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Manufacturing Productivity Improvement by Integrating Digital Tools Illustrated in the Optimization of a Hub Assembly Line

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Abstract

Within the context of Industry 4.0, industrial systems are increasingly integrating digital tools such as discrete-event simulation (DES) and digital twins to enhance operational performance and facilitate data-driven decision-making. This research focuses on the design and implementation of an innovative digital twin to diagnose and optimize the productivity of manufacturing systems. A key advancement of this tool involves the integration of a material flow simulator, specifically WITNESS Horizon, with a suite of mathematical and digital models to create an integrated manufacturing digital tool. Rather than modeling individual pieces of equipment or isolated workstations, this digital twining approach encompasses the entire manufacturing architecture. To demonstrate the capabilities and efficacy of this integrated tool, we applied it to a real-world case study: the "Hub R2-11" production line. Utilizing the diagnostic features of the tool for this case study, we identified significant bottlenecks, revealing that over 70% of the conveyor was blocked and more than 60% of the workstation was underutilized. Utilizing the simulation and optimization features of the tool, we increased productivity by restructuring the manufacturing architecture. This involved implementing parallel machining, regulating inputs, and incorporating robotic palletizing. The resultant manufacturing architecture demonstrated a substantial improvement, increasing weekly pallet output from 17 to 41 while reducing conveyor block time by more than 50%. Additionally, a financial assessment indicated a favorable Net Present Value (NPV) and an Internal Rate of Return (IRR) exceeding 35% over three years. The research presented here employs a digital approach grounded in realistic operational constraints, effectively bridging technical innovations with economic feasibility. The findings underscore that this integrated manufacturing digital tool presents a scientifically robust and economically sound strategy for optimizing production systems.

Keywords: integrated manufacturing digital tool; production line optimization; simulation; discrete-event modeling; automation

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1. Introduction

Within the scope of Industry 4.0, manufacturing systems are progressively integrating simulation tools and digital twin architectures to enhance production efficiency, minimize downtime, and facilitate data-driven decision-making. Nonetheless, numerous small- and medium-sized production environments continue to have difficulties in pinpointing bottlenecks and improving resource allocation efficiently.

This study examines the inefficiencies present in a real-world manufacturing line and proposes a digital tool to correct them, specifically, the "Manufacturing of Hub R2-11", where extended cycle times and unbalanced workflows lead to considerable productivity decline. The research seeks to evaluate and enhance the manufacturing framework via virtual modeling and discrete-event simulation.

This study uses various mathematical models and material flow simulators, such as WITNESS Horizon, to design and develop a digital twin able to increase productivity in a real industrial scenario. The report offers a comprehensive case study that includes simulation-based assessment, virtual layout redesign, and cost–benefit analysis, in contrast to solely didactic demonstrations. The findings significantly influence capital expenditure choices for system enhancements, demonstrating quantifiable performance advancements. Consequently, this study provides scientific insights into how the proposed integrated manufacturing digital tool might facilitate optimization in real-world Industry 4.0 manufacturing processes.

The functionality of this digital twin was demonstrated in a case study. The diagnosis facility of the tool was used to analyze system behavior and simulate various optimization scenarios. The main objectives are to identify flow concentrators, minimize blocked and idle times, and evaluate the impact of automation through the integration of an industrial robot in the palletizing phase.

1.1. Research Gap

Although discrete-event simulation (DES) and digital twins have been widely used for performance evaluation in manufacturing, there is limited research on combining simulation-driven process improvements with investment decision metrics (such as IRR and NPV) in real-world production lines. Most existing studies focus either on technical layout optimization or on theoretical modeling, with few addressing operational constraints, automation integration, and economic impact in a unified framework.

1.2. Problem Statement

This study addresses the significant bottlenecks, imbalanced workloads, and inefficient palletizing procedures in the Manufacturing of HubR2-11, resulting in elevated idle times, material congestion, and diminished throughput.

1.3. Scientific Contribution

This paper's scientific contribution is the development of an integrated manufacturing digital tool that incorporates parallel machining, dynamic input control, and automation inside a novel framework. The research illustrates quantifiable enhancements in performance and economic outcomes within a genuine industrial context, correlating system optimization with evaluations of Internal Rate of Return (IRR) and Net Present Value (NPV). This integrated approach enhances the domain of industrial system engineering by offering a pragmatic and data-informed framework for decision support.

The subsequent sections of this work are organized as follows: Section 2 offers a concise overview of pertinent research on discrete-event simulation and performance enhancement in manufacturing systems. Section 3 presents the case study of the Hub R2-11 assembly line, detailing the system architecture and preliminary performance assessments. Section 4 delineates the simulation-based enhancement strategy, specifying the optimization objectives, variables, methodology, and novel elements. Section 5 examines the outcomes prior to and after the implementation of the enhancement plan, concentrating on performance metrics, system dynamics, and sensitivity analysis. Section 6 assesses the economic ramifications of the proposed modifications via IRR and NPV computations.

Section 7 ultimately summarizes this study and delineates future prospects, encompassing the wider applicability of the proposed technology to additional industrial systems.

2. Related Work

The contemporary manufacturing industry faces an ongoing challenge to enhance production efficiency and optimize workflow operations. This research examines these problems by analyzing the "Manufacturing of Hub R2-11" production line as its case study. The integrated manufacturing digital twin designed and developed in this research enabled detailed modeling, analysis, and optimization of this intricate production system through its advanced capabilities. The main goal of this tool is to increase productivity by detecting system bottlenecks while improving workflow continuity and developing strategies to increase production productivity while minimizing system blockages and inefficiencies.

Ciauşu-Sliwa et al. evaluated four prominent discrete-event simulation (DES) software platforms (Tecnomatix Plant Simulation (by Siemens Industry Software) https://plm.sw.siemens.com/en-US/tecnomatix/plant-simulation-software/; Arena Simulation Software (by Rockwell Automation), https://www.rockwellautomation.com/en-us/products/software/arena-simulation.html; Simio, https://www.simio.com/; AnyLogic (by The AnyLogic Company), https://www.anylogic.com/, all accessed on 4 July 2025) through an assessment of their capabilities and industrial adoption and their compatibility with digital twin technology and risk-based scheduling systems. The research based on the peer-reviewed literature from the last decade demonstrates that DES technology enhances operational efficiency and scalability in manufacturing and healthcare industries. The study revealed ongoing difficulties in managing computational complexity, real-time analytics, interoperability, and autonomous decision-making systems. The research analyzed current manufacturing trends while specifying essential research directions to advance smart manufacturing [1].

West et al. introduced dynamic bottlenecks through relative bottleneck frequency and severity metrics, which they validated using discrete-event simulation across nine serial line scenarios. Our approach to identifying and measuring workstation blockages matches their method before implementing interventions [2].

The research team used WITNESS Horizon to implement a discrete-event simulation model in an Italian facility that manufactures aluminum cabinets for EV charging stations. The system helps to identify process inefficiencies, bottlenecks, and resource constraints and enables strategic production planning under a zero-inventory policy [3].

The team led by Burčiar F focused on the integration of a production system with WITNESS Horizon 23.0. They assessed the feasibility of production orders and examined the extent of MES–simulation data integration. They also noted limitations when manual order rearrangement (MOR) introduced latency and inconsistency in high-volume scenarios [4].

Ricondo et al. designed a digital twin framework that couples sensor data ("digital shadow"), discrete-event simulation, and optimization alternatives. They applied their case study to an automated railway axle manufacturing line and demonstrated optimization across layout, scheduling, and resource use during both design and operational phases [5].

Corsini et al. combined machine learning and metaheuristic optimization in their work simulation. They managed to improve decision-making in production–distribution systems amid disruptions and outperformed static methods on multiple performance metrics under uncertain conditions [6].

Popa et al. modeled an automotive wiring-harness assembly line using WITNESS Horizon 25.0. They compared an initial fixed-station + rotary layout to an optimized hybrid dynamic rotary layout. They found that weekly output doubled (from 160 to 320 units

planned; simulated boost from 132 to 296 units/shift), the blocked time fell to 0%, and idle time became more balanced across workstations [7].

The research team conducted by Erhan Turan used PLC/sensor data with finite-element simulations to build a digital twin of a thermoforming process. As outcomes, they obtained 50% scrap reduction and 10% raw material savings. This showcases sustainable process improvements via twin-based simulation [8].

In their paper, the researchers Sobottka T et al. presented a closed-loop twin framework coupling live shop floor events (sensors, MES/ERP) with a simulation and optimization engine. Triggering re-planning on deviations allows real-time control in flexible assembly systems [9].

Yu et al. outlined, in their paper, a graphical modular digital twin architecture that links virtual and physical line elements. This setup enables real-time visualization, monitoring, and parameter tuning reflective of Industry 4.0 standards [10].

Vysocký et al. developed a DES model of a real manufacturing line using WITNESS Horizon to identify failure points and bottlenecks, implementing adjustments that significantly improved system throughput [11]. Similarly, Khan et al. presented a hybrid business process reengineering method using WITNESS Horizon 22.5 to examine operational interdependencies in a textile finishing line. Their simulation-based restructuring of the sequence led to noticeable improvements in efficiency and throughput [12].

Grznár and Mozolová further demonstrated how RTLS-enhanced digital twins improved production indicators through dynamic scheduling compared to traditional approaches [13].

Increasingly, WITNESS Horizon simulation is being combined with multi-criteria optimization algorithms and AI techniques. Červeňanská et al. demonstrated how intelligent rule parameterization using WITNESS Horizon 22 enhanced order latency across production systems [14]. Tang et al. offered a comprehensive review on bottleneck identification methods, affirming DES as a preferred tool in complex manufacturing settings, although they caution against over-reliance on static models and call for statistical validation [15].

Current trends highlight the transition from static to real-time simulation-based systems integrated with Industry 4.0 technologies (IoT, RTLS, and machine learning) for proactive bottleneck identification. Feng and Wan demonstrated how digital twins can optimize production layouts and generate adaptive scheduling strategies during disruptions [16]. However, several challenges remain: studies are often limited to isolated cases, and full-scale implementation is constrained by cost and complexity. Mozol and Mozolová warned of cybersecurity vulnerabilities in digital twin systems—especially due to cloud and IoT data transfer—and emphasized the high initial investment requirements [17].

In conclusion, while WITNESS Horizon simulation proves to be an effective tool for manufacturing system optimization and bottleneck management—often in combination with digital twins—there is a pressing need for secure and scalable platforms and broader comparative studies to generalize findings.

Despite these developments, there remains a lack of simulation-based studies that combine real industrial modeling, automation integration, and economic analysis (e.g., IRR/NPV) within a single integrated manufacturing digital tool framework. This paper addresses this gap.

3. Case Study: Simulation of the Hub R2-11 Production Line

This section delineates the functionality of the proposed tool on the HubR2-11 production line. The objective is to assess the current condition of the system, identify problems or bottlenecks, and create a basis for performance enhancement. The configuration comprises workstations, buffers, conveyors, and operators, as elaborated upon below.

3.1. Production Line Modeling Using the Integrated Manufacturing Digital Tool

In this chapter, the digital modeling of a production system using the proposed tool was developed. The production line chosen was "Manufacturing of Hub R2-11". After the modeling process took place, a simulation for a week of work was made to see where the bottlenecks are and what can be improved to increase production and reduce the blockages of the conveyors and workpoints.

Figure 1 illustrates the initial layout of the "HubR2-11" production line. It includes system components like conveyors, buffers, operators, and workstations. It reflects the structure and flow of material before optimization and helps identify where inefficiencies might arise (e.g., long conveyor queues and single-machine dependencies).

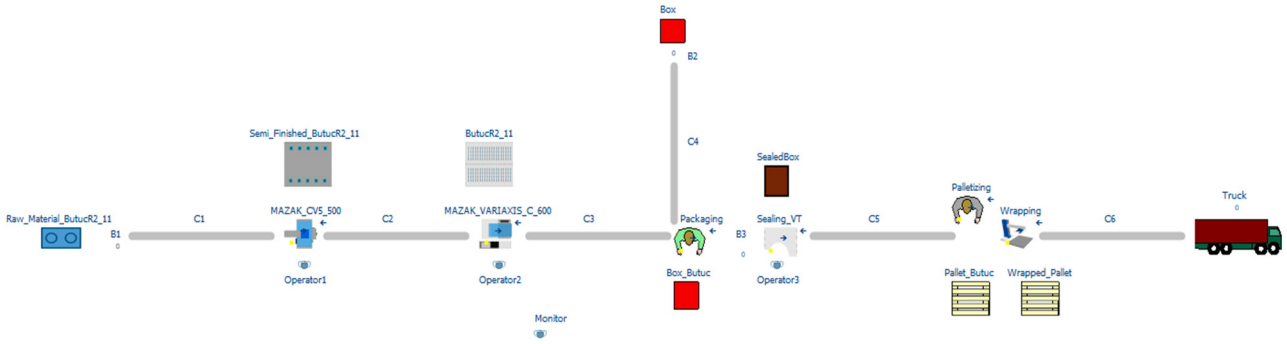


Figure 1. Preliminary system modeling.

3.2. System Components and Resources

Elements present in the model are as follows:

- Raw_Material_HubR2_11, Semi_Finished_HubR2_11, HubR2_11, Box, Box_Hub, SealedBox, Pallet_Hub, and Wrapped_Pallet—parts;
- B1, B2, B3, and Truck—buffer (storage systems);
- Operator1, Operator2, Operator3, and Monitor—operators;
- C1, C2, C3, C4, C5, and C6—conveyor belts;
- MAZAK_CV5_500, MAZAK_VARIAXIS_C_600, (Yamazaki Mazak Corporation, Oguchi-cho, Niwa-gun, Aichi-Pref., Japan) Packaging, Sealing VT, Palletizing, and Wrapping—workpoints;

For a better understanding of the elements present in the model, the final product "HubR2-11" manufactured on the line is presented in Figure 2 with a description of some of the used elements.

The manufacturing process of cardboard boxes utilizes cardboard and corrugated fiberboard materials to create versatile and lightweight containers that serve packaging, shipping, and storage applications. The assembly process of these containers involves folding and securing multiple cardboard panels to create a rigid structure that functions as a durable unit for different logistical needs.

The production line includes modern automation elements such as EPAL-standard pallets (European Pallet Association e.V., Düsseldorf, Germany), stretch film wrapping, and conveyors for internal transport. The transit system includes sidewalls, cleats, and partitions that help separate materials while containing them during movement [18,19].

An AS/RS contains three essential components that function as its main operational components:

Storage racks: These are engineered structures intended to store and organize inventory. The system requirements determine whether racks operate statically or dynamically.

The storage area contains Automated Handling Equipment, which consists of cranes, shuttles, conveyors, and robotic systems that move items between specified locations.



Figure 2. HubR2-11 product.

A central software-driven system controls all automated machinery movements through the Control System. The system uses algorithms to calculate optimal storage, retrieval task sequences, and the most efficient routes.

Industrial trolleys function as industrial carts or hand trucks, which are wheeled apparatuses made to transport heavy or bulky materials inside facilities. Industrial operations such as warehousing, manufacturing, and construction require these tools because manual handling of such items presents both safety risks and operational challenges.

Mazak CV5 500 is a high-accuracy 5-axis machining center designed to deliver high speed and ease of operation. The simultaneous 5-axis VARIAXIS C-600 vertical machining center is automation-ready and uses a solid C-frame, a standard 30-tool changer, a dual-supported tilting table, and quick rapid traverse rates to cut cycle times on difficult work. It can create a wide variety of parts from steel and non-ferrous metals using a wide range of spindles, including high-speed and high-torque choices. With a wide range of advanced programming functions for total usability and repeatable high-accuracy performance, its MAZATROL SmoothAi CNC (Yamazaki Mazak Corporation, Oguchi-cho, Niwa-gun, Aichi-Pref., Japan) increases efficiency and adds value [20].

A Semi-Automatic Turntable-style pallet wrapper, the Arpac Brand Pro Model (nVenia LLC, Wood Dale, IL, USA), is one of the most adaptable and economical options on the market. Heavy-duty welded steel structures are used in the Pro Model's construction to ensure machine stability and a long service life. The Pro Model is a great option for many applications since it comes with convenient Allen-Bradley controls (Rockwell Automation, Milwaukee, WI, USA) [21].

3.3. Material Flow and Process Description

Part Raw_Material_HubR2_11 enters the system, reaches buffer B1 (storage system), gets on conveyor C1, and is then transported to MAZAK_CV5_500, where the raw material is machined and the semi-finished shape of the part is obtained, namely, Semi_Finished_HubR2_11. Then, it gets on conveyor C2, and it is transported to MAZAK_VARIAXIS_C_600, where the semi-finished part is machined, obtaining the final shape of the part, namely, HubR2_11. HubR2_11 then gets on conveyor C3, and it is transported to the assembly workpoint Packaging. Part Box enters the system, reaches B2 (storage system), gets on conveyor C4, and is then transported to Packaging as well. There,

in Packaging, an operator picks one piece of HubR2_11 and one piece of Box and assembles them. After this process, we obtain Box_Hub. Box_Hub is pushed from Packaging to B5 (storage system) and reaches Sealing_VT. Sealing_VT is a workpoint where an operator makes a visual inspection of the box with the parts inside and then seals the box. This process results in the SealedBox part. SealedBox gets on conveyor C5 to the Palletizing workpoint, where an operator waits for 6xSealedBox and places them on a pallet. That way, the palletizing operation is completed, and it results in the Pallet_Hub part. Pallet_Hub gets to the Wrapping workpoint, where it is wrapped and pushed as Wrapped_Pallet on C6. C6 is the final conveyor, where the Pallets end up.

Figure 3 reinforces the understanding of the product in the context of material flow analysis. It supports the narrative of each process step that the part goes through: machining, packaging, sealing, palletizing, and wrapping.

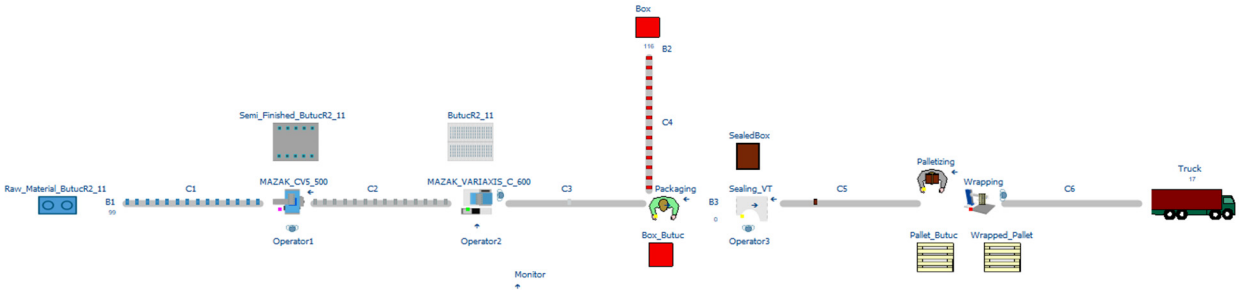


Figure 3. Visual representation of HubR2-11 in workflow.

3.4. Initial Simulation Results and Identified Bottlenecks

The simulation of the preliminary system was conducted for a work week time interval. The tables below provide the statistics for all the elements of the system after the simulation was made.

Table 1 illustrates the quantity of units that entered and successfully moved through each stage. Analysis: only 112 out of 241 raw parts were transformed into final products (HubR2_11), signifying inefficiencies in the process. The significant reduction between semi-finished and final components highlights bottlenecks at the second machining station, while the limited quantity of sealed and wrapped pallets suggests a capacity constraint in downstream processing.

Table 1. Statistics for parts (before optimization).

Name	No. Entered
Raw_Material_HubR2_11	241
Semi_Finished_HubR2_11	128
HubR2_11	112
Box_Hub	111
Box	241
SealedBox	111
Pallet_Hub	18
Wrapped_Pallet	17

Table 2 presents the utilization, blocking, and downtime metrics for each workstation. Analysis: The MAZAK_CV5_500 exhibits a 42% blockage, indicating it is a significant bottleneck. The packaging and Sealing_VT processes remain idle over 90% of the time, implying underutilization due to upstream delays. Additionally, wrapping demonstrates considerable idle time, suggesting that the final stages lack sufficient input.

Table 2. Statistics for workpoints (before optimization).

Name	% Idle	% Busy	% Blocked	% Broken Down	% Repair Wait Labor	No. Of Operations
MAZAK_CV5_500	2.32	38.67	42.04	10	6.97	128
MAZAK_VARIAXIS_C_600	1.97	88.03	0	10	0	112
Packaging	90.75	9.25	0	0	0	111
Sealing_VT	95.38	4.63	0	0	0	111
Palletizing	85	15	0	0	0	18
Wrapping	88.05	1.42	0	9.65	0.89	17

Table 3 illustrates material buildup. The interpretation indicates that input buffers B1 and B2 are saturated, signifying upstream congestion. The truck buffer retains finished pallets but displays zero output, potentially due to a misalignment in transport scheduling.

Table 3. Statistics for buffers (before optimization).

Name	Total In	Total Out	Now In	Max
B1	241	142	99	99
B2	241	125	116	116
B3	111	111	0	1
Truck	17	0	17	17

Table 4 presents details regarding conveyor utilization, emphasizing obstruction and movement duration. Analysis: C1, C2, and C4 exhibit over 70% blocked time, serving as significant flow concentrators. Excessive input and restricted machine availability result in queuing and idle time throughout the production line.

Table 4. Statistics for conveyors (before optimization).

Name	% Empty	% Move	% Blocked	% Queue
C1	0	6.67	73.95	19.38
C2	1.14	1.25	70.76	26.85
C3	12.34	87.66	0	0
C4	0	7.77	85.85	6.38
C5	13.2	85.93	0	0.86
C6	85.83	14.17	0	0

The analysis of the data shown in Table 5 indicates that Operator2 is overburdened at 88% utilization, whilst Operator3 is underutilized at 4.63%. This disproportionate allocation of tasks leads to inefficiency and the squandering of human resources.

Table 5. Statistics for human operators (before optimization).

Name	% Busy	% Idle
Operator1	38.67	61.33
Operator2	88.03	11.97
Operator3	4.63	95.38
Monitor	29.65	70.35

The system performance evaluation reveals that conveyors C1, C2, and C4 experience extended blockages that create major production line efficiency problems. Flow concentrators appear as essential points in the system where material accumulation causes manufacturing delays.

The blockage times of conveyors C1 and C2 become excessive because the MAZAK_CV5_500 and MAZAK_VARIAXIS_C_600 machining centers operate with long cycle durations. The machines maintain high precision levels for complex operations, but their processing times for each unit result in downstream system congestion. The machining throughput rates of the manufacturing units fail to match the arrival frequency of semi-finished parts, which produces system bottlenecks.

The high arrival rate of Box parts causes conveyor C4 to experience continuous blockages. The excess material flow exceeds the conveyor's processing ability, which results in material accumulation that intensifies subsequent station congestion. The system faces major flow restrictions because Box parts arrive at high frequencies, while downstream operations have restricted throughput capabilities.

The production system requires the identification of flow concentrators because it enables the optimization of efficiency and throughput. Productivity decreases because of flow imbalances, while operational costs rise due to idle time and underutilized resources.

Based on the performance issues identified in this section, the following section outlines the simulation-based improvement strategy. The suggested alterations seek to mitigate bottlenecks, optimize equipment usage, and augment system productivity while maintaining economic viability. These obstacles constituted the foundation for the improvement scenarios simulated in the subsequent section.

4. Optimization Strategy and Methodology

This study does not utilize a formal mathematical optimization algorithm. It uses a new integrated manufacturing digital twin to assess and contrast various configuration scenarios of the production system. By modifying critical variables, such as machine availability, work allocation, and part arrival rates, we evaluate the variations in system performance metrics. The objective is to facilitate increased productivity grounded in quantifiable enhancements in throughput, idle time, and resource usage.

4.1. Objective of Optimization

The main goal of the optimization was to make the manufacturing system perform better by fixing flow problems, workstation obstructions, and idle times. This study aimed to improve the productivity and resource usage of an actual production line that makes the HubR2-11 part.

4.2. Optimization Variables

The strategy involved modifying key system parameters across multiple simulation scenarios:

- Machine Duplication: Adding a second MAZAK CV5-500 and a second MAZAK VARIAXIS C-600.
- Input Regulation: Increasing inter-arrival time of Box components to avoid congestion on conveyor C4.
- Automation: Replacing the manual palletizing process with an industrial robot to reduce cycle time and standardize operations.

Different strategic interventions should be implemented to solve these system inefficiencies.

Adjusting the arrival intervals of Raw_Material_ButucR2_11, along with Box parts, could produce better supply and processing alignment to prevent buffer overflow caused by input surges and inefficient stocks of raw materials.

The implementation of new high-performance machinery, along with duplicate resources for the MAZAK_CV5_500 and MAZAK_VARIAXIS_C_600, will enhance the system's capacity to process parts at a balanced rate, thus reducing processing bottlenecks.

The implementation of conveyor logic adjustments combined with dynamic load balancing methods will enable the redirection of excess flow to underutilized paths, thus minimizing local congestion and idle times.

Simulation-based modeling of different scenarios that include machine duplication, buffer size changes, and dynamic scheduling will generate valuable insights for system-wide performance enhancement strategies.

The implementation of flow regulation methods, together with capacity enhancement and intelligent scheduling systems, will decrease the adverse impacts from flow concentrators. The system achieves improved performance through increased throughput, better resource utilization, and operational stability, which leads to enhanced production agility.

The production system received strategic modifications to improve its performance efficiency, which were later analyzed through simulation methods. The system optimization changes aimed to resolve identified system bottlenecks and flow concentrators, especially machine cycle time delays and conveyor congestion.

For the studied system, we changed the following:

- Increased Processing Capacity: The introduction of a second MAZAK_CV5_500 machining center addressed both its extended cycle duration and insufficient machine numbers from the initial system configuration. The addition of a second MAZAK_VARIAXIS_C_600 machine served to spread the workload and minimize processing time.
- Automation of Palletizing Operation: The palletizing duty moved from a human operator working at 20-unit cycles to an industrial robot that operates at 6-unit cycles. The implementation replaced human palletizing operations to reduce idle time and boost production speed while maintaining uniform palletizing quality.
- Inter-arrival Time Adjustment: The 'Box' part inter-arrival time was extended to decrease the high input volume at conveyor C4 since it created major congestion from part accumulation.

Figure 4 illustrates the optimized showcase arrangement, featuring the incorporation of a second machining center for both MAZAK_CV5_500 and VARIAXIS_C_600, as well as the substitution of the manual palletizing station with an industrial robot. This visual representation validates the execution of tactics designed to decrease cycle time and enhance system throughput.

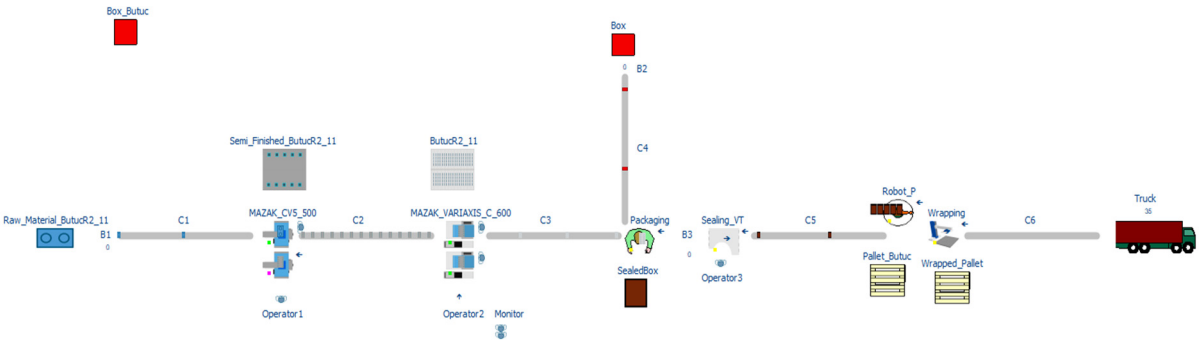


Figure 4. Simulation after the optimization of the system.

4.3. Simulation-Based Evaluation

Instead of employing an algorithmic optimization model with a formal objective function, this work uses an integrated manufacturing digital tool, generating a simulation-

driven methodology. Each system configuration was evaluated through discrete-event simulation using this tool, with the quantitative analysis of performance metrics under constant time conditions.

4.4. Performance Indicators

The following indicators were used to assess improvements:

- System throughput (units/pallets per week)
- Workstation idle time and block time
- Conveyor queue length and blockage percentage
- Operator utilization rates
- Internal Rate of Return (IRR) and Net Present Value (NPV)

4.5. Innovative Aspects

This approach innovatively integrates discrete-event simulation with real economic evaluation (IRR/NPV) to facilitate investment decisions.

- Utilizing digital twin modeling to simulate the complete production system within a virtual environment.
- Substituting human-operated palletizing with robotics, showcasing quantifiable improvements in consistency and performance.
- Implementing dynamic input flow regulation, a seldom-utilized technique in similar case studies, to mitigate upstream overload.

This complex simulation-based technique illustrates how practical configuration modifications can yield scientifically quantifiable performance improvements in an actual industrial environment.

5. Economic Evaluation

Previous studies have emphasized the critical role of system-level optimization in enhancing operational efficiency and reducing indirect costs across advanced manufacturing environments. Wang and Liang [22] investigated the dynamic behavior of tool-changing systems in power tool towers, highlighting how engineering analysis and component reliability directly influence downtime and capital productivity. Similarly, Nicolau [23] underscored the importance of applying systematic design optimization methods to manufacturing technologies, particularly in high-precision industrial contexts, where process stability and performance scalability correlate with significant economic returns. These findings support the notion that capital investments in automated and optimized configurations, such as those examined in this study, offer measurable financial advantages by minimizing idle time, increasing throughput, and maximizing asset utilization.

The implementation of an optimized manufacturing system architecture requires substantial monetary funding, especially when introducing advanced machinery alongside automation technologies and extended production capabilities. The costs of such investments need a thorough economic impact analysis to evaluate their potential advantages for enhanced efficiency and output levels. The evaluation process serves as an essential requirement for verifying that anticipated productivity gains justify all expenses and match the strategic objectives of the organization.

The main basis for investing in optimized manufacturing architecture requires evaluating the relationship between expenses and value generation. Decision-makers need to establish if system enhancements in throughput, alongside operational efficiency and system responsiveness, produce investment returns that surpass the initial capital costs and subsequent operational expenses. The financial assessment of proposed changes usually depends

on cost–benefit analysis, alongside Net Present Value (NPV) calculations, Internal Rate of Return (IRR) determinations, and break-even analysis for financial viability assessment.

Organizations can base their data-driven choices on operational sustainability and profitability through precise calculations of both direct advantages (such as increased production volume, shorter cycle times, and reduced labor expenses) and indirect advantages (like improved product quality and system reliability and minimized downtime).

The decision-making process relies on stakeholders who bring diverse expertise and viewpoints to the table.

The organization's strategic direction and capital expenditure authorization rest with senior executives who lead the decision-making process. These executives need to assess how the investment will impact the organization in the future by checking if it matches corporate objectives that involve market adaptability, business growth, and competition leadership. The company needs their support to obtain funding and deploy cross-functional teams for implementation.

The day-to-day operations of the production system fall under the responsibility of operations managers. Their understanding of shop floor operations makes them fundamental to identifying operational weaknesses and assessing the practical effects of architectural changes. Operations managers lead the deployment of new technologies and workflow modifications while making sure these changes fulfill operational objectives to maximize production and minimize waste.

Manufacturing engineers, process engineers, and systems engineers evaluate the technical feasibility of investments as part of their decision-making process. The technical experts evaluate proposed component performance characteristics through simulation to determine system impacts while checking compatibility with the current infrastructure. Their understanding of real-world operating conditions allows them to determine whether proposed optimizations will meet their intended productivity goals.

Financial analysts perform economic feasibility studies to create detailed cost projections, which help forecast financial outcomes from optimization initiatives. Through revenue gain, combined with cost savings prediction, they help decision-makers assess investment financial results and the risk exposure level. Their financial analyses help organizations maintain responsible budgets and optimize resource deployment.

The economic impact evaluation of manufacturing architecture optimization requires an assessment based on the entire set of organizational strategic goals. The pursuit of investments must prove their value through measurable profits alongside operational efficiency improvements and market-competitive advantage.

Manufacturing system optimization investments require thorough economic evaluation and multidisciplinary teamwork to prove financial stability, operational effectiveness, and strategic alignment. This balanced approach helps reduce investment risks while enabling the organization to use its resources for ongoing performance enhancement and enduring value creation.

The economic evaluation was performed to determine the financial viability of implementing the optimized production architecture for the HubR2-11 line, particularly through the duplication of machining centers and the integration of robotic palletizing. All data used in this section were provided by the industrial partner that supplied the case study for this research.

5.1. Investment Overview

The total estimated investment includes the acquisition of additional high-performance CNC machining centers (Mazak CV5-500 and Mazak Variaxis C-600), as well as a robotic palletizing system. The cost breakdown is presented in Table 6.

Table 6. Total investment.

Equipment	Estimated Cost (€)
MAZAK CV5-500 (5-axis)	204,000
MAZAK VARIAXIS C-600 (5-axis)	370,000
Industrial palletizing robot system	178,000
Installation and training (estimated)	45,000
Total investment	797,000

The investment is planned over a lifespan of five years, with a residual value of 20,000 € and a discount rate of 10%.

5.2. Revenue and Cost Structure

Following optimization, the production output increased to 35 pallets per week, each pallet containing six HubR2-11 units sold at 1000 €/unit, resulting in 6000 €/pallet. On an annual basis, this equates to 1820 pallets/year and a projected gross revenue of:

$$1820 \text{ pallets/year} \times 6000 \text{ €/pallet} = 10{,}920{,}000 \text{ €/year} \quad (1)$$

Variable costs are estimated at 65% of revenue, accounting for raw materials, energy, labor, and consumables. The variable costs are detailed in Table 7. This cost equals 7,098,000 €. Fixed annual costs are projected at 350,000 €, derived as follows (Table 8):

Table 7. Variable annual costs.

Component	Estimated Percentage
Raw materials and semi-finished products	25–35%
Energy and equipment wear	10–15%
Direct labor	15–20%
Consumables and packaging	5–10%

Table 8. Fixed annual costs.

Component	Annual Value (€)
Equipment depreciation	159,400
Maintenance (5% of CAPEX)	40,000
Labor (2 operators)	80,000
Logistics and utilities	70,000
Total	349,400

This yields an annual net cash flow of approximately:

$$10{,}920{,}000 - 7{,}098{,}000 - 350{,}000 = 3{,}472{,}000 \text{ €/year} \quad (2)$$

5.3. Static Profitability Indicators

A simplified static return ratio was calculated using the following formula:

$$\text{Profitability Ratio} = \text{Annual Net Cash Flow}/\text{Average Annual Investment} \quad (3)$$

$$\text{Profitability Ratio} = 3{,}472{,}000/159{,}400 \approx 21.78 \quad (4)$$

This value exceeds the threshold of 1 by a significant margin, indicating strong profitability from a static investment perspective.

5.4. Dynamic Investment Analysis

The Net Present Value (NPV) and Internal Rate of Return (IRR) were used to dynamically assess the economic performance over five years.

- Initial Investment (I_0): 797,000 €
- Annual Cash Flow (FC_i): 3,472,000 €
- Residual Value (VR): 20,000 €
- Discount Rate (r): 10%

The calculated Net Present Value is as follows:

$$\text{NPV} = 13{,}174{,}030 - 797{,}000 = 12{,}377{,}030\ € \tag{5}$$

The Internal Rate of Return (IRR), interpolated between 8% and 10%, yielded approximately 45.25%, while the IRR, calculated numerically using the IRR function in Excel, reached 435.54%, indicating an exceptionally high rate of return.

5.5. Graphical Representation of Economic Indicators

The following figures illustrate the key financial metrics and comparative results obtained from the investment analysis.

The graph in Figure 5 demonstrates that future cash flows lose their real value when discounted at 10% and 8% rates. The discounted cash flows show lower values than the constant (nominal) cash flows because they account for the time value of money.

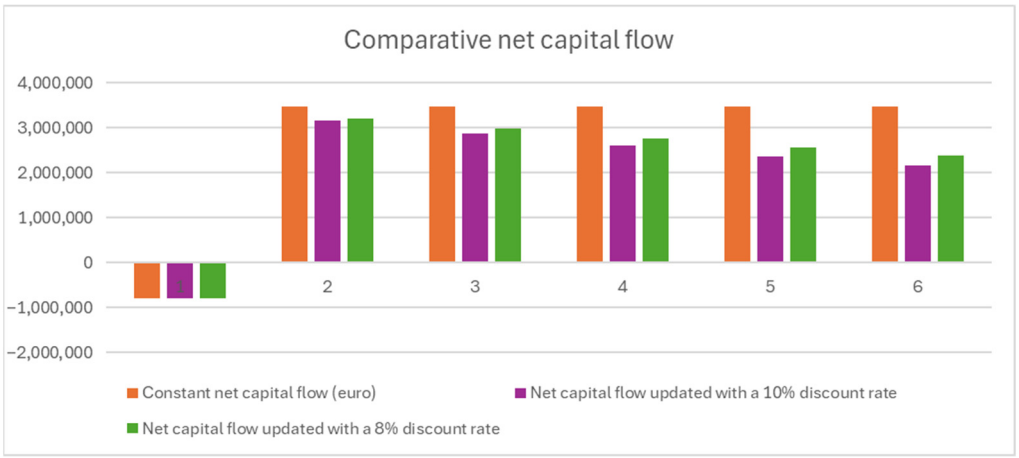


Figure 5. Comparative net capital flows. This chart shows the evolution of constant cash flows versus discounted values at 8% and 10%.

The curves in Figure 6 show how net revenues from the investment grow at a certain rate over time. The blue line (8%) shows a faster recovery than the green line (10%), which shows how sensitive the outcomes are to the discount rate used.

The three IRR values are different (Figure 7) because they stem from distinct calculation methods.

- Numerical IRR (435.54%)

The iterative calculation process determines the exact rate that makes the Net Present Value (NPV) equal to zero. The method used by Excel and other professional financial tools delivers an accurate evaluation of investments with uneven cash flows.

- Interpolated IRR (45.25%)

The approach uses linear NPV changes between 8% and 10% discount rates. This method provides a basic, yet imprecise, calculation that becomes less reliable for profitable investments.

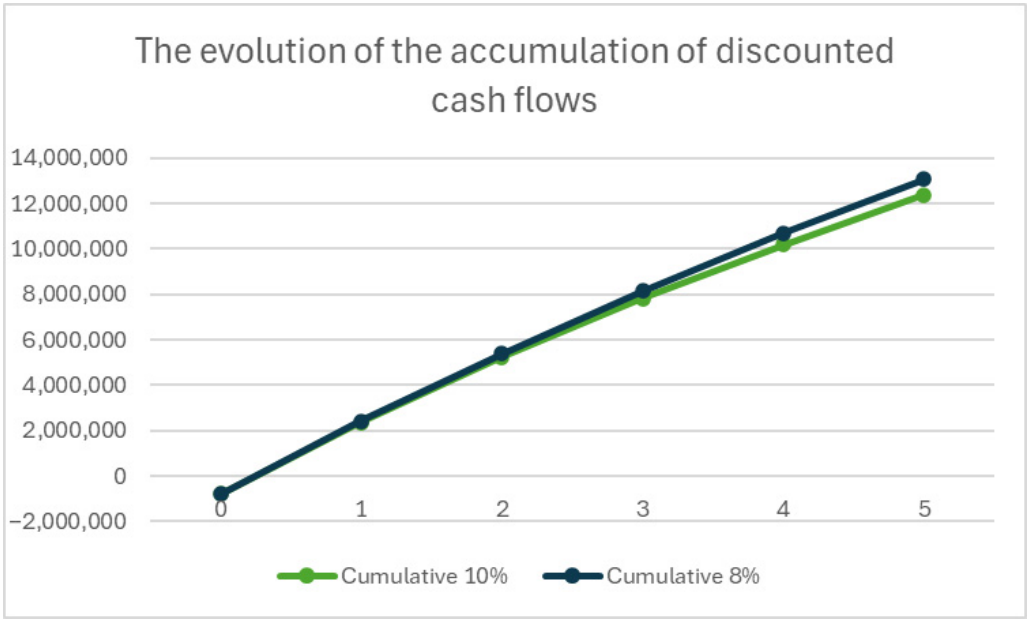


Figure 6. Cumulative cash flow evolution. This graph presents the accumulation of capital over time, highlighting the impact of discount rates.

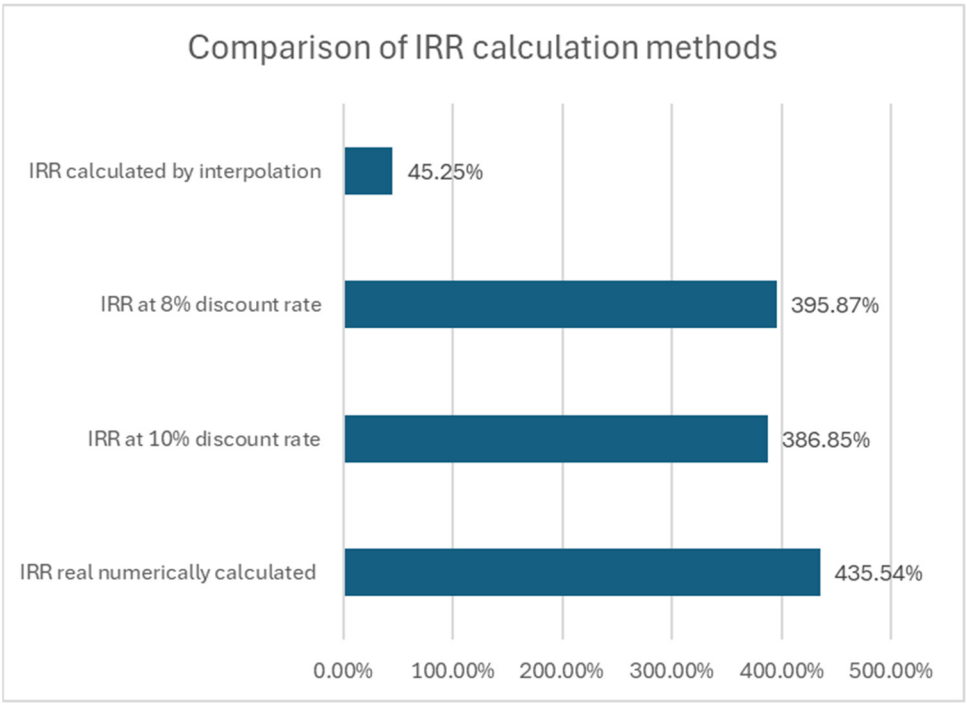


Figure 7. Comparison of IRR calculation methods. Different techniques show varying IRR values, emphasizing the reliability of numerical methods.

- Estimated IRR from the Ratio of Discounted Totals (386.85% and 395.87%)

This method provides an approximate value that fails to account for the timing pattern of cash inflows.

The substantial discrepancies between methods exist because interpolation and direct ratio calculations fail to show the compound effects of returns. The numerical IRR method delivers the only realistic annualized return calculation for this investment because the 797,000 € investment generates cash flows exceeding 17 million €.

Conclusion:

The numerically calculated RIR represents the only dependable value that supports investment choices. The other methods should be used solely for preliminary guidance or secondary validation.

6. Results and Discussion

The system underwent re-simulation after the change in implementation to evaluate optimization impacts under equivalent operational settings. The collected performance data were organized using a table structure with "Before" and "After" columns and directional indicators (↑ and ↓) to display value changes.

The results obtained post-optimization are displayed under "After". The performance change indicators use upward (↑) and downward (↓) arrows to display value increases and decreases, respectively.

The "Preliminary or Optimized" column shows which system configuration (preliminary or optimized) yielded superior performance results for each measured parameter.

The structured comparison method enables a transparent evaluation of optimization effectiveness through data analysis. The evaluation of proposed changes focused on cycle time reduction, along with machine utilization, throughput rates, and part wait times.

The analysis of Table 9 statistics reveals that all output values were enhanced, with wrapped pallets increasing from 17 to 35. The box input was deliberately decreased to alleviate congestion at Packaging, and the significant improvement in the flow of parts indicates that parallel machining and flow management were successful.

Table 9. Statistics for parts (before vs. after optimization).

Name	No. Entered		Preliminary or Optimized
	Before	After	
Raw_Material_HubR2_11	241	241	SAME
Semi_Finished_HubR2_11	128	238 ↑	Optimized
HubR2_11	112	221 ↑	Optimized
Box_Hub	111	217 ↑	Optimized
Box	241	219 ↓	Optimized
SealedBox	111	217 ↑	Optimized
Pallet_Butuc	18	35 ↑	Optimized
Wrapped_Pallet	17	35 ↑	Optimized

Table 10 illustrate variations in idle, busy, and blocked time, as well as the number of operations. Interpretation: The blockage on MAZAK_CV5_500 decreased from 42% to 1.72%. The utilization of packaging and sealing doubled due to an improved upstream flow, while robot-based palletizing diminished operator workload and elevated the operational count from 18 to 35.

Table 11 indicates an enhancement in the material flow at buffer zones. Interpretation: buffers now show zero overload—materials are processed more efficiently, downstream congestion is eliminated, and WIP (work in progress) is minimized.

Table 12 indicates an enhancement in conveyor utilization. The incidence of C1 blockages decreased from 74% to 0%, with analogous reductions observed for C2 and

C4. Queuing rose moderately; yet, this indicates a good system equilibrium rather than obstructions.

Table 10. Statistics for workpoints (before vs. after optimization).

Name	% Idle		% Busy		% Blocked		% Broken Down		% Repair Wait Labor		No. Of Operations		Preliminary or Optimized
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	
MAZAK_CV5_500(1)	2.32	20.34 ↑	38.67	61.93 ↑	42.04	1.72 ↓	10	10	6.97	6.01 ↓	128	205 ↑	Optimized
MAZAK_CV5_500(2)	2.32	69.54 ↑	38.67	9.97 ↓	42.04	1.86 ↓	10	10	6.97	8.63 ↑	128	33 ↓	Optimized
MAZAK_VARIAXIS_C_600(1)	1.97	2.63 ↑	88.03	87.37 ↓	0	0	10	10	0	0	112	111 ↓	Optimized
MAZAK_VARIAXIS_C_600(2)	1.97	3.71 ↑	88.03	86.29 ↓	0	0	10	10	0	0	112	110 ↓	Optimized
Packaging	90.75	81.92 ↓	9.25	18.08 ↑	0	0	0	0	0	0	111	217 ↑	Optimized
Sealing_VT	95.38	90.96 ↓	4.63	9.04 ↑	0	0	0	0	0	0	111	217 ↑	Optimized
Robot_P	85	75.39 ↓	15	8.75 ↓	0	0.62 ↑	0	10 ↑	0	5.24 ↑	18	35 ↑	Optimized
Wrapping	88.05	86.8 ↓	1.42	2.92 ↓	0	0	9.65	10 ↑	0.89	0.28↓	17	35 ↑	Optimized

Table 11. Statistics for buffers (before vs. after optimization).

Name	Total In		Total Out		Now In		Max		Preliminary or Optimized
	Before	After	Before	After	Before	After	Before	After	
B1	241	241	142	241	99	0 ↓	99	1 ↓	Optimized
B2	241	219 ↓	125	219 ↓	116	0 ↓	116	1 ↓	Optimized
B3	111	217 ↑	111	217 ↑	0	0 ↓	1	1 ↓	Optimized
Truck	17	35 ↑	0	0	17	35 ↑	17	35 ↑	Optimized

Table 12. Statistics for conveyors (before vs. after optimization).

Name	% Empty		% Move		% Blocked		% Queue		Preliminary or Optimized
	Before	After	Before	After	Before	After	Before	After	
C1	0	0	6.67	78.39 ↑	73.95	0 ↓	19.38	21.61 ↑	Optimized
C2	1.14	1.49 ↑	1.25	7.1 ↑	70.76	5.11 ↓	26.85	86.3 ↑	Optimized
C3	12.34	8.43 ↓	87.66	84.12 ↓	0	0	0	7.45 ↑	Optimized
C4	0	0	7.77	34.29 ↑	85.85	0 ↓	6.38	65.71 ↑	Optimized
C5	13.2	4.83 ↓	85.93	81.77 ↓	0	0	0.86	13.4 ↑	Optimized
C6	85.83	74.7 ↓	14.17	25.3 ↑	0	0	0	0	Optimized

Table 13 indicates that certain operators were doubled for balancing duties, resulting in a reduction in manual labor dependency, particularly in palletizing. Operator3, previously underutilized, had an increased workload, signifying improved resource allocation.

Table 13. Statistics for human operators (before vs. after optimization).

Name	% Busy		% Idle		Quantity		Preliminary or Optimized
	Before	After	Before	After	Before	After	
Operator1	38.67	35.95 ↓	61.33	64.05 ↑	1	2 ↑	Optimized
Operator2	88.03	86.83 ↓	11.97	13.17 ↑	1	2 ↑	Optimized
Operator3	4.63	9.04 ↑	95.38	90.96 ↓	1	1 ↓	Optimized
Monitor	29.65	30 ↑	70.35	70 ↓	1	2 ↑	Optimized

The simulated production line showed major performance improvements when comparing its optimized state to its initial setup. The optimization delivered improvements across four essential system metrics, which include production capacity, resource management, system traffic control, and automation performance. The optimization strategy achieved its improvements by directly addressing essential system bottlenecks that the analysis previously exposed.

The optimized production line achieved double the output rate of the initial design during the same operational period. The major production enhancement emerged from resolving flow concentration problems and implementing systematic improvements for resource management and process planning. The system's production line achieved uninterrupted material flow because the optimization team eliminated critical system limitations that affected both high-utilization machining centers and overloaded conveyor systems.

The optimization process successfully decreased conveyor blockages that occurred at conveyors C1, C2, and C4 because these systems used to experience prolonged downtime due to uneven material distribution. The production system achieved lower material accumulation at specific locations because the engineers modified Raw_Material_ButucR2_11 and Box part arrival times and added MAZAK_CV5_500 and MAZAK_VARIAXIS_C_600 machines. The conveyor systems thus operated under decreased stress, which led to better material handling process consistency and predictability.

The optimized configuration reduced congestion points that occurred at workpoints. The distribution of an equal workload between duplicated machining centers has two effects: reducing waiting times and boosting the performance of downstream resources. The balanced distribution of tasks between production stages produces synchronized workflows that lead to high output rates in interconnected manufacturing systems.

The system achieved a major advancement in automation because it replaced the manual Palletizing operator, who worked at 20 units per cycle, with an industrial robot that operates at 6 units per cycle. The robotic palletizing station removes all human-related variability and inefficiency from manual labor while creating safer operations that can operate continuously without worker fatigue or mistakes. The reduced cycle time of the production line leads to expanded downstream capacity, which enables the acceleration of the entire production process.

All these modifications combine to form an agile and efficient production system. The system reaches operational stability at lower lead times with enhanced responsiveness to demand and input variability through better machine availability, balanced input flow, reduced buffer saturation, and automated technologies. The optimization follows lean manufacturing principles by minimizing the waste that comes from idle resources, excessive WIP, and unplanned downtimes.

Analysis of Diminishing Returns and Sensitivity

The simulation results show a big improvement in performance when a second machining center is added and robotic palletizing is used, but these changes do not always happen in a straight line. For example, adding a third MAZAK CV5-500 or VARIAXIS C-600 is unlikely to enhance throughput by the same amount because of downstream restrictions (such as packaging and sealing stations), which could become the next bottlenecks. This implies that the system demonstrates declining returns past a specific resource threshold, a prevalent characteristic in intricate production systems. Furthermore, in this scenario, an economic analysis will validate the necessary investment.

Also, even though the current setup worked well with constant demand and input intervals, the system's sensitivity to changes in demand needs to be studied further. For instance, if there is a lot of demand or a delay in the supply chain, the buffers may fill up quickly, causing blockages to happen again. Also, if redundancy is not integrated into the system, things like equipment failure or operator unavailability might have a big effect on throughput.

7. Conclusions and Future Research Directions

The optimization strategy harnessed by the integrated manufacturing digital twin has led to marked improvements in operational performance, as evidenced by a range

of system performance metrics. The application of this tool in the case study presented not only enhanced key performance indicators but also showcased the strategic benefits of simulation-based digital twins in enabling risk-free and data-driven decision-making processes. The role of automation did not supplant human operators; instead, it fostered more efficient resource allocation, promoting a harmonious integration of human and robotic functions. The parallelization of critical machining centers resulted in considerable reductions in wait times and improved workflow synchronization. An analysis revealed that system blockages stemmed not only from inadequate processing capacity but also from unregulated input rates, accentuating the critical need for input flow regulation.

The drastic reduction in idle and blocked times signifies a transition from a constrained system to a robust and responsive architecture. Beyond mere output increases, performance assessments should also incorporate indirect indicators, such as work-in-progress levels and overall resource utilization. The modular and scalable design of the optimized configuration ensures its adaptability to future operational demands. Overall, the findings validate the promise of flexible automation-driven architectures aligned with smart manufacturing objectives for realizing sustainable manufacturing excellence. The strategic combination of capacity expansion, process automation, and flow regulation has effectively addressed existing inefficiencies.

The integration of parallel machining centers, including duplicates of Mazak CV5-500 and Mazak Variaxis C-600, has successfully mitigated critical production bottlenecks. This reconfiguration resulted in higher production rates, achieved by efficiently distributing workloads across various units, thereby minimizing waiting times and effectively doubling output from the baseline model.

Furthermore, the implementation of industrial robotic technology for palletizing operations significantly reduced process variability and cycle times, as it supplanted human operators who traditionally required more time. This robotic framework not only enhances process consistency and safety but also accelerates palletizing operations, thus supporting smart manufacturing principles aimed at achieving superior manufacturing efficiency.

The regulation of the inflow of Box parts effectively alleviated the accumulation problem at conveyor C4, identified as a flow concentrator. This intervention resulted in smoother material flow and diminished buffer saturation by optimizing inter-arrival times for Raw_Material_ButucR2_11 and Box, leading to minimized blockages and improved operational predictability.

Comparative analyses between preliminary and optimized configurations indicate marked improvements across multiple performance indicators. Notably, the system's production output has doubled, demonstrating a significant increase in system capacity and enhancing availability on conveyor lines due to the reduced blockages and improved flow consistency. Enhanced workstation efficiency is attributed to load balancing and parallel processing strategies, paired with an elevated level of automation owing to robotic system integration. The most pronounced time reductions were observed during palletizing operations, which, in turn, bolstered downstream operational efficiency.

The data-driven optimization showcases tangible benefits through these performance improvements. The research substantiates that effective system capacity management, combined with input flow control and the deployment of automation, consistently yields scalable results. Strategic modifications within the system have showcased significant operational advantages, underscoring the efficacy of continuous improvement and scalability through the integration of expanded machining centers with controlled flow systems and automated processes.

Also, the tool investigates how the first capital expenses for advanced machinery and robotic equipment produce value under actual operational limitations while keeping the op-

timized architecture financially viable across production system lifecycles. In the presented case study, the optimized production scenario delivers a compelling economic case:

- A 21.78 static profitability index
- A positive and substantial NPV of 12.37 million €
- An IRR (numeric) of 435.54%

Such values confirm the high profitability of the investment. The economic gains stem directly from increased throughput, reduced cycle time, and improved resource utilization, as observed in the simulation outcomes. Therefore, from both static and dynamic perspectives, the investment is economically justified and financially attractive.

This case study focuses on the Hub R2-11 production line, but the integrated manufacturing digital twin can be effectively adapted to a wide variety of manufacturing environments. This tool is particularly beneficial for assembly lines that experience variability in throughput, workstation imbalances, or prolonged periods of inactivity or blockages. In batch production systems, the digital twin accommodates specific batch arrival patterns and buffer sizing techniques. For continuous flow systems, such as those in chemical or food processing, the simulation can be enhanced with hybrid modeling approaches to represent continuous resource utilization and accumulation accurately. The fundamental workflow of the integrated manufacturing digital twin is consistent across different scenarios: it involves identifying system constraints, simulating alternative configurations, and evaluating performance metrics, such as throughput, idle time, and buffer saturation, under realistic operational conditions. Moreover, incorporating economic indicators like the Internal Rate of Return (IRR) and Net Present Value (NPV) enhances the tool's applicability as a decision-support mechanism across various industries, regardless of cycle times, automation levels, or demand variability. Although the technical details may differ among applications, the integrated manufacturing digital tool is versatile enough to cater to various manufacturing systems.

The scientific contributions of this paper focus on the design and development of an integrated manufacturing digital twin, encompassing:

- A systematic simulation-based methodology for identifying and mitigating bottlenecks in real-world manufacturing systems.
- A quantitative assessment of performance metrics (throughput, idle time, and blockage rate) before and after virtual system redesign.
- An illustration of how discrete-event simulation can support investment justification through IRR and NPV analysis.
- The integration of digital twin concepts and automation scenarios within simulation frameworks pertinent to smart manufacturing contexts.

To conclude, the actual configuration of the integrated manufacturing digital twin demonstrates promising outcomes; however, further investigation is required to assess its long-term viability. Upcoming research will enhance the integrated manufacturing digital twin by incorporating new modules aimed at evaluating operational performance through additional performance metrics, including the following:

- Maintenance Costs: A comprehensive financial analysis module will be introduced to evaluate the operational costs linked to the upkeep of supplementary machinery and robotic systems.
- Environmental and Economic Impact: A quantitative assessment module will be implemented to analyze the effects of increased power consumption on energy use within the automated and expanded frameworks.

– Sustainability Compliance: This module will rigorously assess the environmental implications, such as emissions, waste generation, and resource utilization, to ensure compliance with sustainability standards.

Furthermore, in the financial module, Internal Rate of Return (IRR) calculations will be included to ascertain the financial returns on capital investments related to the additional workpoints over their operational lifespan.

On a broader scale, future investigations should integrate stochastic elements—such as irregular arrival intervals, failure probabilities, and demand fluctuations—to evaluate the resilience of the system. Conducting sensitivity analyses will yield valuable insights, aiding in the development of adaptive control strategies and enhancing the robustness of production systems in the face of real-world uncertainties.

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Abbreviations

The following abbreviations are used in this manuscript:

DES	Discrete-Event Simulation
MOR	Manual Order Rearrangement
MES	Manufacturing Execution System
PLC	Programmable Logic Controller
ERP	Enterprise Resource Planning
EPAL	European Pallet Association
AS	Automated Storage
RS	Retrieval System
CNC	Computer Numerical Control
NPV	Net Present Value
CAPEX	Capital Expenditure
IRR	Internal Rate of Return

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