures that the production processes run smoothly. The intricate choreography of the production cycle involves the skilful use of a forklift to enable the smooth transport of raw materials at the beginning of the system, navigating through the intermediate stages and finally delivering the finished products. The simulation model ingeniously visualises the operation of the system by assuming a two-shift operation, with each shift lasting twelve hours, over the course of a conventional working week. This scheduling strategy is a fundamental part of the simulation as it provides a realistic representation of the daily operation of the system. Crucially, the efficiency of this production system is quantified through theoretical calculations of its production capacity. Based on these calculations, the system has a planned utilization rate of 85 %, which emphasises its ability to effectively convert input resources into products. This utilization metric serves as a valuable benchmark for evaluating and optimising the performance of the production system and provides insights for potential improvements and operational refinements.

Table 1 Digital twin input parameters

Workplace	Cut 1	Cut 2	Machining 1	Machining 2	Machining 3	Assembly 1	Assembly 2
Operating cost (EUR/h)	54	54	42	42	42	38	38
Idle cost (EUR/h)	36	36	21	21	21	13	13
x_{loc} (m)	9.6	9.6	15	22.2	29.4	36.6	43.2
y_{loc} (m)	11.4	5.4	1.2	1.2	1.2	1.2	6.6
Setup time (min)	12	12	18	18	18	9.6	9.6
Machine operation energy consumption (kWh)	12	12	8	8	8	1.5	1.5
Machine idle energy consumption (kWh)	1.5	1.5	1	1	1	0.2	0.2
Machine scrap (%)	2	1.5	4	4.5	5	1.5	2

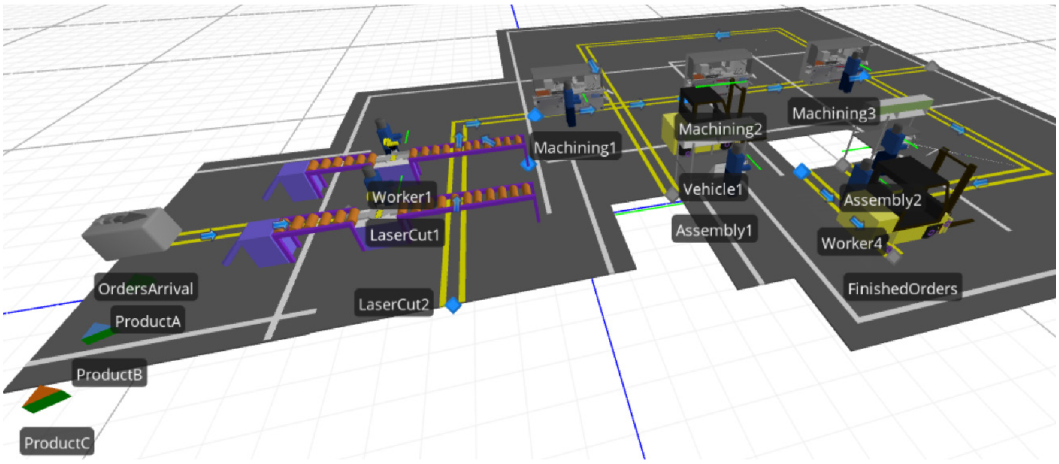

Fig. 2 Digital twin model in Simio

3. Results

The section dedicated to results is primarily concerned with highlighting the discrepancy between the results of a digital twin created in the Simio software environment and the results that emerge from the empirical reality of the real-world production system. The scientific literature emphasises the acceptance of results generated using traditional simulation methods. A discrepancy of less than 3 % between the simulation results and the empirical reality is considered satisfactory. Conversely, any escalation beyond this threshold represents an increased risk of inefficiency of the simulation model, especially in terms of economic, safety and other operational constraints.

Table 2 presents the numerical results of the comparative analysis between the authentic production system and its digital counterpart, specifying the parameters for quantifying the final products and determining the average throughput intervals. The collected comparative results show deviations between the results of the digital twin and the real-world production environment. It is worth noting that a decadal average, derived from ten iterations of the simulation model and representing a normal five-day working week, shows a recognisable discrepancy in four out of seven parameters examined. For three parameters, however, the discrepancy remains below the defined threshold value of 3 %. The limited validity of the results emphasises the fact that the analysis embedded in the presented digital twin shortens its focus in time, while the input data of the authentic production system has a longer temporal extension.

Fig. 3 shows the graphical representation of the empirical production system contrasted with the digital twin, focussing on the parameter describing the quantity of finished products. The empirical evidence shows that the digital twin exactly fulfils the allocation rule for the proportional distribution of the workload depending on the composition of products A, B and C.

The number of completed products under the updated production system exceeds the corresponding yield of the digital twin. This discrepancy is due to the contrast between the use of stochastic distribution functions for the input parameters and the imposition of static values assumed by the real-world production system. The strategic integration of stochastic distribution functions into the simulation model of the digital twin serves to mimic authentic diurnal fluctuations inherent in the operating cadence of the empirical production system.

Table 2 Real-world vs digital twin numerical results comparison

	Real-world results	Digital twin results	Difference [%]
Number of finished products	163	158	-3.07
Number of finished product A	95	92	-3.16
Number of finished product B	46	46	0
Number of finished product C	22	20	-9.09
Average flow time product A (h)	171.67	175.90	+2.46
Average flow time product B (h)	149.80	152.70	+1.94
Average flow time product C (h)	104.70	122.16	+16.68

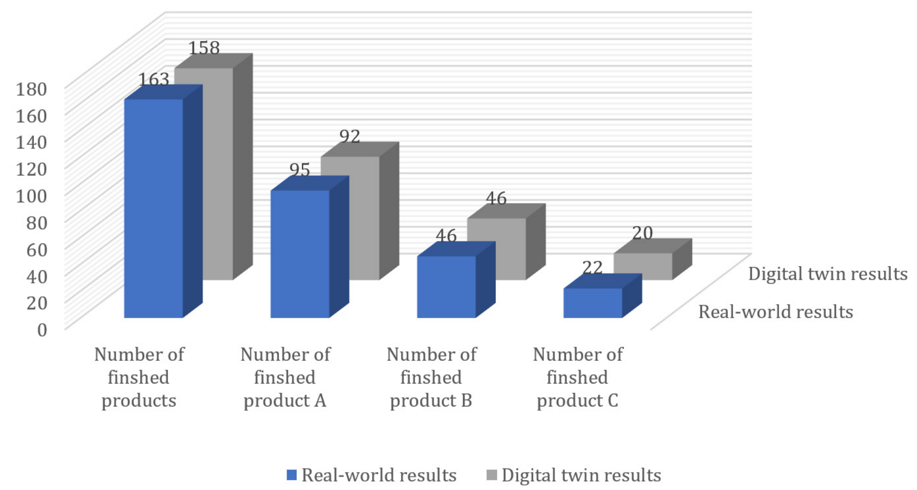

Fig. 3 Number of finished products comparisons

The parameter of an average flow time, as shown in Fig. 4, plays a central role in production system analysis. This graphical representation includes a quantitative representation of the average flow time taken during the entire production process. The average flow time calculated in this way is a key performance indicator that provides sophisticated insights into the complex dynamics that determine the efficiency, effectiveness, and overall vitality of the production system. This metric is a fundamental benchmark that serves not only as an evaluation tool, but also as a catalyst for continuous improvement measures. Its importance stems from its ability to recognise the average flow time efficiency of the production system and to decipher crucial information about the progression of products or services over time from inception to completion. It also serves as a measurement tool for the systematic evaluation of the production process and provides a quantitative basis for identifying areas for optimisation. Average flow time plays a central role in the pursuit of the dual objectives of customer satisfaction and overarching corporate goals. By quantifying the time subtleties of production, it facilitates informed decision-making aimed at harmonising the production process with customer expectations and strategic business objectives. Consequently, the metric serves as a fundament for adaptive strategies that enable companies to proactively address challenges, optimise resource allocation and improve overall operational efficiency.

For the average flow time parameter, we find that the deviation between the results of the real-world production system and the result of the digital twin for products A and B is acceptable. However, for product C, where the production quantity is low, larger deviations occur. This is since a small number of products has a proportionally large influence on the deviation of the result comparison.

Table 3 and Fig. 5 show the comparative results of the workstations utilization and the percentage of well-made products. In this case, the comparative results illustrate the difference between the values of the real-world production system and the results of the digital twin. As the case under consideration is an order-related production, the results show that the system has a high-capacity utilization. The order planning and the utilisation of the available capacities are effective, so that there are only minor delays due to micro-interruptions and irregularities in the transport of raw materials and intermediate stocks. It is noteworthy that the utilisation in the real-world production system is lower than indicated by the digital twin. This emphasises the need for effective management in order-related production, which poses considerable challenges for the long-term sustainable operation of the production system due to its highly dynamic nature.

There are also differences in the parameter of the appropriate number of finished products; the results show that there are relatively higher values of insufficiently manufactured products in the real production system. Errors in production occur in individual operations, during transport and in the completion of the product. The discrepancy between the comparative results of the real-world production system and the digital twin can be attributed to the complexity of tracking and detailed monitoring of irregularities in the production/processing of semi-finished products within the digital twin, which occur continuously at all stages of production in the real-world production system.

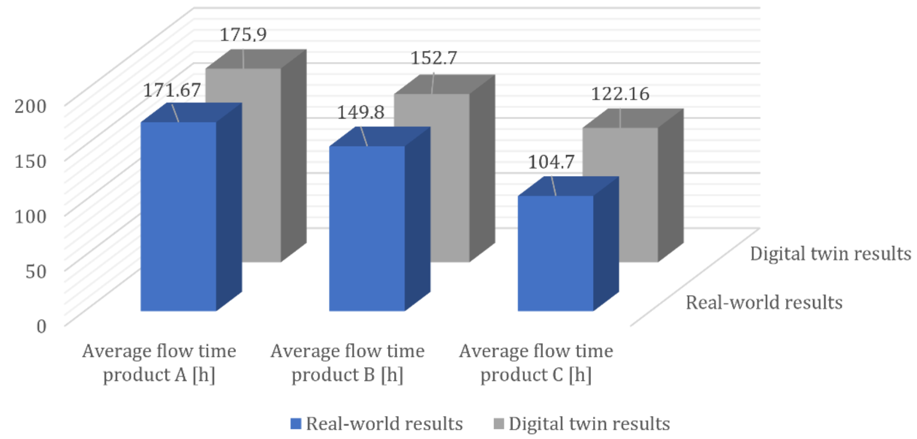

Fig. 4 Average flow time comparison

Table 3 Average utilization and quality products numerical results comparison

	Real-world results	Digital twin results	Difference (%)
Average utilization (%)	83.6	87.8	+4.2
Quality products (%)	91.5	95.3	+3.8

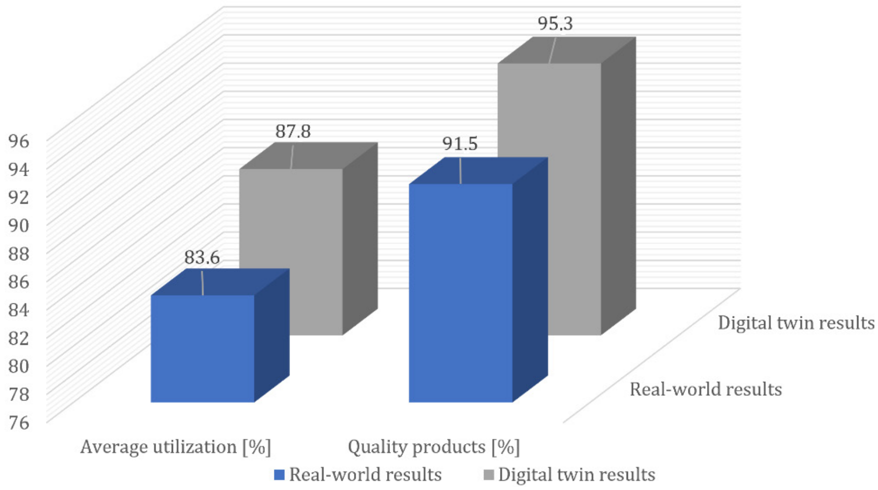

Fig. 5 Average utilization and quality products graphical presentation

4. Discussion

In line with the original research question of whether digital twins can be used to optimise production systems and whether simulation results are comparable with the real state of production, this article presents the construction of a digital twin within the Simio software environment. The digital twin is based on a data-driven simulation model of a real-world production system. The input data describes the digital twin in a complex way and enables its execution in real time through a graphical representation of the task execution in production. The numerical and graphical results obtained show the description of the production system in terms of parameters such as the number of finished products, the average flow time, the average utilization of the work centres and the appropriate quality of finished products.

In a comparative study of the results of the real-world production system and the digital twin, an average deviation of 4.9 % is found. This deviation exceeds the threshold value of 3 % recommended in the literature. From the point of view of exceeding the threshold, there are obvious overruns in parameters describing infrequently repeated measurements where individual measurements account for a significant common proportion. To address this, it would be advisable to extend the operation and calculation of the simulation model beyond the current five-day working week to a longer time frame, e.g., to a monthly or quarterly operation of the production system.

The observed discrepancies are due to the use of random distributions of input data by the digital twin, which is essential in highly dynamic production environments, in contrast to the real-world production system, where the parameters are measured over a longer period and the data represent averages of months. The research presented is limited by the case study considered, which indicates the need for extension and, in certain aspects, generalisation of the study. The results shown within the given limitations show that the implementation of digital twins enables the analysis of the performance of the production system with the aim of optimisation [21]. The main advantage of a digital twin in this regard is its financial justification, as it allows us to predict in advance, what will happen in the production system. The operation of a digital twin is also possible in real time during the continuous operation of the production system to evaluate and track certain parameters of the production system.

The presented approach shows the high benefit of digital twins in intelligent production systems. Given the high market dynamics in production systems, continuous optimisation is encouraged, and digital twins enable this by allowing the investigation of all important parameters in terms of efficiency, finances, environment, etc. When using digital twins, the results show that the right choice of input data is crucial, which must accurately represent the production system being analysed. Even a slight deviation in the data can lead to completely wrong results or a major deviation from the real-world situation. In this case, detailed collection, analysis, filtering and understanding of the input data is of utmost importance. Only in this way we can ensure the accuracy of the numerical and graphical results, whereby the final evaluation of the constructed digital twin also plays a decisive role.

5. Conclusion

In this paper, we explore the use of digital twins as an optimisation method for intelligent manufacturing systems. By using the digital twin, together with intelligent algorithms, companies can achieve data monitoring, improve the operation of the production system, and develop innovative products and services. We emphasise the importance of both studying the real-world production system and creating an efficient simulation model as a basis for a digital twin solution. The results show that digital twins can be used as a basis for the optimisation of production systems where the input data is one of the most important factors.

The experiments conducted were designed in a laboratory environment using input parameters from a real-world production system. In order to fully utilise the potential of the proposed digital twin, the scope of the studied problem needs to be extended to different types of production systems, from job shop to mass production. The proposed concept offers production companies a more comprehensive optimisation perspective for their production systems with the aim of increasing overall efficiency and global competitiveness. Despite the laboratory environment, this work emphasises the importance of using digital twin solutions in real-world production systems. In the current research landscape, our work represents a cutting-edge contribution to the investigation of the possibilities of the digital twin in intelligent production systems. The growing presence of the digital twin in the real world emphasises the importance of our findings.

This study provides new and fascinating insights into the field of digital twin methods as an optimisation tool for intelligent manufacturing systems. Our study lays the foundation for future research and recognises that the results presented here only capture certain findings that cannot be conclusively refuted. To increase the authenticity of our findings, we plan to extend our experiment in the future by expanding the types of manufacturing systems and investigating the usefulness of digital twins depending on the characteristics of the manufacturing systems. In further research steps, we plan to transfer the results of the digital twins to a real-world application where a comparison of real-time optimisation can be performed.

The implications of the presented research go beyond the presented framework and offer potential avenues for further investigation and practical applications in the field of digital twins and smart manufacturing. Through a comprehensive analysis of several parameters (average flow time, total number of finished products, average utilisation of workstations and quality of products), this paper contributes to the current understanding of the optimisation possibilities of smart manufacturing systems and lays the foundation for future research.

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