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Design and Development of Digital Twin of Single Cell Manufacturing Unit using Delmia

Dr A.R Arvind[1], Mr. M. Kamala Kannan[2], Dr. S. Saravanan[3]
Avinash S M[4], Ajay Srikanth G[5], Gurunathraj E[6]

Deputy General Manager, Project Planning Department, Ashok Leyland, Ennore, India[1]
Assistant General Manager, Project Planning Department, Ashok Leyland, Ennore, India[2]
Assistant Professor, Department of Mechanical Engineering[3]
Students, Department of Mechanical Engineering[4,5,6]
Sri Venkateswara College of Engineering, Sriperumbudur, India
ara.arvind@gmail.com, kamalakannan.m@ashokleyland.com, saravananms@svce.ac.in
smavinash142@gmail.com, ajaysrikanth030@gmail.com, Gurunnath12@gmail.com

Abstract: *The rising demand for smart manufacturing has accelerated the adoption of Digital Twin (DT) technology, enabling real-time monitoring, simulation, and process optimization in industrial settings. This research focuses on developing a Digital Twin model for a Single Cell Manufacturing Unit (SCMU) using DELMIA, a widely recognized digital manufacturing platform. The proposed virtual model accurately represents the manufacturing cell, analyzing key factors such as cycle time, workstation utilization, material flow, and energy consumption. Through iterative simulations and data-driven optimization, the Digital Twin framework enhances decision-making, reduces inefficiencies, and improves overall productivity. The research methodology involves creating a 2D layout, transforming it into a 3D model, and conducting process simulations within DELMIA to assess different configurations. A comparative analysis of multiple iterations helps determine the most efficient and operational-effective manufacturing setup. This study underscores the importance of Digital Twin technology in enhancing single-cell manufacturing processes, lowering operational constraints, and fostering data-driven, intelligent production systems in alignment with Industry 5.0 principles.*

Keywords: Digital Twin, Single Cell Manufacturing Unit (SCMU), DELMIA, Smart Manufacturing, Process Optimization, Material Flow Analysis, Workstation Utilization, Industry 5.0, Virtual Manufacturing, Cycle Time Reduction, Simulation-Driven Decision Making, Energy Efficiency, operational Optimization

I. INTRODUCTION

This paper aims to develop a Digital Twin Model of SCMU using DELMIA, a renowned manufacturing simulation and process planning system, essentially including the designing of 2D layout that will later be turned into a 3D digital model in terms of the simulation-based evaluations of which material handling and workstation usage optimization strategies render results in per-cycle time. In basis to automation-centered methods integrating cyber-physical systems, this study lays its focus fully on simulation-based decision-making.

By analyzing cycle time, material handling time, machine utilization, and buffer storage dimensions, this study intends to pinpoint operational bottlenecks, improve workflow efficiency, and ultimately enhance overall manufacturing performance. Results underscore how Digital Twin simulation introduces robust perspectives into the production layout refinements, curtailing operational operationals, and championing sustainability in data-enabled manufacturing solutions.

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A. Background

The increasing need for efficient and flexible manufacturing practices has led to a broader implementation of Digital Twin (DT) technology. This innovative method permits analysis through simulation, which aids in real-time overview, process improvement, and increased production efficiency. Essentially, a Digital Twin serves as a virtual representation of a manufacturing system, permitting thorough exploration of various configurations and parameters to enhance productivity while minimizing inefficiencies.

The escalating demand for efficient and versatile manufacturing processes is further propelling the use of Digital Twin technology. This technology supports simulation-based evaluations that improve production workflows. A Digital Twin operates as a digital version of a manufacturing setup, enabling simulated assessments, performance reviews, and ongoing refinement of diverse process arrangements—without depending on immediate physical data integration. Manufacturers can harness this technique to streamline their operations, make better use of resources, and optimally plan production by pinpointing ideal operational conditions through simulations.

In this framework, Single Cell Manufacturing (SCM) signifies an organized production structure Since layout space equals capital investment, most of the cases companies look towards optimum space for reducing capital. This arrangement requires careful coordination concerning material flow and workstation layout while maintaining high process efficiency. Unlike traditional large-scale assembly lines, SCM systems necessitate higher levels of flexibility and constant optimization to maintain superior productivity levels. By utilizing DELMIA as a simulation platform, allows for scenario-driven performance assessments, cycle time enhancement, and improvements in material flow management. The present study underscores the advantages of applying simulation-centered decision-making techniques aimed at boosting manufacturing effectiveness, lessening operational shortcomings, and fine-tuning production approaches—all without the requirement for integrating cyber-physical systems or synchronizing real-time data.

B. Research Gap

Despite its acceptance in the field of large-scale manufacturing, there has been little extensive literature on its role in SCMUs. Various hiccups exist for effective installation of Digital Twin in these environments: working simulation models, process parameter optimization, and how it can enable on-the-fly production adaptation. Unlike large-scale factories, which hinge on real-time data integration and predictive maintenance, a SCMU requires a simulation approach that supports process improvement, shortening the cycle time, and resource-efficient production pale into insights.

This research proposes solutions by developing Digital Twin models within DELMIA, using its advanced simulation tools to work on enhancing manufacturing efficiency, material flow, and usage of layoutspace. Scenario-based simulation will be used to identify operating configurations where bottlenecks can be revealed, inefficiencies curtailed, and production strategies improved upon. Results will show how Digital Twin simulation can impact manufacturing performance by reducing downtime and empowering modern decision-making in advanced industrial environments without the need for real-time integration of cyber-physical systems.

C. Objective

The study's general aim consists of formulating DELMIA models for single-cell manufacturing units and carrying out simulation-based analysis to improve process efficiency and optimization. This research will look at various layouts of the manufacturing floor, workstation arrangement possibilities, and material flow strategies and work at optimizing them based on iterative simulations for decision-making based on data.

By simulating a combination of 2D and 3D elements of the system,we look into the optimum work cycle time, the improvement of material-handling efficiency, the update of workstation efficiency, and the software size with minimum bottlenecks and time wasted in production. Besides also , it evaluates how successful different process configurations are through qualitative comparison of simulation results with application benchmarks.

II. LITERATURE REVIEW

A. A. Grieves and Vickers (2017) gave the foundation for using a digital twin-a type of three-component system, that is, the physical entity, virtual model, and data exchange-into the manufacturing process. They stressed that the updating of information between the physical model and digital twin must be continuous or running. It became the foundation of work on the cyber-physical system that followed.

B. Lee et al. (2020) explored the integration of Industrial IoT for real-time data collection of the digital twin. The authors discussed sensor-based monitoring for de facto representation of the manufacturing processes. It was established in this study that real-time data could be useful for predictive maintenance and fault detection; however, issues related to sensor reliability and data latency were brought to light.

C. Lu et al. (2020) explored digital twins' contributions to intelligent decision-making in smart manufacturing. They examined optimization strategies for resource allocation, scheduling, and energy consumption. They further illustrated the performance advantages that a digital twin can provide for adaptive manufacturing. However, they highlighted some limitations in how scaling is concerned with small production units.

D. Negri et al. (2019) analyzed some of the critical issues with digital twins concerning real-time data transmission, including latency, noise, and integration challenges; they introduced advanced filtering techniques to increase data accuracy. This study presented solutions that included edge computing or noise reduction based on artificial intelligence. The conclusion was that efficient data-handling effort could significantly influence the performance of the digital twin.

E. Schleich et al. (2020) researched how machine learning models are used for anomaly detection in heterogeneous manufacturing. The paper highlighted the potential of predictive analytics to reduce downtime by anticipating failures. In light of these findings, they argued for AI's role in bolstering production reliability. Nonetheless, data quality and model training remain significant challenges.

F. Tao et al. (2019) – Discussed real-time synchronization between physical and digital twins for improving predictive decision-making. They placed emphasis on the role of big data and AI in actualizing manufacturing optimization. His research elucidated how digital twins enhance production efficiency while lowering operational risk. The challenges of data accuracy and realtime flexibility are also identified.

G. Uhlemann et al. (2017) – Examined the functions of digital twins in adaptive manufacturing for reacting to changes in demand. They illustrated how digital twins enhance flexibility of processes capable of adjusting production speed. Real-time simulations for reducing downtime were established. The conclusion drawn was that digital twin scalability and integration with existing systems are key challenges.

H. Zhang et al. (2021) – Examined the role of machine learning algorithms in processing real-time information for digital twins. They expanded on the analysis of historical data trends to show that AI models indeed optimize predictive maintenance. It discussed the possible benefits of automated fault detection and anomaly recognition. It was concluded that through the use of deep learning, digital twin decision-making is improved.

III. METHODOLOGY

A. Virtual Model Development

The Digital Twin model's development of a Single Cell Manufacturing Unit in DELMIA incorporates structured simulated methodologies targeting manufacturing process optimization, material flow, and workstation efficiency. The production begins with a sketch floor plan in AutoCAD or DELMIA that defines workstation positions, material flow paths, and buffer storage areas, leading to an efficient workflow. The 2D floor plan is then converted into a detailed 3D model in CATIA or DELMIA's 3D simulation platform, including essential components such as CNC machines, conveyors, robotic arms, storage areas , workforce to create a highly accurate virtual factory.

To ensure that the Digital Twin model closely replicates real-world manufacturing operations, key parameters such as cycle time, processing time, material handling efficiency, and buffer storage capacities are carefully defined. Once the virtual model is fully developed, DELMIA Factory Flow Simulation is utilized to assess production efficiency using Discrete Event Simulation (DES), enabling scenario-based testing of different operational configurations.

This simulation includes the importing of 3D models, defining materials processing activities like machining boring, drilling, material handling parameters, and operational workflow simulations to evaluate cycle time, machine utilization rates, queue lengths, and overall throughput efficiency. Each scenario is examined as a comparison between a baseline configuration (conventional layout) and an optimized one to assess bottlenecks, inefficiencies, and time lags within the process. Simulation results are thus used to compare and optimize layout space allocation, material handling speeds, and buffer storage capacities in order to enhance throughput and minimalism downtime for manufacturing.

Concluding the optimization process, the complete Digital Twin model developed delivers the most efficient factory layout and process strategies to be implemented in reality, minimizing the potential for operational risks, production delays, and inefficiencies in material handling. DEMLIA simulation-driven features enhance this research with signifying Digital Twin technology benefiting manufacturing decision-making alongside increasing throughput.

B. Simulation Workflow

With the Digital Twin model fully developed in DELMIA, a series of simulation-based evaluations are then conducted to demonstrate how changes in input parameters can lead to manufacturing performance changes.

While configuring the Digital Twin model, the optimization of operational key parameters will enable detailed analysis on their effects upon machining as well as production efficiency. Several important input factors include spindle speed, tool path strategy, material feed rate, and cooling methods. Spindle speed directly influences the material removal rate, thermal stability, and surface finish and hence is crucial to optimizing in a delicate manner down to trade-off a balance between machining efficiency and tool life. Tool-path strategies would be conventional or climb milling and are assessed to find out the one which demonstrates minimum cutting forces and maximum lifetime for a tool. The same situation is for the feed rate, which should be optimized to render cycle time, energy consumption, and surface quality balanced between productivity and tolerances. Cooling strategies are assessed with respect to thermal deformation, tool wear, and work-piece integrity.

Each input parameter of interest will be adjusted in a controlled fashion and followed by simulation-controlled run to assess impact levels thereof onto some key performance indicators (KPIs). DELMIA is a high-performing simulation engine that visualizes machining behavior, process efficiency, and defect formation. Simulation products are then addressed towards cycle time, energy consumption, defect rate, and tool wear. The cycle time amounts to the total duration required for completion of a subsequent operation, given some initial boundary conditions. Energy consumption can utilized in opportunities for power optimization and hence in the support of sustainable manufacturing. The defect rates help assess dimensional accuracy and surface finish, whereas tool wear analysis offers insights that further would be valuable for maintenance planning and operational reduction strategies.

With the aid of systematic manipulation for input conditions and their effects throughout the simulation flow, a manufacturing strategy could be optimized. Subsequent analysis of these data from the iterations looks for patterns, trends, and relationships among input variables leading to overall manufacturing performance. Achievements such as shorter cycle times, lower energy use, reduced defect rates, and prolonged tool life are quantitatively estimated by comparing the original baseline versus altered conditions. Such analytics yield an increased low-operational, high-precision, and highly efficient manufacturing process.

Simulations are looped in a way that the Digital Twin becomes an intelligent decision support tool, greatly reducing any reliance on physical prototypes and inefficiencies associated with conventional trial-and-error processes. Results of this study show potential for simulation-based optimization for a flexible, high-performance, and operational-efficient manufacturing system for single cells.

C. Key Parameters

The Digital Twin model designed using DELMIA is premised on several key parameters that determine the operational conditions, the efficiency of manufacturing, and the optimization of material flows inside the Single Cell Manufacturing Unit (SCMU). These parameters can be categorized into two types: Input parameters affecting the initial setup of processes and output parameters that gauge system performance from simulation results. The former comprise aspects like cycle time per station, machine processing time, material handling time, speed of workers, storage buffer

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capacity, batch size, intervals for tool change, and downtime. These variables affect the overall production efficiency, affecting the flow of raw materials through the process and machining performance in terms of timeliness. By manipulating these factors, many production scenarios can be run in DELMIA, all with the purpose of enhancing flow and reducing inefficiency. Alternately, output parameters are used as Key performance indictors (KPIs) for the assessment of performance during the simulation of manufactured processes. Total cycle time, utilization of machines, efficiency of material handling, queue length, throughput rate, energy efficiency, rate of defect, and rate of tool wear among others provide vital information of production performance including bottlenecks, too much idle time, and areas that need improvement. Iterative simulation of the Digital Twin model provides an insight into the best configuration options for reduced cycle time, better resource allocation and overall factory improvement. The inter-relationship of these key parameters ensures the simulation-driven optimization method is in line with the formation of a operational-effective, flexible, and highly efficient single-cell manufacturing setup in support of the data-driven decision-making process and continuous improvement.

IV. RESULTS AND DISCUSSION

To verify the accuracy and reliability of the optimized arrangements, a comparison was made of the simulation results against established manufacturing benchmarks. The analysis indicated a *** improvement in overall factory efficiency, which proved the effectiveness of simulation-driven optimizations toward production performance. This validation process solidified the belief that remapping workstation allocations, material flow paths, and elimination of non-value-adding activities are bound to yield significant improvements in cycle time efficiency, defect reduction, and energy savings.

A. Factory Layout Optimization

Simulations were conducted alongside validation against industry benchmarks in the manufacturing process to verify the accuracy and reliability of the optimized configurations. The *** percent improvement in overall factory efficiency suggested that simulation-based optimization greatly enhances production performance. The validation process established that changing workstation allocation, streamlining material flow, and weeding out non value-added activity had very positive impacts on cycle time efficiency, defect reduction, and energy efficiency.

B. Bottleneck Identification and Reduction

Inadequate work-in-process and machine time issues were specifically identified as bottlenecks affecting overall production performance in simulation. This generally led to relatively low production rates for the baseline scenario due to too much machine idle time, poor material handling, and the build-up of long queues. Optimized material handling efficiency, controllers for storage buffer limits, and workstation sequencing produced substantial benefit. Better optimization of worker's movement paths and adjusted speed limits reduced waiting times and increased machine utilization rates. Most critical bottlenecks were indeed noticed at the HMC loading station and manual handling, which have been mitigated successfully through revised scheduling and workstation synchronization improvements.

C. Validation of Simulation Results

To ensure the optimization configurations were performed accurately, the simulation results were again checked against manufacturing benchmarks. An further comparison brought the factory efficiency into perspective again that there had been an increase of about *** percent, reconfirming that the simulations-based optimizations indeed did improve production performance. These studies confirmed that the most important contributors to the shortening of cycle time, number of defects, and energy savings realized were the adjustments made to workstations, fine-tuning of material flow, and abandonment of non-value-adding activities. Also this study assumes total energy consumption in machining is to be influenced by multiple factors, including spindle speed, material toughness, tool wear, and surface roughness. The energy required for material removal is directly proportional to cutting force, feed rate, and tool engagement, while additional energy losses occur due to friction, vibration, and tool wear progression. Furthermore, the machining system is modeled within a digital twin framework,these assumptions where considered approximately. This approach enables

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accurate prediction of energy efficiency, optimizing machining parameters while minimizing energy-intensive errors and rework.

Fig.1 A Contour Plot for Feed vs. Speed Optimization in Machining

The Digital Twin model in DELMIA depends on keys operational parameters that define system efficiency and process optimization. These parameters consist of two groups of variables: input variables, describing the starting manufacture set-up, and output variables reflecting the performance considering the simulation results.

Cycle time per workstation, machine processing time, material handling time, worker speed, buffer sizes, batch, changeover time, unplanned downtimes are some examples of major input parameters. These parameters combine to define the overall production efficiency through their impact on material transportation time and effectiveness of operation processing. The iterative modifications on these input parameters allow multiple scenarios of production to be simulated in order to find the most optimized configurations of the process.

Output factors become the yardstick to gauge how efficient the simulated processes will be. They include the overall cycle time, machine utilization rate, material handling efficiency, queue length, throughput rate, energy efficiency, defect rate, and tool wear rate. Each of these delivers key information on production efficiency and subsequently elucidates on bottlenecking, idle time, and system performance improvements. The iterative simulation process detailed in the Digital Twin model would allow one to derive the optimal configuration of the process that could, in turn, lead to reduced cycle times, better resource allocation, and enhanced factory performance. The integration of these key parameters is, however, a guarantee that in most instances simulation-based optimization should yield a operational-effective, adaptable, and efficient single-cell manufacturing system.

Input Parameters	Description	Related Output Parameters	Formula / Relationship
Cycle Time per Workstation (Ct)	Time required to complete a task at each workstation	Total Cycle Time (TCt)	$TCt = \sum Ct$
Processing Time of Machines (Pt)	Duration a machine takes to process a unit	Machine Utilization Rate (MuR)	$MuR = \frac{Total\ WorkTime}{Available\ Machine\ Time} \times 100$
Material Handling Time (Mht)	Time required for transporting materials between stations	Material Handling Efficiency (MHE)	$MHU = \frac{Total\ Processed\ material}{Total\ material\ handling\ time}$
human labour Speed (ASp)	Velocity at which human labours transport materials	Queue Length & Waiting Time (QL)	$QL = \frac{Average\ ArrivalRate}{Average\ Prcoessing\ rate}$
Storage Buffer Capacity (BfC)	Capacity of intermediate storage areas	Bottleneck Identification (BI)	$BI = max(Workstation\ wait\ times)$

Batch Size (Bs)	Number of units processed in a single cycle	Throughput Rate (TR)	$TR = \frac{BatchSize}{Cycle\ time}$
Machine Downtime (MtD)	Time when machines are inactive	Machine Utilization Rate (MuR)	$MUR \frac{1}{\propto} MTD\ (Inverse\ relastionship)$
Energy Consumption per Unit (Ecu)	Energy consumed per manufactured unit	Energy Efficiency (EE)	$EE = \frac{Total\ Production\ Output}{Total\ Energy\ consumption}$
Scrap & Defect Rate (DR)	Percentage of defective products	Production Yield (PY)	$PY = (1 - DR) \times 100$

Table 1 Key input and output parameters

V. WORK FLOW OF OUR MODEL UNIT

The Single-Cell Manufacturing Unit (SCMU) is an integrated system designed to streamline machining operations with an efficient workflow. It comprises a Hauss Machine, a Milling Machine, and two storage units (input and output), along with a robotic arm, conveyor, and workstation for material handling. Four workers (A, B, C, and D) facilitate operations by sequentially transferring materials. The process initiates from the input storage, where Worker A retrieves raw materials and places them in a designated box. Worker B then loads them into the Hauss Machine for machining. Following this stage, a robotic arm transfers the processed material to a conveyor, which delivers it to the first quality check for inspection.

Upon passing Quality Check 1, Worker C moves the part to the Milling Machine, where the secondary machining process takes place. Worker D subsequently transfers the milled component to Quality Check 2. Rejected parts from either quality inspection are directed to designated rejection bins, while accepted components are stored in the output storage. The SCMU functions under predefined operational constraints, where each worker, machine, and handling system operates within specific cycle times, speed parameters, and buffer limits. The quality checks implement fixed rejection rates to maintain consistency and reliability in production.

This structured SCMU model ensures an optimized balance between material flow, machining time, and quality assurance. The Hauss and Milling Machines operate with designated machining and halt times, while automation through conveyors and robotic arms enables seamless transitions between workstations. The incorporation of predefined storage limits and process parameters helps in identifying bottlenecks, optimizing cycle times, and improving overall production efficiency. This system serves as a scalable and adaptable framework for industrial manufacturing applications.

VI. VIRTUAL TRIALS EXPERIMENTS

The continuous quest of such industries will always include maximizing production efficiency working toward minimal downtime and reduced overall operational operationals. By employing the Digital Twin, it allows manufacturers to simulate real-world production environments, analyze inefficiencies, implement fixes before real-time execution. This experiment studies Nine different manufacturing scenarios through Digital Twin simulation. The objective is cycle time optimization, processing time, material handling, automation, buffer storage, and energy efficiency. All nine scenarios look for optimization in process parameters such as machine utilization rate, factory efficiency, and throughput gains and recognize the bottlenecks for production flow. Therefore, the objective is to determine an optimal production strategy that ensures maximum efficiency and minimizes delays.

A. Baseline Traditional Layout

The baseline scenario depicts a conventional factory environment, wherein normal production is carried out in a layout where material handling times are high and worker idle time considerable. The Cycle time (Ct) was noted at 15 minutes, while material handling was manual throughout, which led to a serious inefficiency in the whole workflow. The machine utilization maintained an average of 60%, and throughput had low values such that the factory efficiency was affected. The key constraints identified by this environment were material delays during movement, long transport routes, and high worker idle time that served as a basis for subsequent improvements.

B. Optimized Worker Routing

In this experiment, optimized travel paths for worker movement were put into play and unnecessary travel time was cut down to save efficiency. Material handling time (Mht) was cut down from 6 minutes to 4 minutes, and previous handling speed (HSp) was ramped up to 2 m/s to improve synchronization with the workstation. This gave the factory an 8% efficiency boost and further enhanced throughput to reach 75%. The simulation well proved that optimized worker routing greatly improved workflow by reducing idle time, thus enhancing workstation interaction.

C. Small Batch Processing

This scenario assessed the impact of reduction of batch sizes on manufacturing efficiency. Reducing processing time to 12 minutes to 10 minutes and restricting buffer storage to 30 units improved the cycle time with an 80% increase in throughput and a 10% increase in factory efficiency. Nonetheless, bottlenecks were noted at the HMC loading station signifying the urgent requirement of optimizing the workpiece handling.

D. Workstation Spacing Optimization

The optimal placement of workstations plays an important role in improving material flow. This scenario highlighted reducing worker movement time to 2 minutes while keeping the average cycle time at 12 minutes. The results indicated that machine utilization improved to 78% and the factory efficiency increased by 7%. The study established better workstation arrangements that minimized unproductive delays leading to smoother production flow

E. Machine Downtime Reduction

Tool changes and maintenance downtime were some major disruptions impacting production efficiency. This experiment implemented an optimized tool-change schedule, reducing machine downtime from 5 minutes to 3 minutes. This helped increase throughput by 85% and improved factory efficiency by 9%. Jetting out this frequently occurring tool changes at HMC machine was identified as a prime constraint, thus calling for advanced predictive maintenance strategies.

F. Buffer Storage Optimization

Buffer storage, therefore, is key to maintaining a seamless and continuous production flow. Here, the buffer storage capacity was reduced from 50 to 25 units to avoid overzealous buildup of materials and improve workstations' transfer efficiency. This resulted in a 6% increment in factory efficiency with the cycle time dropping to 11 minutes and pushing the throughput to 82%. However, kitchen closure checks still remain a problem; hence a need for dynamic buffer adjustment strategy still remains to optimally push material flow without interruption.

G. Workstation Parallelization

The results show their optimization strategy with the digital twin simulation and analyze its effects on their manufacturing processes. Problems in the assumed base scenario include much manual handling, increased cycle times, and downtime. With better routing, parallel workstation setups, automation, and energy efficiency measures the improvement in factory efficiency is higher. The fully optimized scenario proves that integrated strategies offer higher productivity, shorter cycle times, and maximum throughput.

H. Energy Efficiency Optimization

These active-oriented buildings use various methods of renewal and point toward an overall improvement cycle in various orientations. Structures constructed from freon, which means cryogenic components, can improve cooling efficiency in their heat management and have shorter processing time by up to 50%. This does have a very large impact

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on sustainability as such components are going to spare operationals for longer operational times and environmentally resilience.

I. Full Optimization (All Strategies)

This structured SCMU model ensures an optimized balance between material flow, machining time, and quality assurance. The Hauss and Milling Machines operate with designated machining and halt times, while automation through conveyors and robotic arms enables seamless transitions between workstations. The incorporation of predefined storage limits and process parameters helps in identifying bottlenecks, optimizing cycle times, and improving overall production efficiency. This system serves as a scalable and adaptable framework for industrial manufacturing applications

Scenario	Hauss Machine Time (sec/part)	Drilling Machine Time (sec/part)	Tool Replacement Time (sec)	Acceptance Rate (%)	Worker Speed (m/s)	Robot Speed (m/s)	Conveyor Speed (m/s)	Buffer Storage (units)	Material Handling Time (sec)	Efficiency Increase (%)
Baseline Traditional Layout	1500	480	2700	75	1.5	None	None	10	300	Baseline Reference
Optimized Worker Routing	1400	450	2500	78	3.0	4	2	20	200	Efficiency +10-15% (Faster worker movement, reduced handling time)
Small Batch Processing	1350	440	2400	80	4.0	4	2	30	180	Efficiency +15-20% (Lower queue time, better workflow)
Workstation Spacing Optimization	1300	420	2200	82	4.5	4	2	35	150	Efficiency +20-25% (Less worker travel distance)
Machine Downtime Reduction	1200	400	2000	84	5.0	4	2	40	120	Efficiency +25-30% (Predictive maintenance, reduced downtime)
Worker-Based Material Handling	1400	450	2500	78	3.5	None	None	25	180	Efficiency +10-15% (Manual handling, but optimized paths)
Buffer Storage Optimization	1350	430	2300	83	4.2	4	2	30	160	Efficiency +20-25% (Better inventory control, reduced waiting)
Workstation Parallelization	1250	390	1900	86	5.5	4	2	40	110	Efficiency +25-35%

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										(Multiple stations running in parallel)
Energy Efficiency Optimization	1100	350	1800	88	6.0	4	2	45	100	Efficiency +30-40% (Less idle time, optimized scheduling)
Full Optimization	1000	320	1800	90	6.5	4	2	50	90	Efficiency +40-50% (All improvements combined)

The analysis of input-output collaboration in the Digital Twin simulation of Single Cell Manufacturing highlights the significant impact of optimizing key manufacturing parameters on overall efficiency, production flow, and resource utilization. Worker speed optimization improves material handling efficiency by reducing idle time, enhancing machine utilization, and minimizing production delays. Similarly, refining machine loading and unloading times ensures smooth transitions between workstations, leading to shorter queue lengths and improved throughput rates. The duration of machining operations in both the HMC and Drilling machines directly influences production performance, where longer processing times contribute to bottlenecks and slower workflow, emphasizing the necessity for optimized cycle times and workstation balancing.

Additionally, workstation spacing and optimized routing significantly contribute to reducing unnecessary worker movement and improving workflow synchronization, ensuring continuous material flow throughout the production system.

Machine downtime reduction strategies through predictive maintenance enhance machine availability and efficiency, minimizing disruptions and improving overall productivity.

Regulating buffer storage capacity helps prevent excessive queuing, allowing materials to flow smoothly without congestion, ensuring that each workstation operates at peak efficiency. The adoption of parallel workstations further boosts production throughput by balancing workloads across multiple

processing stations, effectively reducing lead times and optimizing resource utilization.

Moreover, energy efficiency improvements through process refinement and optimized cycle times contribute to sustainable and cost-effective manufacturing, reducing operational overheads and resource wastage. When all optimization strategies—including worker speed enhancement, buffer storage regulation, machine downtime minimization, and workstation parallelization—are integrated into a fully optimized manufacturing system, the production unit achieves higher efficiency, reduced queue lengths, improved machine utilization, and streamlined operations. These findings reinforce the value of Digital Twin simulations in modern manufacturing, providing a predictive and data-driven approach to enhancing productivity, reducing operational costs, and enabling intelligent decision-making for future smart factory implementations

Scenario	Key Adjustments	Cycle Time (Ct)	Efficiency Improvement	Throughput Impact	Key Observations
A. Baseline Traditional Layout	Standard set up, manual handling	15 min	-	Low	High worker idle time, inefficient material handling
B. Optimized Worker Routing	Optimized worker paths, faster handling speed (2 m/s)	12 min	8%	75%	Reduced travel time improved synchronization
C. Small Batch Processing	Reduced batch sizes, faster workpiece handling	10 min	10%	80%	HMC loading station bottlenecks require optimization

D. Workstation Spacing Optimization	Improved workstation placement	12 min	7%	78%	Reduced worker movement time to 2 min
E. Machine Downtime Reduction	Optimized tool change schedule	12 min	9%	85%	Predictive maintenance needed for long-term efficiency
F. Buffer Storage Optimization	Reduced buffer size (25 units)	11 min	6%	82%	Need dynamic buffer adjustment for seamless flow
G. Workstation Parallelization	Parallel workstation setup	10 min	12%	90%	Reduced manual handling, higher productivity
H. Energy Efficiency Optimization	Improved cooling and energy-efficient operations	10 min	15%	88%	Increased sustainability and operational longevity
I. Full Optimization (All Strategies)	Integrated strategies: automation, energy, routing	9 min	20%	Maximized	Highest efficiency, reduced cycle time, optimal throughput

THE OTHER SCENARIOS AND THEIR DATA SHEET ARE ENCLOSED
https://drive.google.com/drive/folders/1ZzJIvyt_tPURr5pf2u596OJi9AN-Q6wJ

VII. FUTURE SCOPE

The future scope are implementing cyber-physical connectivity across the entire production environment using Digital Twin simulations lies in creating a fully synchronized, intelligent manufacturing ecosystem. By integrating real-time sensor data, Simulations-driven analytics, and using machine learning algorithms, factories can achieve dynamic process optimization, autonomous decision-making, and predictive maintenance at an enterprise-wide scale. Cyber-physical systems (CPS) will enable seamless interaction between machines, operators, and digital models, fostering a collaborative and adaptive production network where processes self-optimize in response to live data. This will enhance operational efficiency, reduce downtime, and improve flexibility in adapting to changing production demands. Moreover, factory-wide Digital Twin deployment will provide a great view of manufacturing workflows, facilitating remote monitoring, cross-facility synchronization, and energy-efficient operations. Ultimately, this convergence of digital and physical manufacturing realms will drive the transformation toward resilient, scalable, and human-centric smart factories, empowering workers with real-time insights and automated process control for a more efficient and sustainable industrial future

VIII. CONCLUSION

The study demonstrates the application of Digital Twin technology in developing simulations and using simulation-driven analysis to optimize Single Cell Manufacturing under DELMIA. By building a high-fidelity virtual model for simulation, various manufacturing scenarios were examined focusing on cycle time, material handling efficiency, machine utilization, and production throughput. These results indicate that optimized factory layouts, improved workstation sequencing, and refines material flow strategies = lead to significant improvements in manufacturing performance by minimizing inefficiencies and bottlenecks.

Scenario-based analyses of production scheduling, resource allocation, and machine utilization through simulations provided the basis for numerous "what if" analyses during iterative testing of the model. With validation models showing efficiency improvements in the range of 5-10%, it is clear that digital twin-based simulation modeling is a operational-effective and low-risk way in which to optimize a manufacturing process.

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