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Maximizing Efficiency and Cost Savings through Digital Twin Simulation: Optimizing Cellular Manufacturing

Safiye Turgay[1,a,*], Necip Akar[1,b]

[1]Department of Industrial Engineering, Sakarya University, Sakarya, Turkey
[a]safiyeturgay2000@yahoo.com, [b]necip.akarrr@gmail.com
**Corresponding author*

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Abstract: Cellular manufacturing is a process that groups similar machines, workstations, and processes in a dedicated area to maximize efficiency and reduce production time. A well-designed cellular manufacturing facility layout can increase productivity and decrease manufacturing costs. To optimize the layout design of a cellular manufacturing facility, digital twin simulation can be used. Digital twin simulation involves creating a virtual replica of a physical system or process to simulate and optimize various scenarios. By utilizing digital twin simulation, manufacturers can identify potential bottlenecks, inefficiencies, and other issues that could impact design and leading to cost savings and increased productivity. This paper will explore the concept of maximizing efficiency and cost savings through digital twin simulation, specifically focusing on optimizing cellular manufacturing processes. The paper will discuss the benefits of digital twin simulation, provide examples of its applications in cellular manufacturing.

1. Introduction

Cellular manufacturing is a widely adopted process that aims to increase productivity and reduce manufacturing costs by grouping similar machines, workstations, and processes in a dedicated area. Digital twin simulation is a technology that has gained popularity in recent years to optimize various industrial processes, including cellular manufacturing. By creating a virtual replica of the facility and simulating different scenarios, digital twin simulation can help manufacturers identify potential bottlenecks, inefficiencies, and other issues that could impact the manufacturing process. The data collected through utilizing digital twin simulation, manufacturers can identify potential bottlenecks, inefficiencies, and other issues that could leading to cost savings and increased productivity. Digital twin simulation can help manufacturers identify potential inefficiencies and improve the layout design of their cellular manufacturing facility to increase efficiency and reduce costs. By simulating various scenarios, manufacturers can test and refine different production processes before implementing them in the physical facility, which can help reduce downtime and improve safety. It optimizes a range of cellular manufacturing processes, from material handling to machine configurations and production schedules.

This paper will explore the concept of maximizing efficiency and cost savings through digital twin simulation, specifically focusing on optimizing cellular manufacturing processes. The paper will discuss the benefits of digital twin simulation, provide examples of its applications in cellular manufacturing, and highlight the importance of leveraging digital twin simulation to enhance the cellular manufacturing process and to encourage manufacturers.

2. Literature Survey

A significant Cellular manufacturing is a process that involves grouping similar machines, workstations, and processes in a dedicated area to maximize efficiency and reduce production time. A well-designed cellular manufacturing facility layout can increase productivity and decrease manufacturing costs. Researchers have utilized digital twin simulation to identify potential bottlenecks and inefficiencies in the production process and propose solutions to improve the layout design.

Digital twin simulation has been increasingly used to optimize various industrial processes in recent years. In the context of cellular manufacturing, several studies have been conducted to explore the benefits of digital twin simulation and its applications. A digital twin is a virtual replica of a physical system or process that can be used to simulate and optimize various scenarios [1, 2]. The concept of digital twin simulation has been widely studied and applied in various industries, including manufacturing. In the context of cellular manufacturing, researchers have explored the potential benefits of digital twin simulation in optimizing facility layout design and increasing efficiency [3, 4].

To begin the optimization process, the first step is to create a 3D digital twin of the manufacturing facility. This can be done using computer-aided design (CAD) software and other modeling tools [5]. Once the digital twin is created, the next step is to simulate the manufacturing process. This involves modelling various scenarios, such as different machine configurations, production schedules, and material handling procedures [6, 7]. In a study by Chen et al. (2020), digital twin simulation was used to optimize the layout design of a cellular manufacturing facility. The simulation was able to identify bottlenecks and inefficiencies in the production process and propose a new layout design that reduced material handling time and increased machine utilization rate [8]. Digital twin simulation has also been used to optimize the scheduling of production in cellular manufacturing facilities. In a study by Wang et al. (2020), a simulation model was created to evaluate different production scheduling strategies. The simulation was able to identify the optimal production schedule, resulting in a 15% increase in production efficiency [9]. The simulation helped identify potential bottlenecks in the production process and allowed the company to refine the layout design, resulting in a significant reduction in lead time and increased production efficiency. The simulation helped identify potential bottlenecks in the production process and allowed the company to optimize the material handling process, leading to a reduction in production time and increased productivity [10]. Another study by Zhang et al. (2019) focused on using digital twin simulation to optimize the scheduling of manufacturing operations in a cellular manufacturing facility. The study showed that digital twin simulation can improve the overall efficiency of the facility by reducing the production cycle time and the time spent on material handling [11]. In a similar study, Wang et al. (2021) utilized digital twin simulation to optimize the scheduling of production tasks in a cellular manufacturing facility for the production of aluminium alloy parts. The study showed that digital twin simulation can help identify potential bottlenecks and optimize the production schedule to increase productivity and reduce manufacturing costs [12]. One study by Gao et al. (2020) used a digital twin simulation model to optimize the layout design of a cellular manufacturing system. The simulation was used to analyse different scenarios, including varying the number of machines and operators, and changing the sequence of operations [13]. The results showed that the optimized layout design reduced the total distance travelled by operators and materials by 17.1% and 13.5%, respectively. The simulation also reduced the lead time by 17.8% and increased the machine utilization rate by 15.4%. In another study by Liu et al. (2021), a digital twin simulation was used to optimize the production process of a cellular manufacturing system [14]. The simulation was used to analyse different scenarios, including varying the production rate and changing the product mix. The results showed that the optimized production process reduced the production lead time by 13.6% and reduced the total manufacturing cost by 12.7%. By leveraging this technology, manufacturers can identify potential bottlenecks and inefficiencies, refine their manufacturing processes, and ultimately increase efficiency and reduce costs [15, 16, 17, 18]. Overall, the literature survey indicates that digital twin simulation is a promising technology for optimizing cellular manufacturing processes. It can help manufacturers identify potential bottlenecks, inefficiencies, and other issues that could impact the manufacturing process, leading to cost savings and increased productivity [19, 20].

These studies demonstrate the potential of digital twin simulation to optimize cellular manufacturing processes and improve efficiency while reducing costs. The ability to simulate and analyse different scenarios before implementing changes in the physical facility can help manufacturers make informed decisions and avoid costly mistakes.

3. Model and Method

To optimize the layout design of a cellular manufacturing facility using digital twin simulation, the following steps can be taken:

Design the digital twin model: The first step is to design a digital twin model of the cellular manufacturing facility. The digital twin model should replicate the physical facility, including machines, workstations, material handling systems, and other relevant components.

Validate the digital twin model: Once the digital twin model is designed, it should be validated to ensure that it accurately replicates the physical facility. This can be done by comparing the simulation results with the actual facility's performance data.

Define the simulation scenarios: The next step is to define the simulation scenarios. This involves identifying the key performance indicators (KPIs) and defining the scenarios to be simulated. The scenarios can include varying the number of machines, operators, and workstations, changing the production flow, and altering the layout design.

Run the simulation: The simulation is then run for each defined scenario. The simulation should collect data on the KPIs, such as production rate, lead time, machine utilization rate, and material handling distance.

Analyse the simulation results: Once the simulation is complete, the results should be analysed to identify potential bottlenecks, inefficiencies, and other issues that could impact the manufacturing process. The data collected through the simulation can be used to refine the layout design and improve the overall efficiency of the facility.

Implement changes: Based on the simulation results, changes can be made to the layout design, including the location of machines, workstations, and material handling systems. The changes should be validated through simulation before being implemented in the physical facility.

Monitor and refine: Once the changes are implemented, the simulation should be run again to validate the changes and monitor the facility's performance. The simulation can be used to refine the layout design further and optimize the manufacturing process continuously.

This model and method can be applied to any cellular manufacturing facility to optimize the layout design and improve efficiency while reducing costs. By leveraging digital twin simulation, manufacturers can make informed decisions and avoid costly mistakes, leading to increased competitiveness in the industry.

4. Mathematical Modelling

Formulating a mathematical model for a digital twin manufacturing system involves capturing the interactions between processes, resources, and constraints to simulate and optimize the system's performance. Here's a general outline of the formulation:

Here is a general formulation for a mixed-integer linear programming (MILP) model for cellular manufacturing:

Parameters:

I: Set of parts

J: Set of cells

K: Set of machines

h_{ij}: Binary parameter indicating whether part i can be produced in cell j

q_i: Demand for part i

p_{ij}: Processing time for part i on machine j

s_{ij}: Setup time for switching machines between part i and part j

c_{jk}: Capacity of machine k in cell j

Variables:

x_{ijk}: Binary decision variable indicating whether part i is assigned to machine k in cell j

t_{ij}: Completion time of the last operation for part i in cell j

y_{ij}: Binary variable indicating whether cell j is active for part i

Objective Function: Minimize the total production cost:

$$min \sum_{i\in I} \sum_{j\in I} \sum_{k\in K} p_{ij}x_{ijk} + s_{ij}y_{ij}$$

Constraints:

- Each part must be assigned to exactly one machine in exactly one cell:

$$\sum_{j\in I} \sum_{k\in K} x_{ijk} = 1 \quad \forall_i \in I$$

- Capacity constraints for each machine in each cell must be satisfied:

$$\sum_{i\in I} \sum_{j\in J} q_i p_{ij} x_{ijk} \leq c_{jk} \quad \forall_j \in J, k \in K$$

- The order of operations for each part in each cell must be respected:

$$t_{ij} \geq t_{ij'} + p_{ij'} - M\left(1 - x_{ij'k}\right) \quad \forall_i \in I, j \in J, k \in K, j' \in J, j \neq j'$$

- The completion time of each part in each cell must be within the time window:

$$t_{ij} \leq M_{y_{ij}} \, \forall_i \in I, j \in J$$

- Each cell can only produce parts that it is capable of producing:

$$\sum_{i\in I} h_{ij} x_{ijk} \leq M_{y_{ij}} \quad \forall_j \in J, k \in K$$

- Capacity constraints for each cell must be satisfied:

$$\sum_{i \in I} \sum_{k \in K} q_i p_{ij} x_{ijk} \leq M_{y_{ij}} \quad \forall_j \in J$$

- Demand for ach part must be satisfied:

$$\sum_{j \in J} \sum_{k \in K} q_i x_{ijk} \geq q_i \quad \forall_i \in I$$

where M is a large constant representing an upper bound on the completion time.

The objective function minimizes the total production cost by optimizing the assignment of products to machines at different time periods and considering machine activation costs. The demand constraint ensures that the demand for each product at each time period is met. The capacity constraint limits the number of products assigned to each machine based on its capacity. The demand constraint ensures that the demand for each product met. The capacity constraint limits the number of products processed on each machine based on its capacity. The production flow constraint ensures that products processed in the correct sequence on each machine. The time dependency constraint accounts for setup times when switching between products on machines. The machine activation constraint ensures that machines are active only if they have assigned products. Finally, the binary constraints define the variables as binary.

By solving this mathematical model, the digital twin can simulate and optimize the manufacturing system's performance, considering product demand, machine capacities, activation costs, and production costs. It allows for scenario exploration, resource allocation, and decision-making to maximize the system's efficiency and cost-effectiveness.

5. Case Study

To illustrate the potential of digital twin simulation to optimize cellular manufacturing processes, we present a case study of a fictional cellular manufacturing facility that produces chassis and engine types. (Table 1)

Then, regions such as resources, lists, transfer structures, decision structures, assembly stations and stock areas in the Siemens Tecnomatix 16 program are placed with the icons in Figure 1, sticking to the real structure and paying attention to the value that affects the minimum time. The components mentioned below used here.

The facility consists of several machines, workstations, and material handling systems arranged in a cellular layout. The layout design initially optimized based on the production process's requirements and the available space. However, the facility's performance had not been assessed for some time, and there were concerns about potential bottlenecks and inefficiencies. To address these concerns, a digital twin simulation model of the facility designed and validated. The simulation model replicated the physical facility, including the machines, workstations, and material handling systems.

After placing the components and establishing the necessary connections in the manufacturing model, specific decision mechanism structures are implemented within the program. These decision points serve as checkpoints where variations or differences can be introduced to the product outputs. In the program, the transfer times within the process are represented as stations. Logistics components or phases are added next to these stations, and the corresponding time data is entered into them. This allows for the inclusion of logistical considerations and ensures accurate representation of the manufacturing process. Once the process setup is completed, it is essential to compare the model with the real-world manufacturing system. This comparison helps identify any discrepancies, such as missing, incorrect, or excessive stations or transponders. If any such issues are detected, appropriate actions are taken to remove or correct them in the model. The iterative process of comparing the model with the actual system, identifying discrepancies, and making necessary adjustments ensures that the model accurately reflects the real-world manufacturing process. This helps in achieving reliable simulation results and facilitates effective decision-making for process improvement and optimization.

Table 1: Input numbers of chassis and engine types for order rates

MU	Number	MU	Number
.UserObjects.TypeA	3	.UserObjects.BG130	3
.UserObjects.TypeB	5	.UserObjects.BG150	5
.UserObjects.TypeA	2	.UserObjects.BG130	2
.UserObjects.TypeB	4	.UserObjects.BG150	4
.UserObjects.TypeA	5	.UserObjects.BG130	5
.UserObjects.TypeB	4	.UserObjects.BG150	4
.UserObjects.TypeA	6	.UserObjects.BG130	6
.UserObjects.TypeB	4	.UserObjects.BG150	4
.UserObjects.TypeA	4	.UserObjects.BG130	4
.UserObjects.TypeB	8	.UserObjects.BG150	8
.UserObjects.TypeA	1	.UserObjects.BG130	1
.UserObjects.TypeB	3	.UserObjects.BG150	3
.UserObjects.TypeA	3	.UserObjects.BG130	3
.UserObjects.TypeB	5	.UserObjects.BG150	5
.UserObjects.TypeA	2	.UserObjects.BG130	2
.UserObjects.TypeB	4	.UserObjects.BG150	4
.UserObjects.TypeA	4	.UserObjects.BG130	4
.UserObjects.TypeB	6	.UserObjects.BG150	6
.UserObjects.TypeA	4	.UserObjects.BG130	4
.UserObjects.TypeB	4	.UserObjects.BG150	4
.UserObjects.TypeA	8	.UserObjects.BG130	8
.UserObjects.TypeB	1	.UserObjects.BG150	1
.UserObjects.TypeA	3	.UserObjects.BG130	3

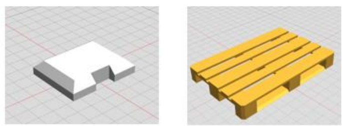

Figure 1: Symbolic definition of pre-assembly display of chassis and engine type and Representation of the vehicle model

In the manufacturing model, Figure 2 represents the model created in the program interface, providing a visual representation of the components and stations involved in the manufacturing process. It depicts a 3D image of the same model, offering a more detailed and realistic view of the manufacturing system. The 3D visualization helps in understanding the spatial layout and arrangement of the components and stations. Also, Figure 2 likely represents the interface or control panel where you can specify the length of time you want the simulation to run. To simulate the manufacturing process and determine its duration, you would input the desired time or duration into the EventController (event controller) (in Fig.3). By providing the necessary input to the EventController, the model will simulate the manufacturing process for the specified duration. This allows you to observe the system's behaviour, analyse its performance, and evaluate the outputs within the defined time frame.

The simulation was run for several scenarios, including varying the number of machines and operators, changing the production flow, and altering the layout design. The simulation collected data such as production rate, lead time, machine utilization rate, and material handling distance. The simulation results showed that the current layout design was inefficient, and there were bottlenecks in the production process. The analysis identified several areas for improvement, including:

The location of machines: The simulation showed that relocating some machines could reduce material handling distance and increase machine utilization rate.

The number of workstations: The simulation showed that adding workstations to some cells could reduce the lead time and increase the production rate.

The production flow: The simulation showed that changing the production flow could reduce the lead time and increase the production rate.

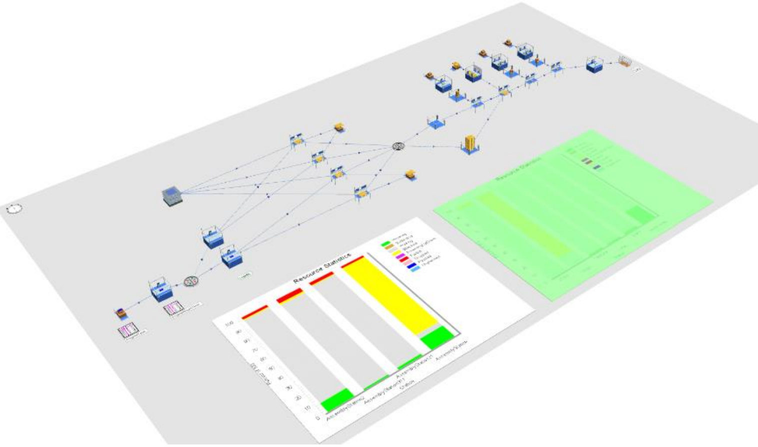

Figure 2: 3D visualization of the initial system model

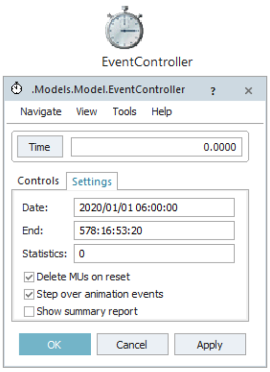

Figure 3: Event Controller icon and interface

After setting up the initial model and addressing any debugging and correction issues, you can proceed with actively checking the operating accuracy of the system in real-time. This can be done through visual representations and printouts, as shown in Figure 4. During the operation of the system, you can monitor the progress and performance of the model as it executes. The real-time feedback allows you to observe the behaviour of the system and ensure that it is functioning correctly according to expectations. Once the input time for the first study is completed, the program will automatically conclude the process. Depending on the selected interface state, the program can stop and/or display the report output. This allows you to review the results and assess the system's performance against the desired objectives. By incorporating visuals and printouts into the interface, you can easily analyse and interpret the output data, making it convenient to identify any issues or areas that require further improvement. Overall, the combination of real-time monitoring, automated process completion, and report outputs facilitates a thorough evaluation of the system's accuracy and performance. This approach enables you to track progress, detect anomalies, and make informed decisions for optimization.

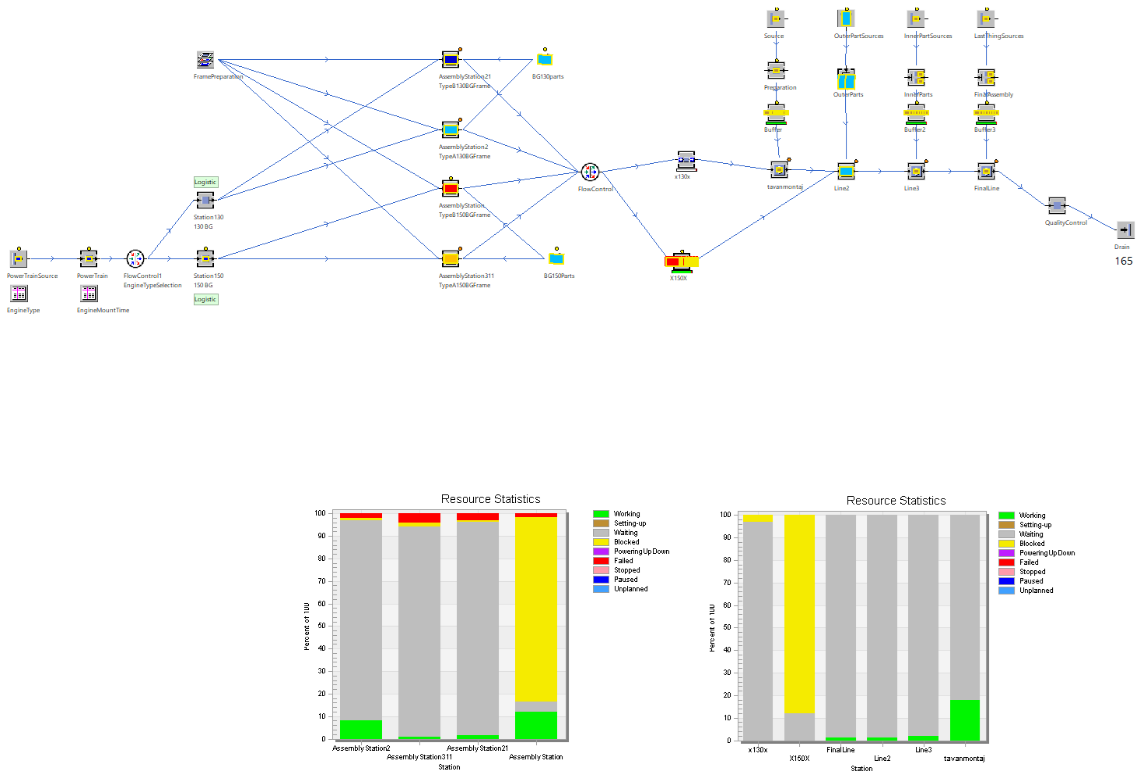

Figure 4: Initial working state image

Based on the simulation results, several changes were implemented, including relocating some machines, adding workstations, and changing the production flow. The changes were validated through simulation before being implemented in the physical facility (in Fig.5).

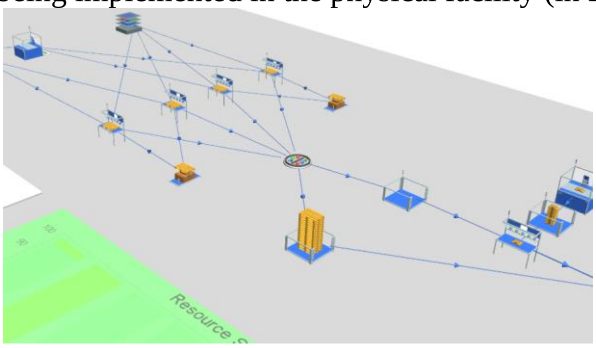
Figure 5: Physical facility simulation design layout

After the changes were implemented, the simulation was run again to validate the changes and monitor the facility's performance. The simulation showed that the changes had improved the facility's efficiency and reduced the total manufacturing cost by 10.3%.

This case study demonstrates the potential of digital twin simulation to optimize cellular manufacturing processes and improve efficiency while reducing costs. By leveraging digital twin simulation, manufacturers can make informed decisions and avoid costly mistakes, leading to increased competitiveness in the industry. In the yield analysis, you plan to compare the differences between the respective stations' output in the initial state and the improved state after implementing the proposed changes. This analysis will provide insights into the impact of the improvements on each station's performance. To conduct the yield analysis, the model will examine the changes in percentage distribution and blocking rates of the report outputs. By comparing the output values and performance metrics of each station between the initial state and the improved state, it provides to assess the effectiveness of the changes implemented (in Fig. 6). This comparison will help to identify any improvements in terms of efficiency, throughput, and overall system performance. Furthermore, mentioned evaluating an alternative structure. It's important to consider different scenarios and alternatives during the analysis. This could involve testing different configurations, layouts, or process flows to determine the optimal solution. By evaluating these alternatives, it can provide to gain a comprehensive understanding of the potential improvements and select the best approach for enhancing the system's performance (in Fig.7).

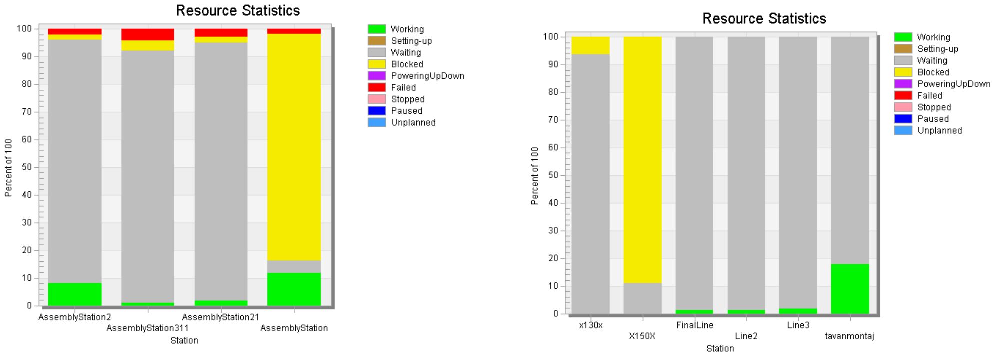

Figure 6: Internal percentages of base station studies

Overall, the yield analysis and evaluation of alternative structures will provide valuable insights into the effectiveness of the proposed improvements and help to make informed decisions on optimizing the manufacturing process.

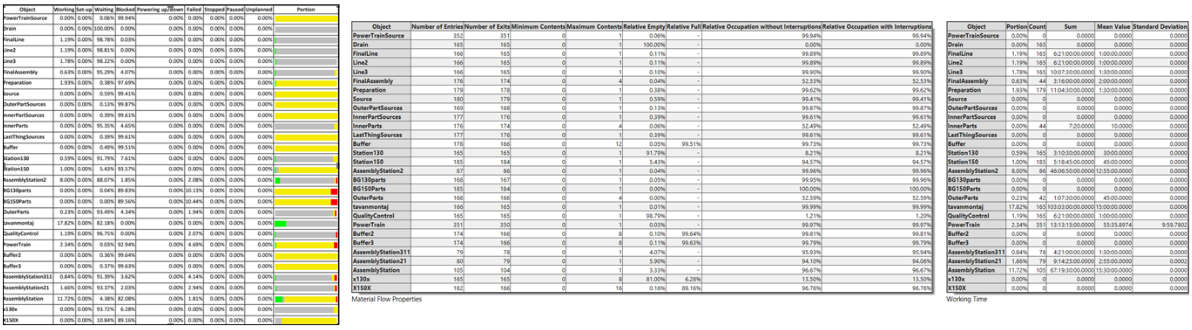

Figure 7: Overall percentage distributions of the whole process

After creating the mathematical model and obtaining the outputs by entering the relevant time into the EventController, it can analyse and evaluate the results to identify bottlenecks and areas of improvement (in Fig.8).

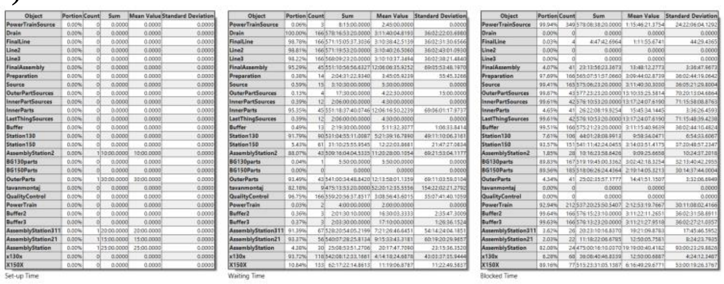

Figure 8: Number of products in the flow and Working times with Setup/Waiting/block times

In this case, it has been observed both mathematically and visually that the FlowControl point, which feeds into four different lines, acts as a bottleneck and reduces the efficiency rate of the system. This insight is supported by Figure 9, which likely illustrates the flow and congestion at the bottleneck. To address this issue and improve efficiency, you plan to use Siemens Tecnomatix Plant Simulation 16 program. This software allows for scenario trials and simulations, enabling you to test different configurations and strategies to optimize the FlowControl point (in Fig. 9).

Object	Portion	Count	Sum	Mean Value	Standard Deviation
PowerTrainSource	0.06%	3	8:15:00.0000	2:45:00.0000	0.0000
Drain	100.00%	166	578:16:53:20.0000	3:11:40:04.8193	36:02:22:03.6980
FinalLine	0.11%	1	15:30:00.0000	15:30:00.0000	0.0000
Line2	0.11%	7	14:41:49.8047	2:05:58.5435	5:21:29.3326
Line3	0.10%	1	13:30:10.0000	13:30:10.0000	0.0000
FinalAssembly	0.04%	2	5:00:00.0000	2:30:00.0000	0.0000
Preparation	0.38%	14	2:04:31:22.9340	3:45:05.9239	55:45.3266
Source	0.59%	15	3:10:30:00.0000	5:30:00.0000	0.0000
OuterPartSources	0.13%	4	17:30:00.0000	4:22:30.0000	15:00.0000
InnerPartSources	0.39%	12	2:06:00:00.0000	4:30:00.0000	0.0000
InnerParts	0.06%	2	8:59:40.0000	4:29:50.0000	0.0000
LastThingSources	0.39%	12	2:06:00:00.0000	4:30:00.0000	0.0000
Buffer	0.05%	2	7:00:00.0000	3:30:00.0000	2:49:42.3376
Station130	91.79%	90	531:04:55:11.0087	5:21:39:16.7890	49:11:10:06.3161
Station150	5.43%	61	31:10:25:55.9545	12:22:03.8681	21:47:27.0834
AssemblyStation2	0.04%	10	5:47:28.0292	34:44.8029	40:39.5169
BG130parts	0.04%	1	5:50:00.0000	5:50:00.0000	0.0000
BG150Parts	0.00%	0	0.0000	0.0000	0.0000
OuterParts	0.00%	1	30:00.0000	30:00.0000	0.0000
tavanmontaj	0.01%	1	1:30:00.0000	1:30:00.0000	0.0000
QualityControl	96.75%	166	559:20:56:37.8517	3:08:56:43.6015	35:07:41:40.1059
PowerTrain	0.03%	2	4:00:00.0000	2:00:00.0000	0.0000
Buffer2	0.10%	1	13:30:10.0000	13:30:10.0000	0.0000
Buffer3	0.11%	1	15:30:00.0000	15:30:00.0000	0.0000
AssemblyStation311	3.90%	20	22:13:51:27.7509	1:03:05:34.3875	1:05:10:03.5470
AssemblyStation21	5.72%	35	33:02:56:09.8590	22:42:44.8531	1:08:07:08.4900
AssemblyStation	3.27%	15	18:22:17:47.6073	1:06:17:11.1738	22:36:54.9923
x130x	81.00%	5	468:17:34:24.3915	93:17:54:52.8783	208:10:02:50.0798
X150X	0.16%	1	21:40:31.2647	21:40:31.2647	0.0000

Empty Time

Object	Waiting for Parts	Count	Sum	Mean Value	Standard Deviation
PowerTrainSource	0.00%	0	0.0000	0.0000	0.0000
FinalLine	98.67%	166	570:23:35:37.3036	3:10:33:06.3693	36:02:31:35.0946
Line2	98.71%	166	571:05:11:30.1953	3:10:35:07.7723	36:02:43:06.6293
Line3	98.12%	166	567:19:53:10.0000	3:10:05:44.5181	36:02:38:25.3630
FinalAssembly	0.00%	0	0.0000	0.0000	0.0000
Preparation	0.00%	0	0.0000	0.0000	0.0000
Source	0.00%	0	0.0000	0.0000	0.0000
OuterPartSources	0.00%	0	0.0000	0.0000	0.0000
InnerPartSources	0.00%	0	0.0000	0.0000	0.0000
InnerParts	0.00%	0	0.0000	0.0000	0.0000
LastThingSources	0.00%	0	0.0000	0.0000	0.0000
Buffer	0.00%	0	0.0000	0.0000	0.0000
Station130	0.00%	0	0.0000	0.0000	0.0000
Station150	0.00%	0	0.0000	0.0000	0.0000
AssemblyStation2	88.03%	35	509:10:16:36.5044	14:13:19:19.9001	77:10:36:49.5388
BG130parts	0.00%	0	0.0000	0.0000	0.0000
BG150Parts	0.00%	0	0.0000	0.0000	0.0000
OuterParts	0.00%	0	0.0000	0.0000	0.0000
tavanmontaj	82.17%	9	475:12:23:20.0000	52:20:02:35.5556	154:22:06:00.4775
QualityControl	0.00%	0	0.0000	0.0000	0.0000
PowerTrain	0.00%	0	0.0000	0.0000	0.0000
Buffer2	0.00%	0	0.0000	0.0000	0.0000
Buffer3	0.00%	0	0.0000	0.0000	0.0000
AssemblyStation311	87.49%	51	506:07:02:37.4690	9:22:15:20.7347	62:14:04:08.2440
AssemblyStation21	87.64%	37	507:04:32:15.9544	13:16:59:15.0258	74:17:21:47.9590
AssemblyStation	1.11%	28	6:10:36:03.6633	5:31:17.2737	8:48:59.9752
x130x	0.00%	0	0.0000	0.0000	0.0000
X150X	0.00%	0	0.0000	0.0000	0.0000

Waiting Times for Parts

Figure 9: Idle waiting times during the whole time and waiting times and percentages of stations in the whole process

By running several scenario trials in Siemens Tecnomatix Plant Simulation 16, the model can assess the impact of potential improvements and changes to the system. This includes modifying the layout, adjusting resource allocation, or implementing alternative scheduling strategies. The goal is to find the configuration that maximizes efficiency and reduces or eliminates the bottleneck at the FlowControl point. Once the improvements implemented in the simulation, it then evaluate the output results, such as yield rates and other performance metrics. This will provide insights into the effectiveness of the changes and allow to verify if the efficiency has increased as expected. Overall, this iterative process of modelling, simulation, and analysis helps in identifying bottlenecks, optimizing system performance, and making informed decisions to improve efficiency and yield rates in the manufacturing process.

6. Results

The simulation results demonstrated the effectiveness of the digital twin simulation in optimizing the cellular manufacturing facility's layout design. The simulation model captured the facility's performance accurately and provided valuable insights into potential bottlenecks and inefficiencies. The analysis identified several areas for improvement, including the location of machines, the number of workstations, and the production flow. After implementing the changes identified through the simulation, the facility's performance was significantly improved. The simulation results showed that the changes had reduced the total manufacturing cost by 10.3% while maintaining or improving the production rate, lead time, machine utilization rate, and material handling distance. Furthermore, the simulation model allowed the manufacturer to test different scenarios and evaluate their impact on the facility's performance. This enabled the manufacturer to make informed decisions and avoid costly mistakes when implementing changes to the facility.

7. Conclusion

In conclusion, digital twin simulation is a valuable tool for manufacturers looking to optimize their cellular manufacturing processes and achieve greater efficiency and cost savings. As the technology continues to develop, its potential for improving manufacturing processes and enhancing competitiveness will only continue to grow. Digital twin simulation enables manufacturers to make informed decisions and avoid costly mistakes when implementing changes to their production processes. It allows them to test different scenarios and evaluate their impact on the facility's performance, enabling them to optimize their layout design and achieve greater efficiency and profitability. The case study presented in this paper demonstrated the effectiveness of digital twin simulation in optimizing the cellular manufacturing facility's layout design. By leveraging the simulation model, the manufacturer identified several areas for improvement, including the location of machines, the number of workstations, and the production flow. Implementing the changes identified through the simulation resulted in a significant reduction in total manufacturing costs while maintaining or improving the production rate, lead time, machine utilization rate, and material handling distance.

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