applied sciences

MDPI

Article

A Comprehensive Digital Model Approach for Adaptive Manufacturing Systems

Patrik Grznár, Natália Burganová, Štefan Mozol * and Lucia Mozolová

Department of Industrial Engineering, Faculty of Mechanical Engineering, University of Žilina, Univerzitná 8215/1, 010 26 Žilina, Slovakia; patrik.grznar@fstroj.uniza.sk (P.G.); natalia.burganova@fstroj.uniza.sk (N.B.); lucia.mozolova@fstroj.uniza.sk (L.M.)
* Correspondence: stefan.mozol@fstroj.uniza.sk

Abstract: In the current global economy, where rapid changes and constantly shifting market demands define the competitive landscape, adaptive manufacturing systems become essential for businesses striving to remain relevant and efficient. In the context of this growing need, this study focuses on planning as a part of adaptive manufacturing system. This methodology provides a systematic framework that spans from foundational groundwork to meticulous verification and validation phases. By employing advanced simulation techniques, seamless data integration, and process optimization, this methodology ensures the smooth realization of robust and efficient adaptive manufacturing systems. A detailed case study on competency islands showcases the versatility of this approach, demonstrating its efficacy in enhancing manufacturing agility and overall performance. As a significant contribution to the field of smart manufacturing, this methodology offers a structured blueprint for the realization of adaptive manufacturing systems.

Keywords: adaptive manufacturing system; digital model; competency islands; simulation

Citation: Grznár, P.; Burganová, N.; Mozol, Š.; Mozolová, L. A Comprehensive Digital Model Approach for Adaptive Manufacturing System. *Appl. Sci.* **2023**, *13*, 10706. https://doi.org/10.3390/app131910706

Academic Editor: Guijun Bi

Received: 21 August 2023
Revised: 11 September 2023
Accepted: 24 September 2023
Published: 26 September 2023

1. Introduction

In the rapidly evolving landscape of Industry 4.0, the concept of adaptive manufacturing systems has gained significant attention. These systems exhibit a high degree of flexibility and responsiveness, enabling seamless adjustments to changing production requirements. A pivotal tool in the design and analysis of such systems is the creation of a comprehensive digital model [1–3].

The digital model serves as a virtual representation of the adaptive manufacturing environment, incorporating various elements such as production processes, resources, and decision-making logic, and allows dynamic simulations, optimization, and real-time monitoring, facilitating informed decision-making and system refinement [4,5].

As the manufacturing landscape continues to evolve towards greater adaptability and intelligence, one of the challenges lies in the complexity of real-world manufacturing environments, which can involve intricate interdependencies and uncertainties that might not be fully captured by the digital model.

The development of adaptive manufacturing systems is driven by the need to respond quickly and effectively to changing market demands and production requirements [6]. These systems are characterized by their ability to adapt to new situations and conditions in real time, allowing for greater flexibility and responsiveness in production processes. The creation of a digital model is an essential tool in the design and analysis of such systems, providing a virtual representation of the manufacturing environment that can be used for simulation, optimization, and real-time monitoring [7–9].

The digital model incorporates various elements of the adaptive manufacturing system, including production processes, resources, and decision-making logic. By accurately representing these elements in the model, it is possible to simulate different scenarios and evaluate their impact on system performance. This allows for informed decision-making and system refinement, enabling practitioners to design and manage adaptive manufacturing systems more effectively. The fusion of digital models, simulation models, and adaptive manufacturing systems holds immense significance in the contemporary industrial landscape. The purpose of integrating these components is to revolutionize the way manufacturing is conceived, executed, and optimized [10–12].

Risk mitigation and cost efficiency: Developing and implementing manufacturing systems involves substantial investments. By identifying and rectifying issues before physical implementation, manufacturers can significantly reduce the risks associated with costly design flaws and operational disruptions [13,14].

Accelerated innovation: The synergy between digital models, simulation tools, and adaptive manufacturing fosters a culture of innovation. This accelerates the innovation cycle, allowing companies to introduce innovative products and processes with greater speed and confidence [15–17].

Enhanced flexibility: Adaptive manufacturing systems thrive on flexibility. The integration of digital models and simulations empowers manufacturers to evaluate the impact of changes on their systems without disrupting ongoing operations. This flexibility enables agile responses to market shifts, production fluctuations, and unforeseen challenges [18,19].

Optimized resource utilization: A key goal of adaptive manufacturing systems is optimal resource allocation. Digital models and simulations provide insights into resource usage patterns, allowing for the identification of underutilized assets and processes. This optimization reduces waste, enhances energy efficiency, and improves overall sustainability [20].

Data-driven decision-making: In the context of Industry 4.0, data serves as a critical asset. The plethora of data generated by digital models and simulations becomes a valuable resource for guiding decision-making processes [18]. By analyzing these datasets, manufacturers can gain deeper insights into performance trends, system behaviors, and potential areas for improvement. Embracing cloud-based IoT technologies further amplifies the data-driven decision-making capabilities by providing real-time analytics and system controls, allowing manufacturers to dynamically adapt to various production scenarios and optimize resource allocation [21].

Competitive advantage: Companies that can swiftly adapt to changing circumstances and meet customer demands with precision gain a significant edge in the market. This adaptability enhances customer satisfaction and brand reputation [22].

Continuous improvement: Manufacturers can iterate on their digital models, fine-tuning simulations based on real-world data and outcomes [23]. This iterative approach results in progressively refined systems that achieve higher levels of efficiency and effectiveness [24].

The integration of digital models, simulation models, and adaptive manufacturing systems embodies a transformative force in manufacturing [25]. It empowers companies to anticipate challenges, optimize operations, and stay at the forefront of technological advancements. By fostering innovation, flexibility, and data-driven decision-making, this convergence paves the way for a new era of manufacturing excellence in the dynamic landscape of Industry 4.0 [26,27]. Beyond technological gains, this integration leads to tangible business outcomes, such as increased performance, enhanced quality, and elevated efficiency, which directly contribute to a company's economic viability and competitive edge [28].

Drawing insights from available literature, the characteristics of adaptive manufacturing systems (AMS) can be delineated based on criteria like autonomy, self-organization, and reconfigurability. The conventional perception of the manufacturing system as an amalgamation of manufacturing rules, as posited by prior researchers, faces limitations in practical application due to the lack of technological support at the time of formulation [29]. In light of contemporary research on self-adaptive manufacturing with digital twins, the technological advancements now offer new dimensions of real-time adaptability and system dynamics, thereby overcoming the limitations faced by traditional AMS frameworks due to previously lacking technological support [30].

Given the intricate nature of the solution, the implementation of an adaptive manufacturing system is primarily for specific production categories, as further elaborated in the design segment. The human aspect profoundly impacts the success of incorporating adaptability into the manufacturing system, given the integration of new technical tools necessitating appropriately skilled personnel [31,32]. The amalgamation of digitalization and the digital production model stands as a pivotal constituent in the construction of an AMS to meet its criteria. Simulation of logistics can be achieved in many ways, especially with a focus on logistics elements [33,34]. Leveraging software aid and the theory of an adaptive manufacturing system, it becomes viable to craft a digital model of an AMS. The comprehension of simulation software is indispensable in this endeavor, as it entails encapsulating the fundamental elements of an AMS [26,35].

The creation of a digital model for an adaptive manufacturing system holds significant importance in achieving optimized collaboration between humans, information systems, and physical systems. This digital model offers an overview of operations and supports ongoing continuous improvement initiatives within the real system. Digital modeling and simulation technology play a crucial role in manufacturing systems, enabling the realization of manufacturing environment digitalization. This technology not only aids industrial engineers in analyzing complex production systems but also assists decision-makers in studying the impact of operational strategies on system parameters.

1.1. Aim of Paper

From the analysis of existing knowledge and literature, several key points can be discerned:

- Emphasis is placed on swiftly responding to customer demands. Customers now seek not only to select from offered products but also to configure products themselves. This inclination toward personalized products necessitates changes in manufacturing systems to accommodate such demands [36,37].
- Achieving the cost of a mass-produced product for personalized goods is challenging due to the high costs of product variations. Adaptive manufacturing aims to imbue production systems with flexibility and adaptability at the operational level. It seeks to enhance efficiency and reduce costs by responding to changing market conditions [38].
- An adaptive enterprise is better positioned to exploit fleeting opportunities and rapid shifts in customer requirements. To qualify as an adaptive manufacturing entity, specific conditions must be met, including adaptability, which involves responding based on "if-then-else" rules, which entails preparing potential scenarios and alternative strategies using "what if..." scenarios, and ultimately expressing and processing knowledge [39].
- Companies are focusing on developing new technologies that bolster manufacturing system flexibility. Adaptive manufacturing systems must learn to effectively utilize available technologies. The enterprise itself is considered a network integrating advanced technologies, computers, communication systems, management strategies, and cognitive agents (whether human or advanced intelligent systems). These agents are capable not only of overseeing processes and products but also of generating novel behavior to adapt to dynamic markets.
- Several manufacturing systems exhibit varying degrees of adaptability. Reconfigurable manufacturing systems are one example, while further development leads to the emergence of competency islands within manufacturing systems [40].

1.2. Research Questions

There are some research question that need to be asked:

- How can a digital model be effectively utilized to enhance the adaptability of manufacturing systems?

This question addresses the core premise of the paper, exploring the role of digital models in enabling adaptive manufacturing. The methodology aims to demonstrate how digital models can simulate, analyze, and optimize production processes to achieve adaptability.

- What insights and benefits can manufacturers derive from utilizing the digital model created through the proposed methodology?

This question focuses on the practical outcomes of implementing the methodology. By evaluating the insights and benefits gained from the digital model, the paper aims to highlight the real-world impact of the methodology in enhancing manufacturing processes' adaptability, efficiency, and overall performance.

- How can the proposed methodology contribute to the realization of Industry 4.0 principles in the realm of adaptive manufacturing?

This research question situates the paper within the context of Industry 4.0, aiming to explore how the methodology aligns with the principles of intelligent, interconnected manufacturing. It investigates how the digital model's capabilities resonate with the vision of Industry 4.0 and pave the way for smarter, more responsive manufacturing systems.

- How can the proposed methodology be adapted and applied across various adaptive manufacturing contexts?

This question delves into the applicability of the methodology beyond competency islands. It explores the potential extension of the methodology to other adaptive manufacturing systems, such as reconfigurable systems, and examines how the structured approach can be tailored to suit different production scenarios.

1.3. Methodological Framework

The methodology presented in this article provides a systematic approach to building a digital model of an adaptive manufacturing system. It outlines the steps involved in data integration, entity definition, event identification, and performance evaluation. The methodology also emphasizes the importance of validating the model against real-world scenarios to ensure its accuracy and relevance.

A crucial aspect of the methodology is the system for evaluating adaptability, which forms the cornerstone of successful adaptive manufacturing. This system involves assessing various performance metrics in the context of adaptability, including response time to market changes, production flexibility, resource utilization, and customer satisfaction. The challenge here is not only defining these metrics but also integrating them into the digital model to provide real-time feedback on the system's adaptability performance. Striking a balance between accurate representation and computational efficiency in this evaluation system is essential.

This approach differs from that of other authors in terms of perceiving the adaptive manufacturing system and its development with a digital model. While some authors emphasize real-time adaptability and simulation-based optimization, others highlight the concept of competency islands and their autonomous collaboration. Despite these variations, the common thread is the recognition of the significance of digital modeling and simulation for achieving efficient and adaptive manufacturing processes. This unique perspective stems from a blend of professional backgrounds and experiences in the realms of manufacturing and informatics.

The novelty of the current study resides in its contribution to adaptive manufacturing systems by introducing the ability to dynamically modulate both system capacity and object count in real-time simulation environments. This feature necessitates the incorporation of system dynamics, a dimension heretofore unaddressed by traditional simulation frameworks which are typically constrained to static states or predefined system parameters. While existing digital twin technologies do offer emulation capabilities, they are largely designed to function within the bounds of static operational settings. In contrast, our proposed model is uniquely equipped to adapt to fluctuations in object dynamics and system capacities. Furthermore, the scholarly merit of this work is augmented by its applicability to 'competency islands'—sophisticated modular systems capable of reconfiguration and scalability—thereby extending its relevance beyond conventional manufacturing setups.

2. Materials and Methods

Methodology

Overall, this methodology provides a systematic approach to creating a digital model of an adaptive manufacturing system, ensuring its accuracy, validity, and functionality. Each block contributes to the development of a robust and reliable digital representation that can be used for analysis, optimization, and decision-making in the context of adaptive manufacturing. Figure 1 is a scheme of the proposed methodology.

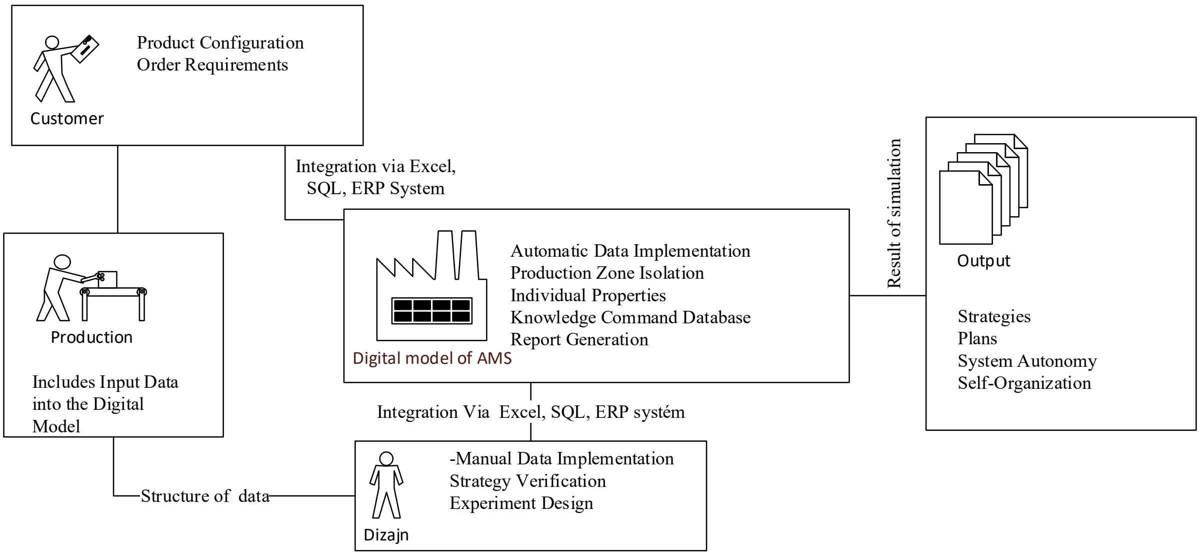


Figure 1. Scheme of the proposed methodology.

The methodology consists of four main parts. The first two parts are depicted in Figure 2.

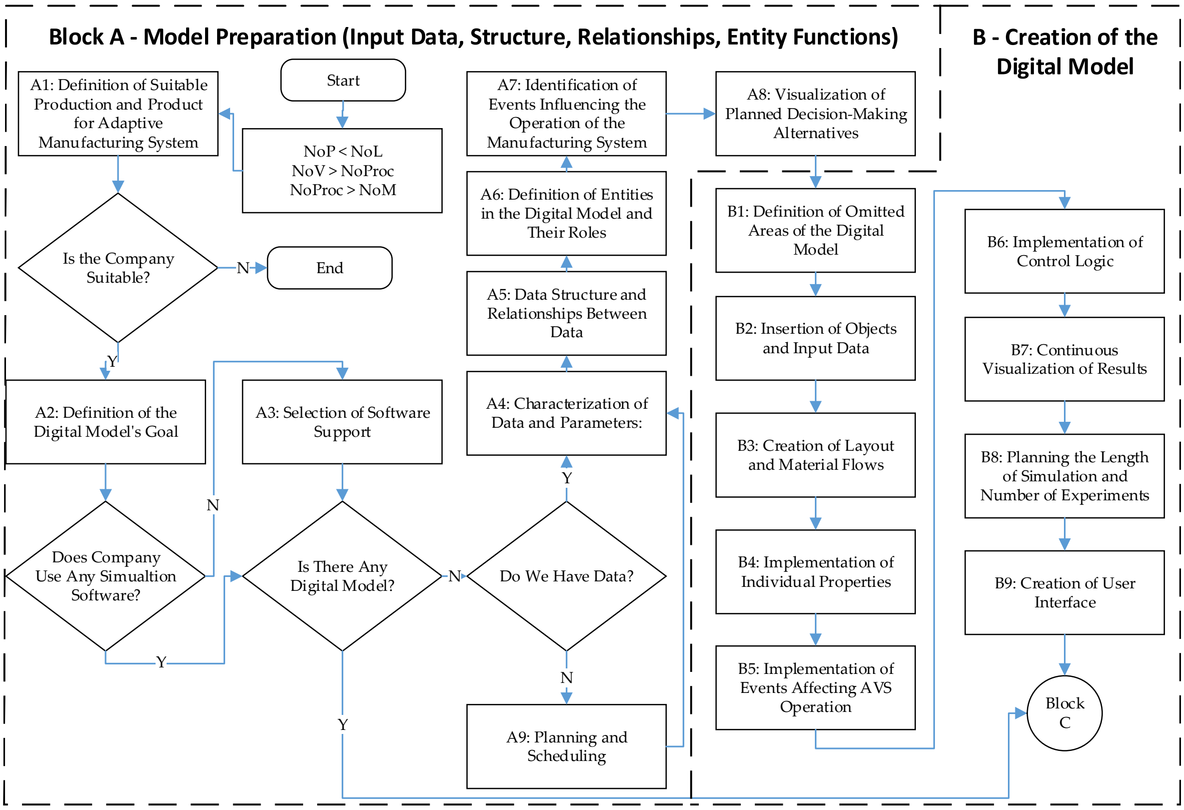


Figure 2. Methodology of creating adaptive manufacturing system blocks A and B.

Block A—Model Preparation (Input Data, Structure, Relationships, Entity Functions): In this phase, the initial groundwork for the digital model is laid. This involves gathering the necessary input data, defining the structural components of the model, establishing relationships between these components, and determining the functions or behaviors of the entities within the system. It is the foundational step that sets the stage for creating a comprehensive digital representation of the adaptive manufacturing system.

This phase involves preparing the adaptive manufacturing system's model. It defines suitable production and product, sets the digital model's goal, selects software tools, characterizes data and parameters, establishes data structure and relationships, defines entities and their roles, identifies influential events, visualizes decision options, and plans scheduling.

Steps:

A1: Definition of suitable production and product for adaptive manufacturing system: This step involves determining the types of production and products that are appropriate for the adaptive manufacturing system. This decision considers the nature of the system and its capacity for adaptability to various production requirements.

A2: Definition of the digital model's goal: Here, the primary purpose and objectives of creating the digital model are defined. This could include goals like optimizing production processes, analyzing system behavior, or testing different scenarios.

A3: Selection of software support: This step focuses on selecting the software tools that will be used to build the digital model. The choice of software is crucial as it affects the capabilities and functionalities of the model.

A4: Characterization of data and parameters: The data and parameters relevant to adaptive manufacturing are identified and described. This could involve aspects such as production metrics, resource availability, demand variability, and other factors that influence the system's behavior.

A5: Data structure and relationships between data: In this step, the structure of the data is designed, and the relationships between different data elements are established. This forms the basis for how information flows and interacts within the digital model.

A6: Definition of entities in the digital model and their roles: Entities, which could represent various components of the manufacturing system, are defined along with their roles and functions in the digital model.

A7: Identification of events influencing the operation of the manufacturing system: Events that can affect the functioning of the manufacturing system are identified. These events could include changes in demand, availability of resources, breakdowns, etc.

A8: Visualization of planned decision-making alternatives: Different decision-making scenarios are visualized, which could involve considering various production strategies, resource allocations, or response plans to changing conditions.

A9: Planning and scheduling: The planning and scheduling aspects of the adaptive manufacturing system are designed. This could include strategies for adjusting production schedules in response to changing demands or resource availability.

The data and parameters of adaptive manufacturing were characterized, and the structure and relationships among them were analyzed. In the preparation of the model, entities in the digital model were defined along with their assigned roles. Influential events affecting the manufacturing system's operations were identified. Planned decision alternatives were visualized, and data availability from production was assessed through question blocks. The planning and scheduling of the adaptive manufacturing system were also devised.

Collectively, this section underwent a thorough examination, forming the foundational basis for the adaptive manufacturing model. These insights will serve as a cornerstone for subsequent phases and the integration into the digital model, with the aim of achieving efficient and flexible production.

Block B—Creation of the Digital Model (Structure and Logic):

This stage focuses on the actual construction of the digital model. It includes the detailed design of the model's structure, how different elements interact, and the logic that governs their behavior. This phase involves translating the real-world processes, operations, and interactions of the adaptive manufacturing system into a digital format. The result is a virtual representation that mimics the behavior and characteristics of the actual system.

An important step in creating a digital model was to create a suitable layout and material flows. This ensured the flexibility and efficiency of the production system. Individual properties of individual elements were implemented and events affecting the operation of the adaptive production system were properly set. Control logic was implemented to ensure the proper functioning of the system and monitoring its performance and quality. Continuous visualization of results will allow monitoring and evaluating the development and proper functioning of the system. When planning the length of simulation and number of experiments, parameters were properly set to achieve sufficient accuracy and reliability of results. It also deals with the creation of a user interface that allows easy and intuitive manipulation with the model. Overall, in this chapter, a successful digital model of an adaptive production system was created, capable of simulating and visualizing its operation and proper functioning.

Steps:

B1: Definition of omitted areas of the digital model: In this step, any areas or aspects that were not initially included in the digital model are defined. This might involve specifying particular processes, components, or interactions that were left out in the earlier stages. This step helps ensure that the digital model provides a comprehensive and accurate representation of the adaptive manufacturing system. In essence, models are developed at a certain level of abstraction and from a specific perspective. The reason for abstracting a model is that it can simplify and speed up the model this way, thereby also saving computational memory, which can be crucial for complex models of production systems. Figure 3 shows a diagram of such abstraction at a specific workstation in the digital model.

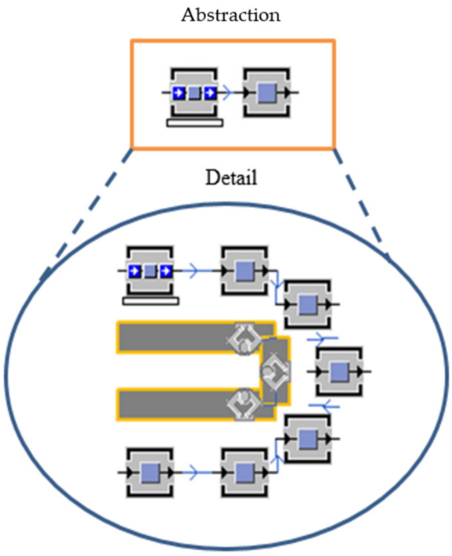


Figure 3. Abstraction of competency island.

B2: Insertion of objects and input data: Here, the various objects and entities that make up the adaptive manufacturing system are inserted into the digital model. This includes all relevant components, resources, tools, and products. Additionally, the required input data for running the simulation is integrated into the model, ensuring that the simulation is based on real-world parameters.

B3: Creation of layout and material flows: This step involves arranging the inserted objects and entities within the digital model to mimic the physical layout of the adaptive manufacturing system. The material flows, which represent the movement of materials or products within the system, are also defined. This step is crucial for accurately simulating how materials move and interact within the production environment.

B4: Implementation of individual properties: Here, the specific properties and attributes of each object or entity in the digital model are implemented. For instance, if an object has certain physical dimensions, operational characteristics, or capacity limits, those details are incorporated into the model. This level of detail helps in achieving a high-fidelity simulation.

B5: Implementation of events affecting AMS operation: This step involves incorporating events that can influence the operation of the adaptive manufacturing system (AMS). These events could include factors such as machine breakdowns, changes in demand, or supply chain disruptions. Simulating the impact of these events helps in understanding how the AMS responds to real-world uncertainties.

B6: Implementation of control logic: Control logic refers to the rules, algorithms, and decision-making processes that govern the behavior of the adaptive manufacturing system. This step involves programming the logic that dictates how the different components interact, how decisions are made, and how the system adapts to changing conditions.

Selected strategies are described in Table 1.

Table 1. Different strategies and their descriptions.

Strategy	Description
Sorting Strategy	This refers to the approach or plan used to arrange items or products in a specific order. In manufacturing, it involves determining how items should be organized based on certain criteria such as size, type, or destination. Sorting strategies optimize the flow of materials or products through the production process.
Output Strategy from Active Object	This strategy involves deciding how products or materials should exit an active process or machine. It determines the sequence and timing of releasing finished products from a particular production stage. The goal is to ensure a smooth and efficient transition of items from one phase to another.
Transport Means Strategy	This refers to the plan for moving materials or products between different points within the manufacturing environment. It includes decisions about the types of conveyors, vehicles, or other transportation methods to use. The strategy aims to optimize the movement of items while minimizing delays and congestion.
System Dynamics	This term pertains to the behavior and changes that occur within a manufacturing system over time. It involves understanding how various factors, such as input variables, processes, and feedback loops, interact and influence the overall performance of the system. System dynamics analysis helps in predicting how the system responds to different conditions and adjustments, including changes in positions.

B7: Continuous visualization of results: Throughout the simulation, it is important to continuously visualize the results. This might involve generating graphs, charts, or animations that show how various metrics and performance indicators evolve over time. Continuous visualization helps in monitoring the system's behavior and identifying any anomalies or areas for improvement.

B8: Planning the length of simulation and number of experiments: Before running the simulation, it is essential to determine the duration of the simulation and the number of experiments to be conducted. This planning ensures that the simulation captures a meaningful timeframe and a sufficient number of scenarios to provide reliable insights into the system's behavior and performance.

B9: Creation of user interface: The user interface allows researchers and engineers to interact with the digital model, input parameters, start simulations, and analyze results. Creating an intuitive and user-friendly interface enhances the usability of the digital model and facilitates experimentation and analysis.

Overall, this block successfully culminated in the creation of a digital model of the adaptive manufacturing system, adept at simulating and visualizing its operation and functional integrity. This model furnishes crucial tools for analysis, optimization, and planning of adaptive production. Blocks C and D are depicted in Figure 4.

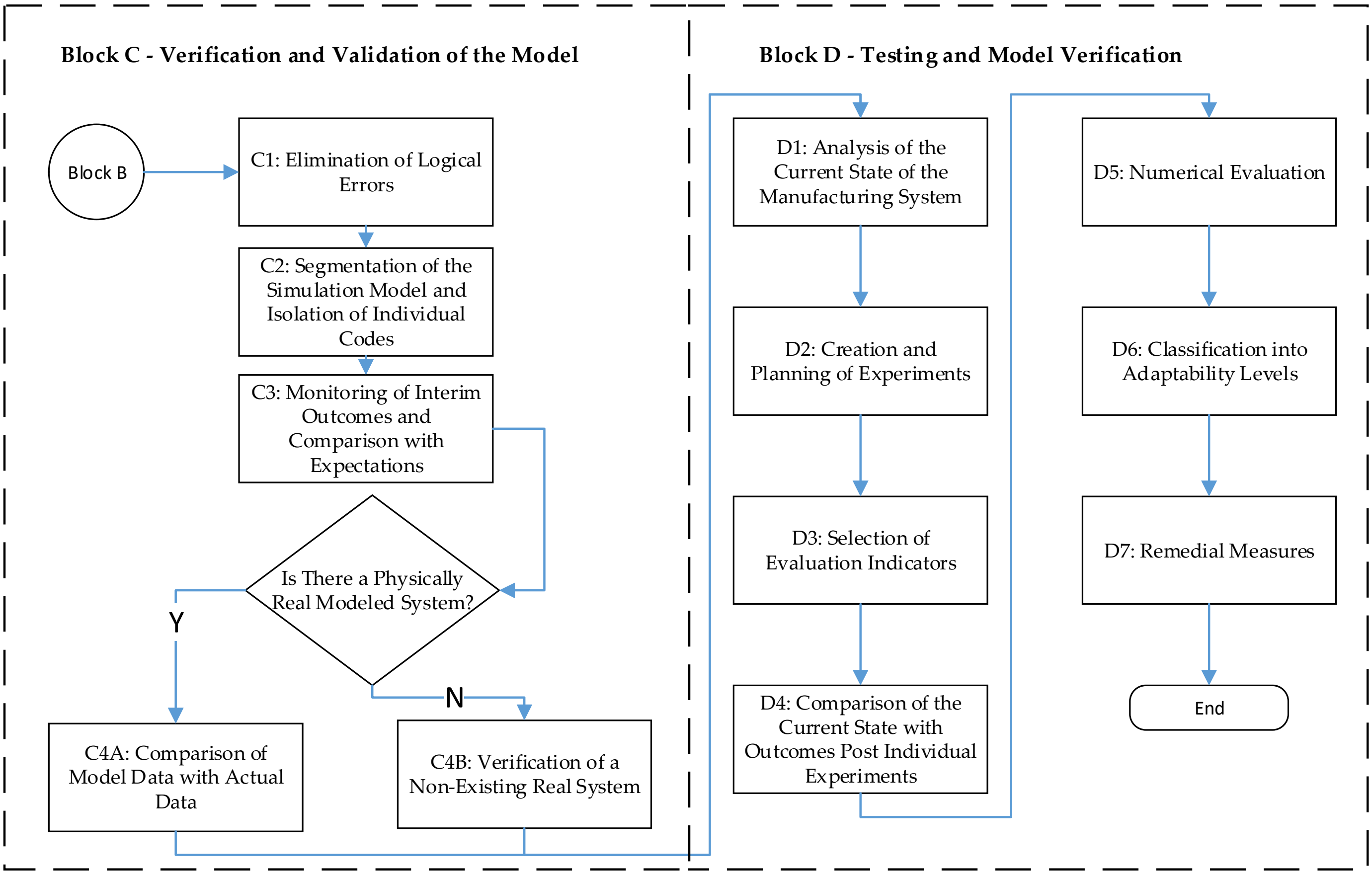


Figure 4. Methodology of creating adaptive manufacturing system blocks C and D.

Block C—Verification and Validation of the Model:

In this part, the accuracy and reliability of the digital model are assessed. Verification involves checking whether the model was built correctly according to the defined specifications. Validation, on the other hand, involves ensuring that the model accurately represents the real system's behavior. This is typically achieved by comparing the model's outputs with real-world data or benchmark scenarios. This phase is crucial to ensure that the digital model is a trustworthy representation of the adaptive manufacturing system.

The overarching goal of this block was to ensure the credibility and accuracy of the digital model of the selected adaptive system. Through the process of verification and validation, we had the opportunity to test and confirm that the digital model is capable of accurately simulating and predicting the behavior of the system under diverse circumstances. Despite the measures taken to ensure the precision and reliability of the model, it is crucial to acknowledge that every model simplifies reality and may possess limitations and imperfections. Therefore, it remains important to continue the verification and validation of the model in the future, potentially updating or enhancing it based on new insights. Throughout these steps, rigorous attention was given to the identification and rectification of logical discrepancies. The simulation model underwent segmentation to isolate individual code components, ensuring clarity and simplifying error detection. Monitoring the ongoing results and their comparison with anticipated outcomes allowed for the identification of discrepancies and potential areas of refinement. Additionally, the comparison of model-generated data with real-world data served as a pivotal method to verify the model's alignment with actual circumstances. Finally, an innovative aspect involved the verification process for a hypothetical system, a technique enhancing the overall robustness of the model validation process.

C1: Elimination of logical errors: In this initial step, a meticulous review of the digital model was conducted to identify and rectify any logical errors. This process ensured that the model's underlying algorithms, equations, and computations were consistent and accurate. The aim was to eliminate any inconsistencies or contradictions that could potentially lead to erroneous simulation results.

C2: Segmentation of the simulation model and isolation of individual codes: To enhance clarity and simplify the identification of errors, the simulation model was divided into distinct segments or components. This segmentation allowed for a focused analysis of each component's functionality and interaction with others. Isolating individual codes made it easier to identify any bugs or inconsistencies within specific sections, which could then be addressed more effectively.

C3: Monitoring of interim outcomes and comparison with expectations: Throughout the simulation process, interim results were continually monitored and compared to expected outcomes. This step aimed to detect any unexpected deviations or discrepancies between the model's predictions and the anticipated behavior of the system. Any disparities that arose were investigated and addressed to ensure the model's accuracy.

C4A: Comparison of model data with actual data: This step involved comparing the data generated by the digital model with actual data obtained from the real-world system. By juxtaposing model-generated data with real measurements, researchers could validate the model's predictive capabilities. Any disparities could indicate areas of improvement or fine-tuning to enhance the model's accuracy.

C4B: Verification of a non-existing real system: An innovative approach was the verification of the model's predictions against a hypothetical system that does not exist in reality. This exercise aimed to test the model's ability to forecast outcomes for scenarios that were intentionally designed and did not have corresponding real-world data. This served as an additional layer of validation, affirming the model's predictive capacity.

Block D—Testing and Model Verification:

The final phase involves thorough testing and verification of the digital model's performance. Various scenarios, inputs, and conditions are simulated to observe how the model responds. Any discrepancies or deviations between the model's behavior and expected outcomes are identified and addressed. This phase ensures that the digital model behaves as expected under different circumstances and provides valuable insights into its reliability and usefulness in analyzing the adaptive manufacturing system.

The aim of this chapter was to provide an assessment and evaluation of the effectiveness of various strategies within the adaptive manufacturing system. The chapter began by conducting an analysis of the current state of the manufacturing system. This analysis provided us with fundamental insights into the system's functioning and shortcomings, which allowed us to identify areas requiring improvement.

Subsequently, we delved into the creation and planning of experiments. Key performance indicators were defined to quantify the results and facilitate comparisons across different experiments. Additionally, in this chapter, we compared the present state of the system with the outcomes achieved after each experiment. This approach enabled us to identify and assess the impact of individual strategies on the system's performance and efficiency. The numerical evaluation then enabled us to gauge the level of enhancement and the attained outcomes.

Overall, this chapter offered an evaluation of the chosen strategies using the digital model of the adaptive manufacturing system. This process yielded valuable insights into the effectiveness and efficiency of each strategy, leading to the formulation of measures for improvement.

Steps:

D1: Analysis of the current state of the manufacturing system: In this initial step, a comprehensive assessment of the existing manufacturing system was undertaken. This involved scrutinizing its operational aspects, strengths, weaknesses, and limitations. Gathering insights about the current state set the foundation for subsequent evaluations and improvements.

D2: Creation and planning of experiments: This phase involved the formulation of structured experiments aimed at testing different strategies within the adaptive manufacturing system. The experiments were meticulously designed, taking into account the identified areas for enhancement. A well-structured plan ensured that each experiment would yield valuable insights and measurable outcomes.

D3: Selection of evaluation indicators: Key performance indicators (KPIs) were strategically chosen to measure and quantify the effectiveness of various strategies. These indicators provided a quantitative basis for assessing the impact of each strategy on the system's performance, efficiency, and adaptability.

D4: Comparison of the current state with outcomes post-individual experiments: In this step, the outcomes of individual experiments were systematically compared with the initial state of the manufacturing system. This facilitated a clear understanding of how each strategy influenced the system's behavior and performance. Comparisons provided empirical evidence of improvements or potential areas for concern.

D5: Numerical evaluation: Quantitative assessment played a vital role in this phase. Data collected from experiments and the initial analysis were subjected to rigorous numerical evaluation. This evaluation provided a deeper insight into the extent of improvements achieved through different strategies, enabling data-driven decision-making.

D6: Classification into adaptability levels: Based on the outcomes of experiments and the evaluations, the adaptive manufacturing strategies were classified into distinct adaptability levels. This categorization facilitated a clear understanding of the strategies' effectiveness and their implications for enhancing the system's agility and responsiveness. Let us assume that A represents adaptability, the index for each degree, R_i is the value of each adaptability evaluation index, and W_i is the weight of each evaluation index. The adaptability evaluation index system A is defined as follows:

$$A = \sum_{i=1}^{N} R_i * W_i \tag{1}$$

$$where \sum_{i=1}^{N} W_i = 1 \tag{2}$$

Adaptability is described according to the ranges shown in Table 2.

Table 2. Evaluation of adaptability.

Variable	Range
Extremely Adaptive	(<1–0.8)
Above Avg. Adaptive	(<0.8–0.6)
Adaptive	(<0.6–0.4)
Moderately Adaptive	(<0.4–0.2)
Non-Adaptive	(<0.2–0)

D7: Remedial measures: The final step involved formulating remedial measures based on the insights gained from the entire evaluation process. Strategies that demonstrated notable effectiveness were recommended for integration into the manufacturing system. In contrast, strategies that did not yield desired outcomes led to the identification of areas for further exploration or refinement

3. Results

In this study, the feasibility of the proposed solution was experimentally verified in collaboration with a company focused on the automotive industry. The aim was to evaluate the ability of an adaptive production system to respond to various unexpected situations. The entire methodology was verified using Tecnomatix Plant Simulation 16 software. For the simulation runs, we used a PC with an AMD Ryzen 5 2600 Six-Core Processor 3.40 GHz with a Radeon (TM) RX 580 graphics card.

3.1. Creation

By utilizing commands and methods within the simulation, we were able to construct a digital AMS model. Figure 5 displays a panel featuring these commands. The simulation event control and AMS settings were directives and configurations encompassing the establishment of a general infrastructure. Commands falling under adaptive manufacturing system control denoted the creation of custom attributes and properties for objects, which involved defining agents. Additionally, these commands impacted the implementation of control logic, thereby outlining agent behavior.

Through experimentation, we defined scenarios that could adversely affect the functioning of the AMS. The final section, on performance measurement, showcases simulation-defined outcomes supported by graphs. This panel eloquently signifies the customized definition of simulation behavior and its characteristics. By employing object inheritance and duplication, we modified commands within the control panel, consequently altering the fully verified model.

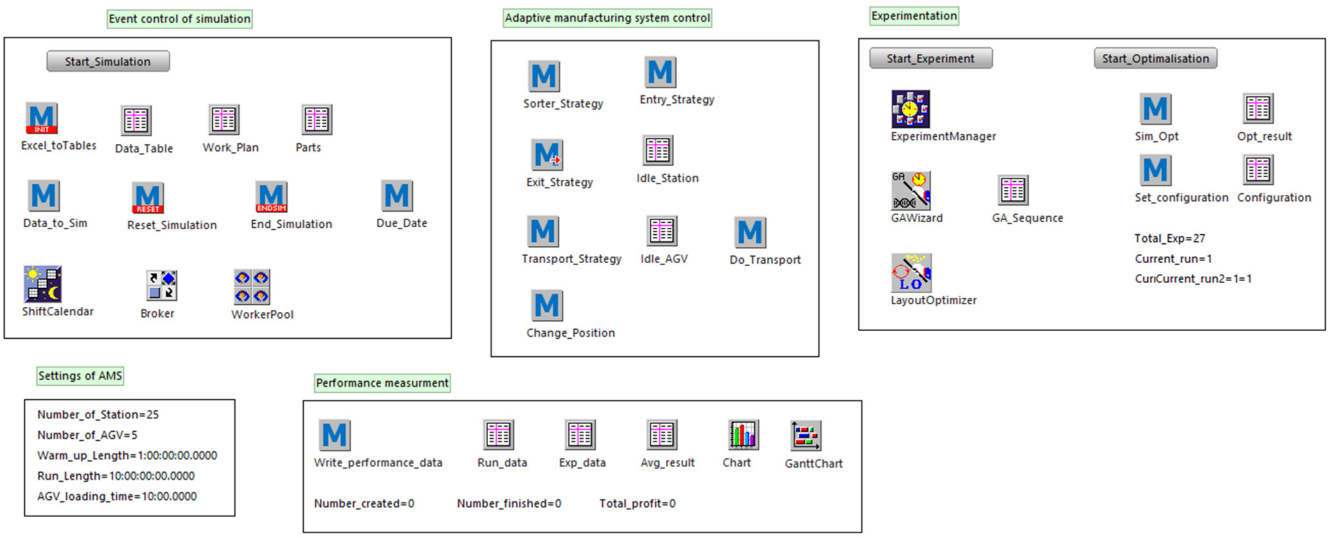


Figure 5. Control panel of model.

The authors created a user interface in Tecnomatix Plant Simulation software, which is shown in Figure 6. The created digital model was available to the system user for processing the information input into the system to create a logic of entity behavior and system logic.

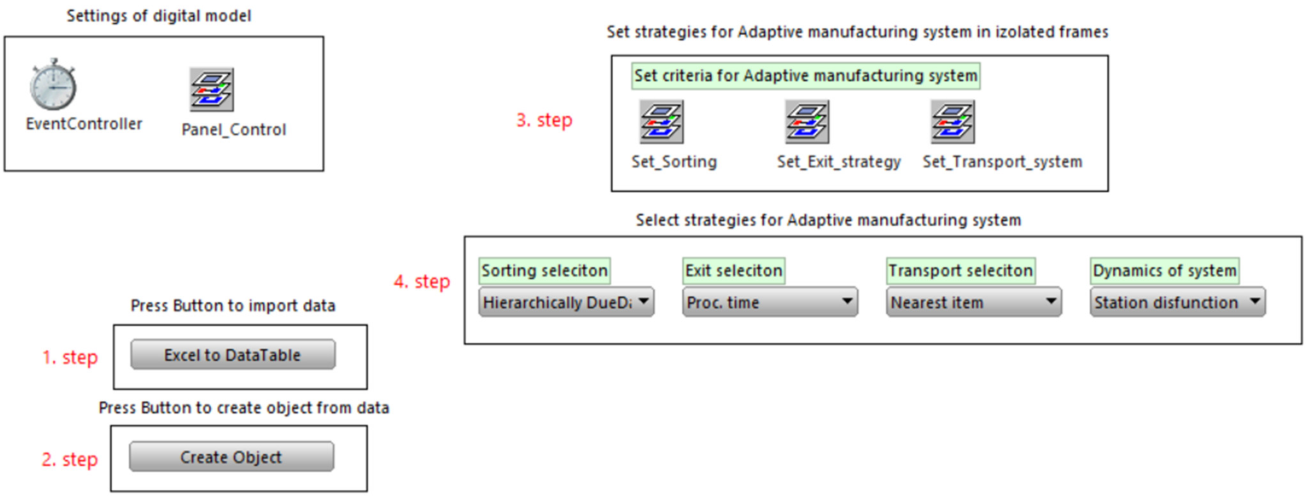


Figure 6. Layout of the input area in the digital model.

In the case where data are already known and a structured database has been created as described in the previous chapter, it is possible to convert the data into simulation software. In this scenario, it is better to establish an intermediate step between the external database and the simulation software. This is done for the purpose of faster and smoother data conversion. This intermediate step will involve creating a database or table directly within the software. Data will then be loaded from this table directly into individual objects. The structure of the digital model is shown in Figure 7.

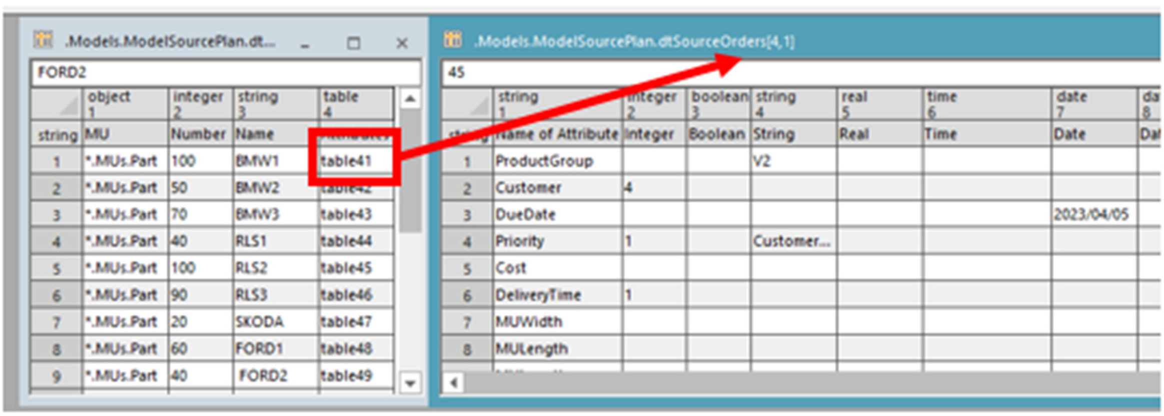


Figure 7. Relationships many to many in digital model.

From the perspective of the complexity of creating a digital model, we have chosen to divide the model into submodules to present the functions of the adaptive manufacturing system more effectively. These modules describe the general crucial functions of the adaptive manufacturing system. When these functions are set according to the correct rules, they can maintain a smooth production flow based on the attributes and properties of objects. Furthermore, in conjunction with rules, they can achieve autonomy and self-organization of the system.

Different possibilities of utilizing the individual functions of the simulation software were tested on these separate modules. Based on the partial results from these modules, decisions were then made about the strategy to be employed in creating the comprehensive digital model of the adaptive manufacturing system.

Another reason for opting to use these smaller models is their easier comprehensibility in terms of simulation behavior. This makes it simpler to verify the accuracy of the proposed functions, facilitated by the isolation of these functions. Figure 8 shows submodules of the adaptive manufacturing system.

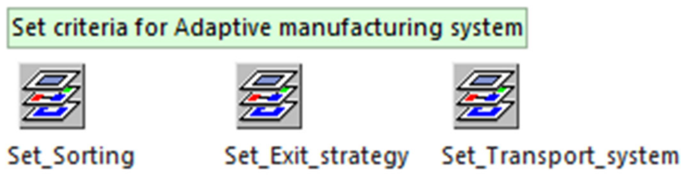


Figure 8. Setting criteria for the adaptive manufacturing system.

3.2. Evaluation

Given the structure and objectives of the study, the practicality of the solution was experimentally verified. The verification of the proposed methodology was conducted through collaboration with a company focused on the automotive industry. The data are available upon request. The data were structured according to tables where Table 3 represents the structure of data objects and Table 4 is a nested table showing attributes of the products.

Table 3. Structure of data: objects.

Name	Object	X	Y	Processing Time	Setup Time	Availability
String	Object type	Real	Real	Table	Table	Real

Table 4. Nested table: attributes of products.

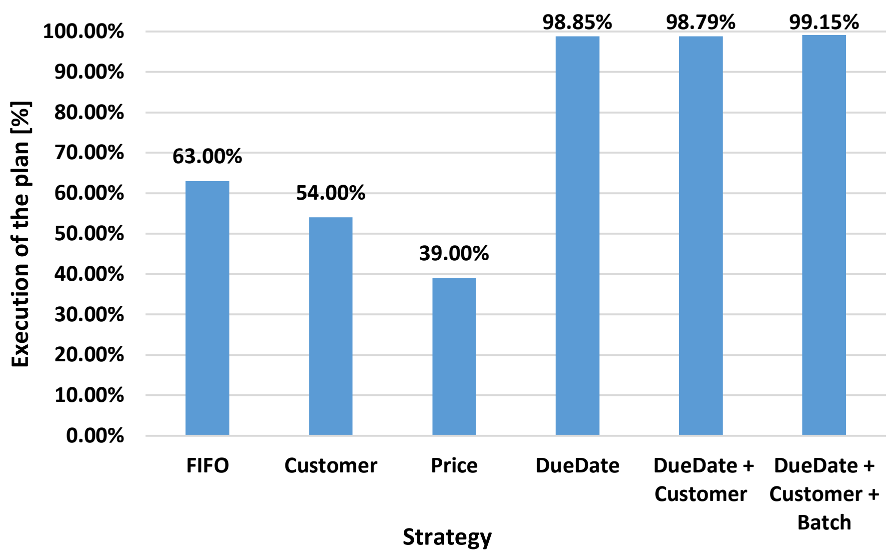
Name of the Attribute	Integer	Boolean	String	Date	Date/Time	Length	Cost
Product group			V2				
Customer	4						
Priority	1						
MUWidth						1.1	
MULength						1.1	
Due date				4 May 2023			
Delivery time					4 May 2023 00:00:00.000		
Proces1		True					
ProcesXY		False					
Cost							30

The design describes how various factors affect this system. Given the challenges in creating a digital model, the decision was made to partition the model into submodules, facilitating the presentation of adaptive manufacturing system functions. These modules outline the fundamental functions of the adaptive manufacturing system which, when correctly configured, can uphold a seamless production flow based on object attributes and properties. Furthermore, by adhering to specific rules, these functions can achieve system autonomy and self-organization.

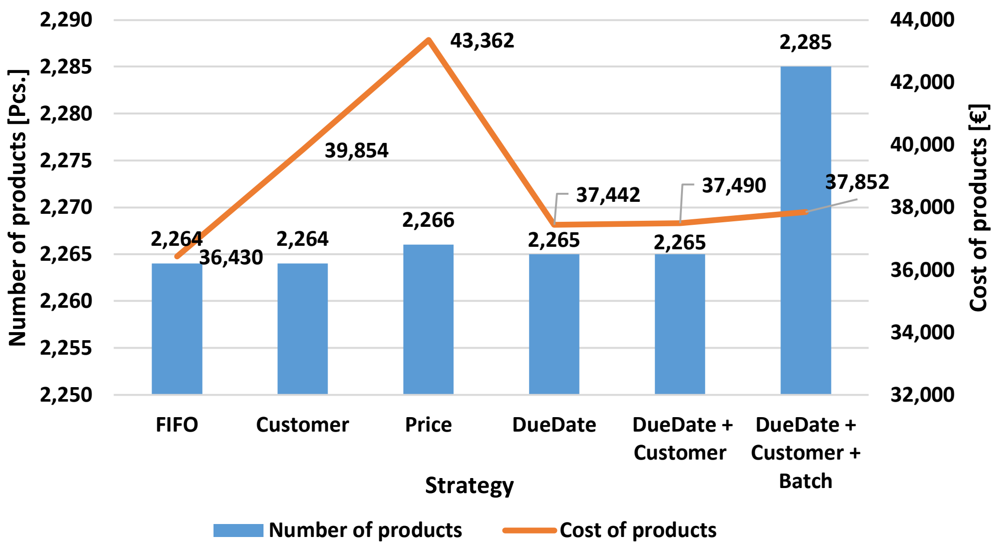
The potential of each function within the simulation software was assessed across these modules. Subsequently, decisions on the progression strategy for building a comprehensive digital model of the adaptive manufacturing system were derived based on partial results obtained from the modules.

The first module encompasses the sorting function, a critical aspect for routing orders into production. In the context of an adaptive manufacturing system, one prerequisite is the presence of various products with distinct attributes, necessitating the rearrangement of production orders.

The results of the testing for different strategies are depicted in Figure 9.



(a)



(b)

Figure 9. Result for strategies from the point of view of (**a**) percentual execution of the plan; (**b**) number of products and cost of products.

The second module represents the initial strategy. The initial strategy determined the subsequent steps after completing one operation. The initial strategy is crucial in an adaptive manufacturing system because we have multiple machine options suitable for processing the next operation. The results of the testing are shown in Table 5 and Figure 10.

Table 5. Results of exit strategy.

	Strategy							
	1.	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**
Mean life time	2:04:11	2:01:11	1:59:12	2:03:47	2:15:11	1:49:54	1:47:15	1:32:12

1. Relatively; 2. the longest waiting production facility; 3. minimum total load; 4. minimum number of processed entities; 5. shortest processing time + shortest retyping time; 6. free resource then longest waiting production equipment; 7. free means then minimum total load; 8. free resource then minimum total load then shortest processing time + shortest retyping time.

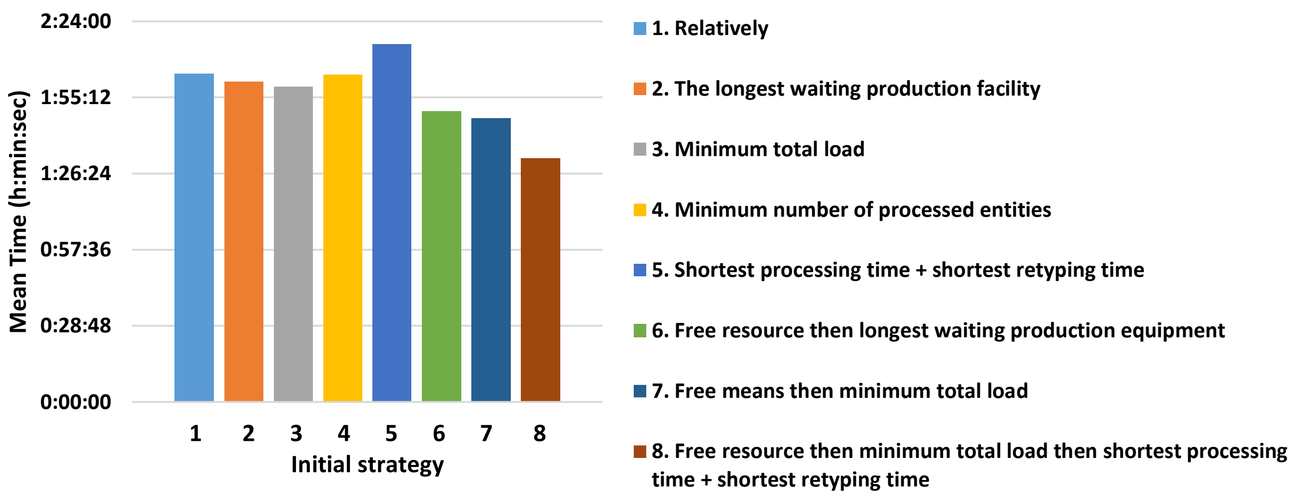
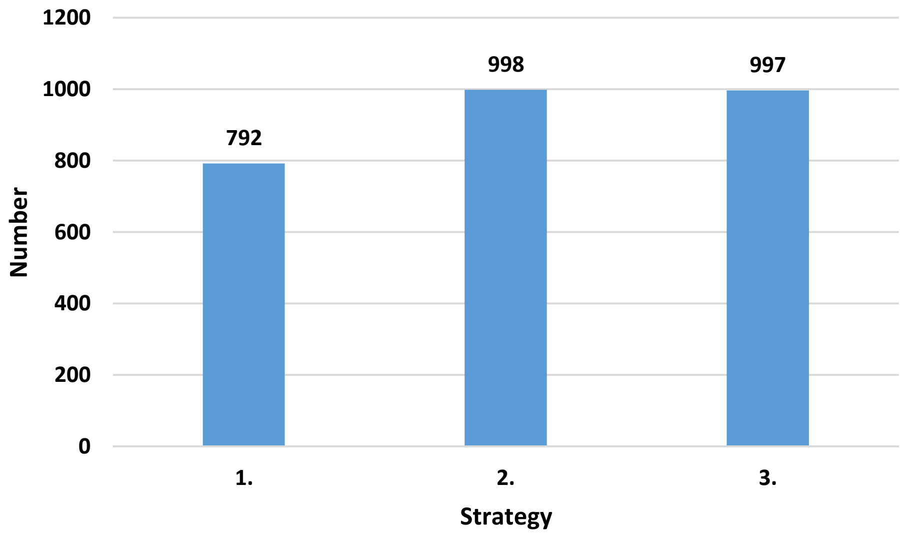


Figure 10. Results of exit strategy shown graphically.

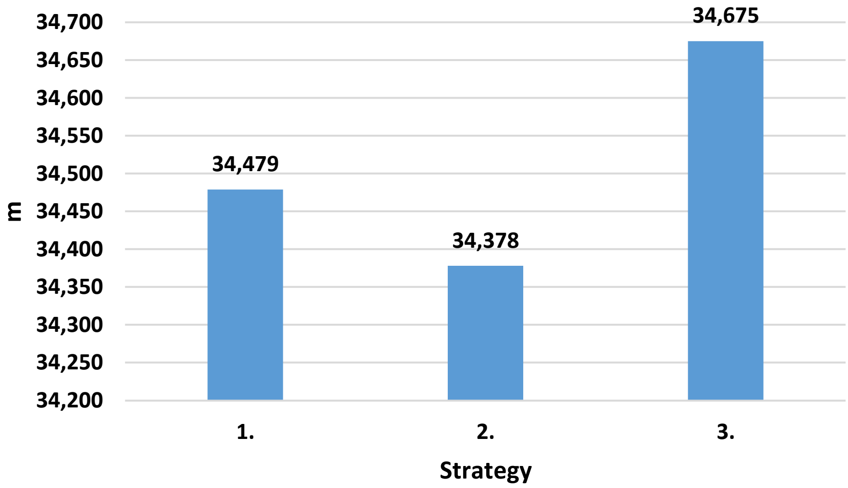
In the third module, the transportation system strategy was verified. An adaptive manufacturing system is unique in that it features a mobile transportation system. This transportation system does not have a predefined route regularity and is required to communicate with product and manufacturing resource agents. The results of the testing are shown in Table 6 and Figure 11.

Table 6. Results of transport strategy.

	Strategy		
	1.	**2.**	**3.**
Distance traveled (m)	34,479	34,378	34,675
Number of orders	792	998	997



(**a**)



(**b**)

Figure 11. Results of transport strategy graphically for (**a**) number of orders; (**b**) distance traveled.

1. The transport resource returns to the WorkPool where it receives jobs. 2. The means of transport returns to the WorkPool location but can receive tasks remotely in the production area. 3. The means of transport remains at the place of the last workplace and receives tasks remotely in the production area.

Given that one of the characteristics of an adaptive manufacturing system is its ability to adapt to unexpected situations, it is necessary to verify this capability. In the experimental verification, the number of factors was reduced to those that could be verified in a specific digital model, and subsequently the significance of these factors was evaluated using Plackett–Burman experimental designs in a digital model without implemented strategies. The levels of experiments were determined based on the obtained values and depended on whether the factor was influential or not. A total of 12 runs and 600 simulation runs were required. The computational time was 8.42 min. From the simulation runs conducted for model creation, it became evident that an increase in the number of objects led to a corresponding rise in simulation time, even when object abstraction was applied. The number of these objects was inherently limited as they were generated at the beginning of each simulation, constrained only by the size of the data table. For accurate results, multiple verification simulation runs are essential, and the computational power, particularly the processor performance, cannot be ignored. A higher number of processors and threads allows for parallel simulation runs, thereby reducing the time needed for simulation evaluation. This has a direct impact on the model's applicability; for instance, if the simulation is intended for real-time operational decision-making on the scale of seconds, then a higher object count would prolong the decision-making process. Therefore, for scenarios requiring quick decisions, a model with fewer elements is more appropriate, whereas a model with a higher number of elements is better suited for situations where a decision can be deferred for several minutes.

The effects of various factors analyzed by simulation using statistical software Minitab 18 were found to be most significant for the availability of production equipment with the highest utilization, followed by the number of vehicles for transport/production workers. Other factors such as warehouse capacity, process time, and setup time were also considered. The next step was to implement the use of strategies proposed in previous sections in a digital model with the assumption that these factors would not have the same impact on the production system as currently. The experiment continued with fewer key factors at multiple levels to study the curve and optimize the process.

Genetic algorithms were used on influential factors to reduce the number of simulations needed to study the impact of adjustable factors. The goal was to find a suboptimal solution to create a functional adaptive production system with cost minimization. For non-influential factors, an experimental manager was used again within the simulation. Despite verifying significantly fewer factors, the number of simulation runs in this case exceeded 2000. Tested factors are shown in Table 7.

Table 7. Tested factors and levels.

Factor	Description	Lower Level (−)	Upper Level (+)
A	Order Frequency (mean, min, max)	Triangle (02:30, 1:30, 5:00)	Triangle (04:30, 2:30, 10:00)
B	Order Size (Pcs.)	20	75
C	Product Variability (Pcs.)	4	9695
D	Storage Size (Pcs.)	5	15
E	Order Priority	1	4
F	Availability of Manufacturing Resources with Highest Utilization (%)	60	95
G	Time for Setup of New Product Variants on Manufacturing Resources with Highest Utilization	Depends on the Manufacturing Resource	Depends on the Manufacturing Resource
H	Process Time of Manufacturing Resources with Highest Utilization	Depends on the Manufacturing Resource	Depends on the Manufacturing Resource
I	Time of Completion of Production Order (Stream, LowerBound, UpperBound)	Eventcotroler.Simtime + z_uniform (20:00, 10:00, 50:00)	Eventcotroler.Simtime + z_uniform (50:00, 20:00, 1:00:00)
J	Number of Transport Vehicles/Production Workers	2	7

Figure 12 shows the significance of factors assessed using Minitab 17 software.

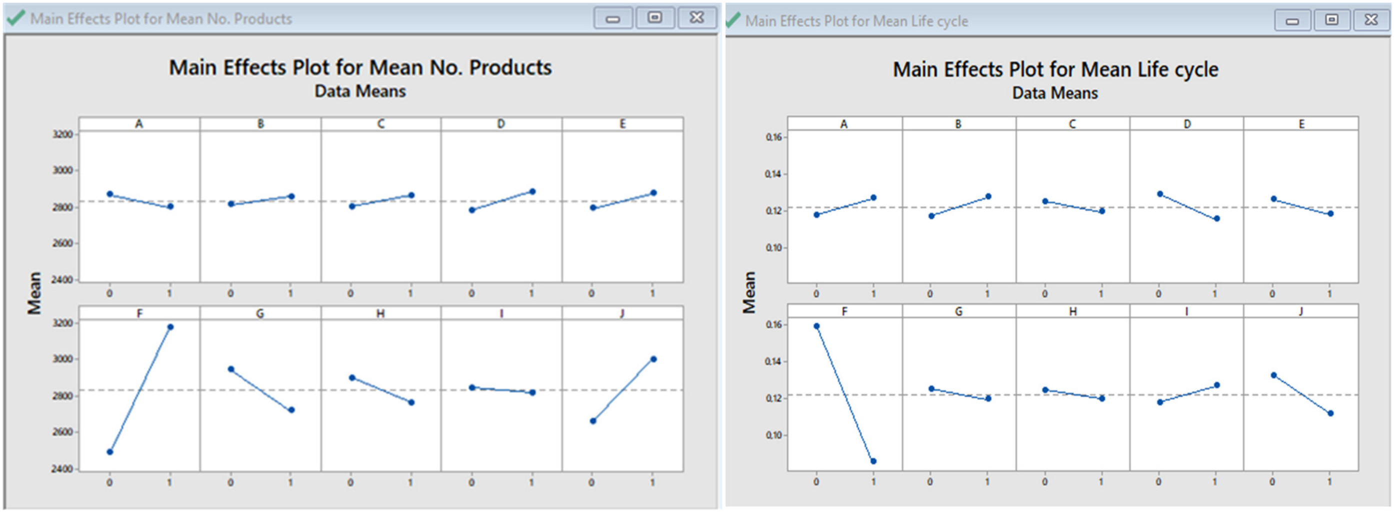


Figure 12. Factor effect before implementing strategies.

The evaluation of production strategies was based on meeting the main objectives of simulation: optimizing resource utilization, increasing delivery speed, and fulfilling orders from the main customer. The results of implementing the strategies are shown in Table 8.

Table 8. Results of implementing strategies.

	Before Implementation of AMS Strategies		After Implementation of AMS Strategies	
	Negative Scenario	Positive Scenario	Negative Scenario	Positive Scenario
Average Number of Produced Products (Pcs.)	2420	3409	3470	3630
Average Lead Time of Production (h:min:s)	3:19:15	1:24:49	1:37:13	1:09:23

The table of production strategy evaluations shows evaluations of individual objectives and their weights. The evaluation result was 0.866, indicating that the system was extremely adaptive and strategies were appropriately assigned based on established objectives and rule hierarchy was set correctly. The rule hierarchy can be rebuilt if objective weights change, achieving different results suitable for selected objectives (see Table 9).

Table 9. Assessment of production strategies.

Goals	Evaluation	Weight
Customer satisfaction	0.95	0.3214
Delivery speed	0.97	0.2143
Resource utilization	0.9	0.1786
Production waiting time	0.9	0.1429
Order costs	0.5	0.1071
Energy savings	0.3	0.0357
Order quality	0	0

The result was 87%, which reflects the achievement of all goals. Note that some goals were contradictory, or achieving certain goals required investment in production that could not be influenced by the adaptive manufacturing system strategies.

4. Discussion

The digital model of an adaptive manufacturing system differs significantly from that of a traditional manufacturing system (see Table 10). The digital model is dynamic, responsive to real-time data, and capable of simulating various scenarios [41]. It autonomously adjusts operations based on changing conditions, optimizing efficiency and resilience. In contrast, traditional models are static representations that lack real-time adaptability and scenario testing [18]. They rely on historical data and human intervention for decision-making. The digital model's data-driven autonomy and adaptability make it a powerful tool for navigating uncertainties and enhancing manufacturing efficiency [42].

Table 10. Differences between digital model of adaptive manufacturing system and traditional manufacturing system.

(A.) Basic Characteristics	**Traditional Manufacturing System**	**Adaptive Manufacturing System**
Description	Displays the existing manufacturing process, its structure, procedures, and flow of materials and information. This includes static and dynamic parameters that influence its performance.	Considers flexible and dynamic characteristics. It incorporates mechanisms to adapt to changing conditions such as order variations, resource availability (production, transportation), or production strategy.
Objectives	The goal of this model is to analyze and optimize the current production process based on existing parameters and data.	The proposed model of the adaptive system focuses on simulating and testing responses to various change and uncertainty scenarios. Its aim is to understand how the system behaves under different conditions and what is required to achieve adaptive manufacturing.
(B.) Goals	**Traditional Manufacturing System**	**Adaptive Manufacturing System**
Description	The objective of this model is to analyze and optimize the current production process based on existing parameters and data.	The proposed model of the adaptive system focuses on simulating and testing responses to various change and uncertainty scenarios. Its aim is to understand how the system behaves under different conditions and what is required to achieve adaptive manufacturing.
(C.) Adaptability and Autonomy	**Traditional Manufacturing System**	**Adaptive Manufacturing System**
Description	The model of the current system is often used to analyze efficiency, identify weaknesses, and plan improvements in the existing system.	The proposed model of the adaptive system is capable of automatically responding to real-time changes and optimizing its operations according to current conditions.
(D.) Benefits	**Traditional Manufacturing System**	**Adaptive Manufacturing System**
Description	Traditional systems are generally easier to set up and manage, often requiring lower initial investment. These systems excel at high-volume production of a single or limited range of products, with workers often specializing in repetitive tasks for increased efficiency.	Adaptive systems can quickly adjust to production changes, optimizing efficiency through real-time data monitoring. These systems are highly scalable and can easily adapt to produce customized products without halting the entire production line.
(E.) Type of system	**Traditional Manufacturing System**	**Adaptive Manufacturing System**
Example	Job shop, mass production systems, batch production, fixed position layout, cellular manufacturing.	Reconfigurable manufacturing system, competency islands, modular manufacturing systems.

This study introduces a comprehensive methodology for developing a digital model of an adaptive manufacturing system, with a focus on competency islands. These specialized production units are autonomous, modular, and highly skilled in their respective domains. The methodology emphasizes data analysis, simulation modeling, and strategic optimization to enable competency islands to perform optimally and meet unique production requirements.

In contrast to competency islands, reconfigurable production systems prioritize the ability to quickly reconfigure the manufacturing setup to meet changing product demands. While they share the flexibility of competency islands, their broader scope of adaptability presents challenges in coordination and synchronization. The proposed methodology's emphasis on digital modeling can be applied to reconfigurable systems, allowing manufacturers to simulate different configurations and evaluate their performance before implementation.

Unlike traditional models, which primarily rely on static simulations, the novelty of this article lies in its proposed digital model that offers dynamic simulation capabilities. This innovation is particularly relevant as it allows for the assessment of various production strategies while taking into account real-time changes in capacity at different workstations, something most existing models fail to do.

The methodology presented in this article can be applied to a range of adaptive manufacturing systems, including reconfigurable ones. Whether assessing the impact of configuration changes in reconfigurable systems or optimizing the operations of competency islands, the methodology provides a structured approach. However, this does not exclude the use of the described model for traditional manufacturing systems as well.

As Industry 4.0 emerges, the interplay between digital models, simulation, and real-time responsiveness will shape the future of manufacturing. Further research could explore refining the methodology's implementation for reconfigurable systems and integrating it with emerging technologies such as IoT and artificial intelligence. In future investigations of adaptive production systems, the size of the number of objects and entities in the system will be the basic limiting factor. This is because even with abstraction, a higher number of objects can slow down simulation speed, potentially affecting the speed of decision-making in operative planning for system elements that rely on a digital model for calculations.

This study highlights the potential of digital models in shaping adaptive manufacturing systems. Whether applied to competency islands, reconfigurable systems, or beyond, the methodology serves as a framework for harnessing data-driven intelligence to guide manufacturing towards a future characterized by efficiency, agility, and innovation.

Several areas for future research can be identified based on the insights gained from this doctoral dissertation and previous work. The study describes adaptive manufacturing systems such as reconfigurable production systems and competency islands, but existing literature does not provide clear distinctions between these systems. Further research should specify the scenarios in which either system is most applicable. Additionally, developing expert systems and knowledge databases are essential for establishing adaptability within manufacturing systems. This applies not only to manufacturing systems but also to supply chain management, inventory control, and production operator work. Continuous updating of the knowledge database is crucial during ongoing processes. Advancing adaptive manufacturing systems should also include the use of hierarchical task network (HTN) methods for production task planning. In this approach, planning problems are specified in an HTN, providing a set of tasks that can be derived from the initial task network by decomposing complex tasks into simpler ones while maintaining ordering constraints. The Tecnomatix Plant Simulation software was used in this research however, comparing simulation results from this software with those from AnyLogic, which includes built-in agent-based simulation methods, could provide insights into data accuracy and software suitability. A deeper exploration of next-generation modeling and simulation technologies is necessary to align with the upcoming networkoriented, service-based, individualized, and intelligent manufacturing environment. This includes aspects like advanced digital models, model-based engineering, cloud-based simulation, data-driven modeling and simulation, and embedded simulation, among others.

5. Conclusions

This study marks a significant step forward in the field of adaptive manufacturing systems, particularly in the realm of competence islands. The proposed methodology offers a systematic route for building, verifying, and evaluating the efficacy of digital models designed for these complex systems. A unique aspect of this research lies in its approach to evaluating adaptive manufacturing systems. Unlike traditional static models that rely on fixed data, our model dynamically evolves over time, reacting to system inputs. This allows for real-time layout adjustments and strategy selection, optimizing the system based on selected performance indicators. Consequently, the output is not just an optimal layout but also the number of required devices on the production line for a given simulated period. Looking ahead, the integration of emerging technologies like machine learning and artificial intelligence could further enhance the model's adaptability and predictive capabilities. Applying this methodology to other industries could also provide valuable insights, expanding its applicability and relevance. The findings of this research not only align with but also extend existing literature, offering new perspectives and practical solutions for the challenges in modern manufacturing contexts.

Author Contributions: Conceptualization, P.G.; methodology, N.B.; software, Š.M.; formal analysis, Š.M.; investigation, N.B.; resources, P.G.; data curation, L.M.; writing—review and editing, N.B. and P.G.; visualization, Š.M.; supervision, L.M.; project administration, P.G.; funding acquisition, P.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Slovak Research and Development Agency grant number APVV-21-0308.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. Due to company privacy, the full text of the data is not publicly available.

Acknowledgments: This work was supported by the Slovak Research and Development Agency under the contract no. APVV-21-0308.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Trojan, J.; Trebuna, P.; Mizerak, M. Application of Digital Engineering Methods in Order to Improve Processes in Heterogeneous Companies. *Appl. Sci.* **2023**, *13*, 7681. https://doi.org/10.3390/app13137681.
2. Kliment, M.; Pekarcikova, M.; Trebuna, P.; Trebuna, M. Application of TestBed 4.0 Technology within the Implementation of Industry 4.0 in Teaching Methods of Industrial Engineering as Well as Industrial Practice. *Sustainability* **2021**, *13*, 8963. https://doi.org/10.3390/su13168963.
3. Basl, J.; Sasiadek, M. Comparison of Industry 4.0 Application Rate in Selected Polish and Czech Companies. In *Idimt-2017—Digitalization in Management, Society and Economy*; Petr, D., Gerhard, C., Vaclav, O., Eds.; Schriftenreihe Informatik; Trauner Verlag: Linz, Austria, 2017; Volume 46, pp. 401–410.
4. Raska, P.; Ulrych, Z.; Malaga, M. Data Reduction of Digital Twin Simulation Experiments Using Different Optimisation Methods. *Appl. Sci.* **2021**, *11*, 7315. https://doi.org/10.3390/app11167315.
5. Mleczko, J.; Dulina, L. Manufacturing Documentation for the High-Variety Products. *Manag. Prod. Eng. Rev.* **2014**, *5*, 53–61. https://doi.org/10.2478/mper-2014-0027.
6. Nielsen, I.; Dang, Q.-V.; Nielsen, P.; Pawlewski, P. Scheduling of Mobile Robots with Preemptive Tasks. In *Distributed Computing and Artificial Intelligence, 11th International Conference*; Omatu, S., Bersini, H., Corchado, J.M., Rodriguez, S., Pawlewski, P., Bucciarelli, E., Eds.; Advances in Intelligent Systems and Computing; Springer: Berlin/Heidelberg, Germany, 2014; Volume 290, pp. 19–27. https://doi.org/10.1007/978-3-319-07593-8_3.

7. Gromova, E.A. Quick response manufacturing as a promising alternative manufacturing paradigm. *IOP Conf. Ser. Mater. Sci. Eng.* **2020**, *898*, 012047. https://doi.org/10.1088/1757-899X/898/1/012047.
8. Ciampi, E.; de Pommerol, C.; Touloumian, A. The Factory of the Future Is Happening Today. 2018. Available online: https://www.oliverwyman.com/our-expertise/insights/2018/nov/perspectives-on-manufacturing-industries-vol-13/new-sources-of-value/the-factory-of-the-future-is-happening-today.html (accessed on 20 August 2023).
9. Axtell, R. Why Agents? On the Varied Motivations for Agent Computing in the Social Sciences; University of Oxford: Oxford, UK, 2000.
10. Salmen, Z. What is "Internet Of Things" (IOT)? Absolute Beginners. 2020. Available online: https://salmenzouari.medium.com/what-is-internet-of-things-iot-absolute-beginners-5e1cd2817d4c (accessed on 10 August 2023).
11. Sjödin, D.R.; Parida, V.; Leksell, M.; Petrovic, A. Smart Factory Implementation and Process Innovation. *Res. -Technol. Manag.* **2018**, *61*, 22–31. https://doi.org/10.1080/08956308.2018.1471277.
12. Groover, M.P. Automation, Production Systems, and Computer-Integrated Manufacturing, 3rd ed.; Pearson Education Inc.: Upper Saddle River, NJ, USA, 2008.
13. Stofkova, J.; Poliakova, A.; Stofkova, K.R.; Malega, P.; Krejnus, M.; Binasova, V.; Daneshjo, N. Digital Skills as a Significant Factor of Human Resources Development. *Sustainability* **2022**, *14*, 13117. https://doi.org/10.3390/su142013117.
14. Schenk, M.; Wirth, S. Factory Planning and Factory Operation, Methods for the Agile and Networked Factory; Springer: Berlin/Heidelberg, Germany, 2004.
15. Spano, M. Applied Artificial Intelligence, Part 3: 6 Examples of Using Artificial Intelligence in Production. KROS. 31 May 2021. Available online: https://www.kros.sk/blog/aplikovana-umela-inteligencia-cast-3-6-prikladov-vyuzitia-umelej-inteligencie-vo-vyrobe/ (accessed on 10 August 2023).
16. Arai, T.; Aiyama, Y.; Maeda, Y.; Sugi, M.; Ota, J. Agile Assembly System by "Plug and Produce". *CIRP Ann.* **2000**, *49*, 1–4.
17. Emmert-Steib, F. Defining a Digital Twin: A Data Science-Based Unification 2023. *Mach. Learn. Knowl. Extr*. **2023**, *5*, 1036–1054. https://doi.org/10.3390/make5030054.
18. Svetlík, J. *Modularity of Production Systems*; IntechOpen: London, UK, 2020. https://doi.org/10.5772/intechopen.90844.
19. Jamil, F.; Pang, T.Y.; Cheng, C.T. Developing an I4.0 Cyber-Physical System to Enhance Efficiency and Competitiveness in Manufacturing. *Appl. Sci.* **2023**, *13*, 9333. https://doi.org/10.3390/app13169333.
20. Bonabeau, E. Methods and Systems for Generating Business Models. U.S. Patent 09/801,130, 20 December 2001.
21. Khan, S.I.; Kaur, C.; Al Ansari, M.S.; Muda, I.; Borda, R.F.C.; Bala, B.K. Implementation of Cloud Based IoT Technology in Manufacturing Industry for Smart Control of Manufacturing Process. *Int. J. Interact. Des. Manuf.-IJIDeM* **2023**, *17*, 1–13. https://doi.org/10.1007/s12008-023-01366-w.
22. Hnilica, R.; Jankovsky, M.; Dado, M.; Messingerova, V. Experimental Evaluation of Combined Effects of Risk Factors in Work Environment. In Proceedings of the 12th International Scientific Conference Engineering For Rural Development, Jelgava, Latvia, 23–24 May 2013; Osadcuks, V., Ed.; Engineering for Rural Development; Latvia University of Agriculture, Faculty Engineering, Institute of Mechanics: Jelgava, Latvia, 2013; pp. 577–583.
23. Buckova, M.; Krajcovic, M.; Plinta, D. Use of Dynamic Simulation in Warehouse Designing. In *Intelligent Systems in Production Engineering and Maintenance*; Burduk, A., Chlebus, E., Nowakowski, T., Tubis, A., Eds.; Advances in Intelligent Systems and Computing; Springer International Publishing Ag: Cham, Switzerland, 2019; Volume 835, pp. 485–498. https://doi.org/10.1007/978-3-319-97490-3_47.
24. Moldavska, A.; Welo, T. Development of Manufacturing Sustainability Assessment Using Systems Thinking. S*ustainability* **2016**, *8*, 5. https://doi.org/10.3390/su8010005.
25. Sokolov, B.; Ivanov, D.; Dolgui, A. *Scheduling in Industry 4.0 and Cloud Manufacturing*; Springer Nature: Berlin, Germany, 2020.
26. Gómez, P.F.J.; Filho, M.G. Complementing lean with quick response manufacturing: Case studies. *Int. J. Adv. Manuf. Technol.* **2017**, *90*, 1897–1910. https://doi.org/10.1007/s00170-016-9513-4.
27. Pekarcikova, M.; Trebuna, P.; Markovic, J. Case Study of Modelling the Logistics Chain in Production. In *Modelling of Mechanical and Mechatronic Systems*; Trebuna, F., Ed.; Procedia Engineering; Elsevier Science Bv: Amsterdam, The Netherlands, 2014; Volume 96, pp. 355–361. https://doi.org/10.1016/j.proeng.2014.12.125.
28. Keskin, H.; Akgun, A.E.; Esen, E.; Yilmaz, T. The Manufacturing Adaptive Capabilities of Firms: The Role of Technology, Market and Management Systems-Related Adaptive Capabilities. *J. Manuf. Technol. Manag*. **2022**, *33*, 1429–1449. https://doi.org/10.1108/JMTM-01-2022-0021.
29. Malaga, M.; Ulrych, Z. Physical Modelling of the Industry 4.0 Concept. In Education Excellence and Innovation Management: A 2025 Vision to Sustain Economic Development During Global Challenges; Soliman, K.S., Ed.; Int Business Information Management Assoc-Ibima: Norristown, PA, USA, 2020; pp. 17540–17549.
30. Bolender, T.; Buervenich, G.; Dalibor, M.; Rumpe, B.; Wortmann, A. Self-Adaptive Manufacturing with Digital Twins. In Proceedings of the 2021 International Symposium on Software Engineering for Adaptive and Self-Managing Systems (Seams 2021), Madrid, Spain, 18–21 May 2021; IEEE Computer Soc: Los Alamitos, CA, USA, 2021; pp. 156–166. https://doi.org/10.1109/SEAMS51251.2021.00029.
31. Wozniak, W.; Jakubowski, J. The Choice of the Cost Calculation Concept for the Mass Production during the Implementation of the Non-Standard Orders. In *Innovation Management and Sustainable Economic Competitive Advantage: From Regional Development to Global Growth*; Soliman, K.S., Ed.; Int Business Information Management Assoc-Ibima: Norristown, PA, USA, 2015; Volumes I—VI, pp. 2364–2371.

32. Guttières, D.; Stewart, S.; Wolfrum, J.; Springs, S.L. Cyberbiosecurity in Advanced Manufacturing Models. *Front. Bioeng. Biotechnol.* **2019**, *7*, 210. https://doi.org/10.3389/fbioe.2019.00210.
33. Rosen, M.A.; Kishawy, H.A. Sustainable Manufacturing and Design: Concepts, Practices and Needs. *Sustainability* **2012**, *4*, 154–174. https://doi.org/10.3390/su4020154.
34. Felsberger, A.B.; Qaiser, F.H.; Choudhary, A.; Reiner, G. The impact of Industry 4.0 on the reconciliation of dynamic capabilities: Evidence from the European manufacturing industries. *Prod. Plan. Control* **2020**, *33*, 277–300. https://doi.org/10.1080/09537287.2020.1810765.
35. Kantaros, A.; Piromalis, D.; Tsaramirsis, G.; Papageorgas, P.; Tamimi, H. 3D Printing and Implementation of Digital Twins: Current Trends and Limitations. *Appl. Syst. Innov*. **2022**, *5*, 7. https://doi.org/10.3390/asi5010007.
36. Grzegorz, B.; Izabela, N.; Arkadiusz, G.; Zbigniew, B. Reference Model of Milk-Run Traffic Systems Prototyping. *Int. J. Prod. Res*. **2021**, *59*, 4495–4512. https://doi.org/10.1080/00207543.2020.1766717.
37. Worobel, R.; Capek, J.; Kovacova, L.; Bubenik, P.; Krajcovic, M. Improving Business Processes Using Simulation Tools. *MM Sci. J.* **2018**, *2018*, 2244–2251. https://doi.org/10.17973/MMSJ.2018_03_2017103.
38. Pekarcikova, M.; Trebuna, P.; Kliment, M.; Mizerak, M.; Kral, S. Simulation Testing of the E-Kanban to Increase the Efficiency of Logistics Processes. *Int. J. Simul. Model* **2021**, *20*, 134–145. https://doi.org/10.2507/IJSIMM20-1-551.
39. Wiecek, D.; Wiecek, D.; Dulina, L. Materials Requirement Planning with the Use of Activity Based Costing. *Manag. Syst. Prod. Eng.* **2020**, *28*, 3–8. https://doi.org/10.2478/mspe-2020-0001.
40. Zhang, H.; Buchmeister, B.; Li, X.; Ojstersek, R. Advanced Metaheuristic Method for Decision-Making in a Dynamic Job Shop Scheduling Environment. *Mathematics* **2021**, *9*, 909. https://doi.org/10.3390/math9080909.
41. ElMaraghy, H.; ElMaraghy, W. Adaptive Cognitive Manufacturing System (ACMS)—A New Paradigm. *Int. J. Prod. Res*. **2022**, *60*, 7436–7449. https://doi.org/10.1080/00207543.2022.2078248.
42. Jakabova, M.; Babcanova, D.; Caganova, D.; Hrablik, M.; Urdzikova, J.; Beno, R. Developing the Competency of the Managers in Selected Manufacturing Enterprises Operating in the Slovak Republic. In Proceedings of the 8th European Conference on Management Leadership and Governance, Pafos, Cyprus, 8–9 November 2012; Politis, J., Ed.; Acad Conferences Ltd.: North Reading, MA, USA, 2012; pp. 256–264.