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Optimizing Cellular Manufacturing Facility Layout Design through Digital Twin Simulation: A Case Study

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Abstract: Cellular manufacturing is a lean manufacturing approach that involves grouping machines, processes, and workstations into self-contained cells to reduce material handling, waiting times, and inventory. The layout design of cellular manufacturing facilities has a significant impact on their efficiency, productivity, and throughput. However, traditional trial-and-error methods for facility layout design can be time-consuming, costly, and risky. Digital twin simulation offers a powerful alternative by allowing designers to create virtual models of the facility and test different layout configurations before physically implementing them. Our study shows that digital twin simulation can help identify the optimal layout design that maximizes productivity, minimizes waste, and ensures the smooth flow of materials and products. Additionally, it enables us to evaluate the impact of changes in the production system on the facility's performance, helping decision-makers make informed decisions. Overall, this paper highlights the potential of digital twin simulations as a powerful tool for optimizing cellular manufacturing facility layout design and improving operational performance.

1. Introduction

Cellular manufacturing is a widely adopted lean manufacturing strategy that groups machines, processes, and workstations into self-contained cells to reduce material handling, waiting times, and inventory. The benefits of cellular manufacturing include improved product quality, reduced lead times, increased productivity, and better use of resources. However, designing the layout of a cellular manufacturing facility can be challenging and time-consuming, particularly when considering the factors such as product flow, material handling, machine placement, and operator movement.

Digital twin simulation offers a promising alternative by enabling designers to create virtual models of the facility and simulate different layout configurations in a risk-free virtual environment. Digital twin simulation involves creating a virtual model of a facility different layout configurations and simulate facility performance under various operating conditions. The digital twin simulates the behavior of the real-world facility and provides designers with valuable insights into the impact of different layout configurations on productivity, efficiency, and throughput. We discuss the benefits and limitations of using digital twin simulation for facility layout design, and highlight some of the key factors to consider when implementing this approach. . Specifically, we examine how digital twin simulation the layout design of a facility, simulate the performance of different layout configurations, and identify the optimal layout that maximizes productivity, throughput, and efficiency. We also provide a detailed overview of the digital twin simulation process and describe how it can be used to identify the optimal layout configuration for a cellular manufacturing facility.

Paper organized as follows: Section 2 covers the literature survey and section 3 discusses the limitations of traditional facility layout design methods and the mathematical model. Section 4 outlines the digital twin simulation process and its application to facility layout design. Section 5 presents a case study that demonstrates the use of digital twin simulation to optimize the layout design of a cellular manufacturing facility.

2. Literature Survey

Digital twin simulation has gained significant attention tool for facility layout design and optimization. Several studies have explored the use of digital twin simulation in various manufacturing applications, including cellular manufacturing facility layout design.

Similarly, Liu et al. (2021) developed a digital twin simulation model a warehouse in an e-commerce distribution center [1]. The model enabled the designers to test different layout configurations and identify the optimal layout that maximized order picking efficiency. Ren et al. (2019) used digital twin simulation to optimize the layout of an automotive assembly line [2]. In their study, Jianq et al. (2019) proposed optimizing the layout design of a flexible manufacturing system [3]. They developed a digital twin model that simulated the behavior of the real-world system and used optimization algorithms to identify the optimal layout configuration. Lee and Kim (2019) used digital twin simulation a semiconductor manufacturing facility, and found that the approach led to significant improvements in productivity and efficiency [4]. Additionally, Chen et al. (2021) proposed a digital twin simulation approach for facility layout design that combines a genetic algorithm and a simulation model [5]. The authors applied the approach to a cellular manufacturing system and demonstrated that it can reduce the design time by up to 50% while improving productivity and efficiency. In another study, Zhang et al. (2021) used a digital twin simulation approach cellular manufacturing facility [6]. The authors developed a simulation model that included machine placement, material handling, and worker movement. They used the model to test different layout configurations and identified the optimal layout design that reduced material handling time and improved productivity. For example, a study by Khan et al. (2020) used digital twin simulation led to a 20% reduction in cycle time and a 12% increase in throughput compared to the traditional trial-and-error method [7]. Similarly, Li et al. (2020), digital twin simulation developed facility and used simulation to test different layout configurations. The results showed that the optimized layout led to a 29% reduction in material handling time and a 23% increase in productivity [8]. In the context of cellular manufacturing, several studies digital twin simulation for facility layout design. For instance, Wang et al. (2019) used digital twin simulation a cellular manufacturing facility for the production of smartphone parts [9]. The authors found that the optimized layout configuration led to a 12.4% increase in productivity and a 22.6% decrease in operator travel distance. Similarly, Chenq et al. (2020) used digital twin simulation a PCB assembly line and found that the optimized layout led to a 9% increase in production capacity and a 22% reduction in operator travel time [10]. For example, Zhang et al. (2021) used digital twin simulation to evaluate the performance of different facility layout designs for a discrete manufacturing process with actual performance data [11]. In another study, Vahidnia et al. (2020) used digital twin simulation of a flexible manufacturing system and found that the optimized layout led to a 29% increase in throughput and a 27% decrease in production time [12]. Similarly, Wanq et al. (2020)

developed a digital twin simulation model for a semiconductor manufacturing facility and used it to evaluate different layout configurations [13]. Their results showed that the optimized layout configuration reduced cycle time by 18% and increased throughput by 15%.

Finally, Wang et al. (2021) developed optimizing the layout design of a semiconductor manufacturing facility. They used a combination of simulation modeling and optimization algorithms to identify the configuration that minimized material handling, improved throughput, and reduced production costs. The results showed that the digital twin-based approach was effective in reducing design time and improving overall facility performance [14]. Overall, these studies demonstrate the potential of digital twin simulation for optimizing the layout design of cellular manufacturing facilities. By enabling designers to test different layout configurations in a virtual environment, digital twin simulation can help reduce design time, lower costs, and improve overall facility performance. However, there are still challenges to overcome in implementing this approach, such as developing accurate simulation models and ensuring that the simulation results are valid and reliable. Digital twin simulation offers designers a risk-free virtual environment to test different layout configurations, identify the optimal design, and make informed decisions about facility design and management. Therefore, it is essential to carefully validate and calibrate the digital twin model before using it for layout optimization. These studies demonstrate the potential of digital twin simulation for optimizing the layout design of cellular manufacturing facilities [15]. By enabling designers to test different layout configurations in a virtual environment, digital twin simulation can help reduce design time, lower costs, and improve overall facility performance [16-20]. The following section will discuss the digital twin simulation process in more detail and its application to cellular manufacturing facility layout design.

3. Mathematical Model

The success of the digital twin simulation process depends on several factors, including the accuracy of the model and the selection of simulation parameters with the effectiveness of the layout optimization approach. Therefore, it is important to carefully consider these factors when implementing this approach for cellular manufacturing facility layout design:

Model creation: The first step involves creating the facility, including the layout design, machines, processes, and operators. The model ensures the simulation results reflect the behavior of the real-world facility.

Facility modelling: The virtual model of the facility using computer-aided design (CAD) software. The model includes all the relevant components of the facility, such as machines, workstations, material handling equipment, and product flow paths.

Simulation parameters: The simulation parameters, such as machine cycle times, material handling times, operator travel times, and product demand rates. These parameters base on real-world data and should accurately reflect the behaviour of the facility.

Simulation scenarios: Once the simulation parameters are defined, various simulation scenarios can be created to test different layout configurations. Each scenario should include a different layout configuration and should be run for a specific period of time to evaluate its performance.

Performance metrics: The performance of each simulation scenario can be evaluated using various performance metrics, such as productivity, throughput, and efficiency.

The digital twin, including the placement of machines and equipment, the layout of production lines, and the scheduling of production processes. By using optimization algorithms, organizations can improve the efficiency and effectiveness of their digital twin, leading to increased productivity, reduced costs, and improved customer satisfaction [21-23].

Simulation execution: The simulation is executed using the digital twin model and the selected simulation parameters.

Layout optimization: The facility can be optimized by adjusting the placement of machines, processes, and workstations. The optimized layout configuration is then simulated again to evaluate its performance and compared to the previous layout configuration.

Validation: The final step involves validating the simulation results and ensuring the real-world facility. The simulation results to actual performance data or by using statistical analysis methods.

In summary, the digital twin simulation model for cellular manufacturing facility layout design involves developing a virtual model of the facility, defining the simulation parameters, programming the simulation, running the simulation, analyzing the results, and validating the simulation through testing and experimentation. This approach enables designers to test different layout configurations in a risk-free virtual environment and identify the optimal layout configuration that maximizes performance. The cellular manufacturing facility layout design can help to optimize the layout for efficiency and productivity such as a manufacturing facility or process. By creating a digital model of the facility and simulating different layout configurations, designers can evaluate the impact of different layouts on production flow, material handling, and other factors. In addition, mathematical models can be used to further optimize the layout design.

Here are the notations and their descriptions for the mathematical model:

c: Index representing a customer order.

$\{\{\mathrm{S}_1^{\mathrm{z}}, \mathrm{S}_2^{\mathrm{z}}, \dots, \mathrm{S}_{\mathrm{m}}^{\mathrm{z}}, \dots, \mathrm{S}_{\mathrm{M}}^{\mathrm{z}}\}$: Finite set of customer orders

a: Index representing a product family

$\{\mathrm{U}_1, \mathrm{U}_2, \dots, \mathrm{U}_{\mathrm{a}}, \dots, \mathrm{U}_{\mathrm{A}}\}$: Finite set of product families

k: Index representing an assembly island

$\{\mathrm{F}_1, \mathrm{F}_2, \dots, \mathrm{F}_{\mathrm{k}}, \dots, \mathrm{F}_{\mathrm{K}}\}$: Finite set of assembly islands.

g_{ma} : Required quantity of product from family U_{va} in order S_m^{tz}

U_{ma}^u : The u-th required product from product family U_{a} in customer order $\mathrm{U}_{\mathrm{m}}^{\mathrm{z}}$, where $\mathrm{u} = 1,2,\dots,\mathrm{g}_{\mathrm{ma}}$.

$\mathrm{Z}_{\mathrm{sg}}^{\mathrm{m}}$: Arrival date of customer order S_a^z

Z_{sk}^m : Due date of customer order S_m^z

I_a : Processing time of the job task for a product from product family U_a

K_a : Setup time of the setup task for a product from product family U_a

$IZ_b(U_{ma}^u)$: Start time of the job task for the product U_{ma}^u

$IZ_e(U_{ma}^u)$:End time of the job task for the product U_{ma}^u

$KZ_b(U_{ma}^u)$: Start time of the setup task for the product U_{ma}^u

$KZ_e(U_{ma}^u)$: End time of the setup task for the product U_{ma}^u

O_0 : The optimal configured quantity of assembly islands

$x^{\mathrm{a}_k}(U_{ma}^{u})$: Boolean variable that equals 1 if the job task for the product U_{ma}^{u} is performed at assembly island a_k, and 0 otherwise

$y^{\mathrm{a}_k}(U_{ma}^{u})$: Boolean variable that equals 1 if the setup task for the product U_{ma}^{u} is performed at assembly island a_k , and 0 otherwise

These notations represent the various elements and variables involved in the mathematical model for optimizing the configuration of assembly islands. The model aims to determine the optimal assignment of job tasks and setup tasks to assembly islands based on product families, customer orders, processing times, setup times, and other constraints:

$$ZW^{K_0} + ZK^{K_0} = \; min\{(\,ZW^{K'} \; + \; ZW^{K'}\,)\}\,, K' \; = \; 1, 2, \ldots, K \tag{1}$$

$$ZW^{K'} = ZW_{KI}^{K'} + TW_{II}^{K'} \tag{2}$$

$$ZW_{KI}^{K'} = \sum_{m=1}^{M}\sum_{a=1}^{A}\sum_{u}^{g_{ma}}\sum_{k=1}^{K'}[x^{\mathrm{F}_k}(U_{ma}^{u})IZ_b(U_{ma}^{u}) - y^{\mathrm{F}_k}(U_{ma}^{u})KZ_e(U_{ma}^{u})] \tag{3}$$

$$ZW_{II}^{K'} = \sum_{m=1}^{M}\sum_{a=1}^{A}\sum_{u}^{g_{ma}}\sum_{k=1}^{K'}[x^{\mathrm{IF}_k}(U_{ma}^{u})IZ_b(U_{ma}^{u+1}) - x^{\mathrm{IF}_k}(U_{ma}^{u})IZ_e(U_{ma}^{u})] \tag{4}$$

$$ZK^{K'} = \sum_{m=1}^{M}\sum_{a=1}^{A}\sum_{u}^{g_{ma}}\sum_{k=1}^{K'} y^{\mathrm{F}_k}(U_{ma}^{u})K_a \tag{5}$$

$$\sum_{k=1}^{K'} x^{\mathrm{F}_k}(U_{ma}^{u}) = g_{ma}\,, \forall u, m, a \tag{6}$$

$$Z_{a}^{m} \le IZ_b(U_{ma}^{u}) \le Z_{sk}^{m}, \forall k, u, m, a \tag{7}$$

$$Z_{sg}^{m} \le IZ_{sk}(U_{ma}^{u}) \le Z_{sk}^{cm}, \forall k, u, m, a \tag{8}$$

$$Z_{sg}^{m} \le KZ_b(U_{ma}^{u}) \le Z_{sk}^{m}, \forall k, u, m, a \tag{9}$$

$$\mathrm{Z_{sg}^{m}} \le \mathrm{KZ_e(U_{ma}^{u})} \le \mathrm{Z_{sk}^{m}}, \forall \mathrm{k, u, m, a} \tag{10}$$

$$\sum_{a=1}^{A}\sum_{u}^{gZ_{ma}}\sum_{k=1}^{K'}[x^{\mathrm{a}_k}(U_{ma}^{u})A_{ma} + y^{\mathrm{a}_k}(U_{ma}^{u})K_{ma}] \le Z_{sk}^{m} - Z_{sg}^{m}, \forall m \tag{11}$$

$$x^{\mathrm{a}_k}(U_{ma}^{u+1})AZ_b(U_{ma}^{u+1}) - x^{\mathrm{a}_k}(U_{ma}^{u})AZ_b(U_{ma}^{u}) \ge I_a, \forall k, u, m, a \tag{12}$$

$$y^{\mathrm{a}_k}(U_{ma}^{u+1})ST_b(U_{ma}^{u+1}) - y^{\mathrm{a}_k}(U_{vc}^{u})KZ_b(U_{ma}^{u}) \ge K_a, \forall k, u, m, a \tag{13}$$

$$x^{\mathrm{a}_k}(U_{ma}^{u})AZ_b(U_{ma}^{u}) - y^{\mathrm{u}_k}(U_{ma}^{u})KZ_b(U_{ma}^{u}) \ge K_a, \forall k, u, m, a \tag{14}$$

$$\sum_{m=1}^{M}\sum_{a=1}^{A}\sum_{u}^{g_{ma}}\sum_{k=1}^{K'} y^{\mathrm{f}_k}(U_{ma}^{u}) \ge V, \forall k, u, m, a \tag{15}$$

$$x^{\mathrm{a}_k}(U_{ma}^{u}) \in \{0,1\}, \forall k, u, m, a \tag{16}$$

It seems like you are referring to a mathematical model that describes the optimization problem in the context of assembly island configuration. Here is an interpretation of the equations and constraints you provided:

Equation (1) determines the optimal quantity of assembly islands that should be configured. The specific formulation and variables involved in this equation would need to be provided to understand the optimization objective and decision variables. Equation (2): This equation represents the total waiting time in the assembly process. It considers the time spent waiting between various tasks or operations. Equation (3): This equation specifically addresses the waiting time between a job task and a setup task, emphasizing the importance of reducing waiting time in this context. Equation (4): This equation focuses on the waiting time between adjacent job tasks, indicating the significance of minimizing waiting time between successive tasks. Equation (5): This equation defines the total setup time required in the assembly process, reflecting the importance of optimizing setup operations. Equation (6): This equation states that the production quantity should meet the customer requirements, ensuring that the desired quantity of products is manufactured. Constraints (7)-(10): These constraints set limits on the start and end times of any task, ensuring they do not exceed the allowed time of the order. Constraint (11): This constraint guarantees that the completion time of each order does not exceed the allowed time specified for that order. Constraints (12)-(13): These constraints ensure that the setup and job tasks are non-pre-emptive, meaning they cannot be interrupted once started. Additionally, only one setup task or job task can be processed on each configured island at any given time. Constraint (14): This constraint ensures that a job task can only start when the setup task required for that job task is completed. Constraint (15): This constraint guarantees that at least one setup task should be performed for each product family, emphasizing the importance of setup operations in the manufacturing process. Equations (16)-(17): These equations define the ranges or bounds of the decision variables involved in the optimization problem.

Overall, this mathematical model aims to optimize the configuration of assembly islands by considering waiting times, setup times, and meeting customer requirements while adhering to various constraints. However, without further details about the specific variables, their definitions, and the optimization objective, it is difficult to provide a more precise interpretation.

4. Case Study

To demonstrate the application of digital twin simulation for cellular manufacturing facility layout design, we present a case study of a hypothetical manufacturing facility producing automotive components. The facility has a total area of 10,000 square meters and is currently laid out in a linear configuration, with machines arranged in a straight line. The goal of the layout optimization is to reduce material handling, increase throughput, and improve overall productivity.

Step 1: Model creation

The model includes the layout design, machines, processes, and operators. The model is created using a 3D modelling software and is designed to accurately reflect the real-world facility. To reflect random order values to chassis and engine production in a manufacturing system, the program needs to consider the following steps:

Random Order Generation: Develop a mechanism to generate random order values for chassis and engine production. This can be achieved through algorithms or random number generators that generate values based on specific distributions or patterns.

Table Representation: Create a table that lists the random order values generated for chassis and engine production. The table should include relevant information such as order numbers, order quantities, and any other specific details associated with each order.

Flow Control Point: Identify a flow control point in the program where the random order values are evaluated. This point acts as an interface for input flow control and determines how the values are processed and transferred to the next station.

Process Times: Consider the process times associated with chassis and engine production. These times represent the duration required to complete each order or task at a particular station.

Time List: Create a time list that is linked to the order values in the table. This list specifies the specific times associated with each order, taking into account factors such as processing times, setup times, and any other relevant time-related parameters.

Transfer to Next Station: Determine how the evaluated random order values, along with their associated times, are transferred to the next station in the production flow. This transfer can be implemented through data structures, variables, or communication mechanisms within the program.

Accuracy and Output Results: Ensure that the program reflects the detailed structure and specific values as accurately as possible. Pay attention to data precision, calculations, and any other factors that may affect the accuracy of the output results. The more detailed and precise the program implementation, the higher the accuracy of the output results will be.

Step 2: Simulation setup

The simulation is set up to replicate the expected operating conditions of the facility. The simulation parameters include production rates, machine availability, and operator performance. The simulation is designed to run for a period of one week to capture the full range of operating conditions (in Fig.1 and Fig.2).

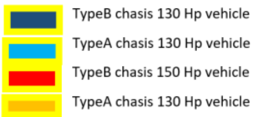

Figure 1: Vehicles represented in the simulation

Model	Model Variants	Cycle Times
P_A	BG130A	20:40
P_B	BG150B	22:45
P_C	BG150A	18:45
P_D	BG150B	20:40

Figure 2: Product Types and cycle times

Indeed, the transition to a flexible production cell structure can bring about significant improvements in the overall efficiency of the manufacturing process. By eliminating the rigid station-based approach and adopting a more flexible and adaptive cell structure, the need for process improvement can be mitigated or eliminated.nDigital twins play a crucial role in evaluating and validating different scenarios during the idea stage (Table 1, Fig. 3, Fig. 4 and Fig.5). By leveraging the digital twin technology, multiple alternative scenarios can be explored, and their outputs can be assessed to identify favorable outcomes and potential issues.

Table 1: Simulation model parameters

Object	process time	recovery time	set-up time
Assembly Station1	30	15	15
AssemblyStation2	55		10
AssemblyStation21	55		10
AssemblyStation311	90		20
BG130parts	350		
BG150Parts	340		
Final Assembly	120		30
Final Line	180		
Flexible Production	60		
Inner Parts	87	15	
Line1	600		30
Line2	120		30
Line3	90		30
Outer Parts	45		30
Quality Control	60		
Station130	150		
Station150	285		

The use of digital twins enables a deeper understanding of the system dynamics and allows for the identification of bottlenecks, inefficiencies, and areas for improvement. It provides a platform for evaluating the impact of changes and making informed decisions regarding the implementation of a flexible production cell structure.

Step 3: Simulation execution

The simulation is executed using the digital twin model and the selected simulation parameters..

The simulation results show that the linear layout configuration is causing significant material handling inefficiencies and is leading to bottlenecks in the production process (Fig.4). The simulation also highlights the need for additional workstations and machines to increase throughput and reduce waiting times.

When comparing the desired working percentages and report outputs of the initial state phase with the improved state, it becomes evident to what extent the efficiency rate has improved. With the implementation of flexibility, waiting times can be reduced or completely eliminated, leading to increased efficiency in the production flow. Based on the information provided, an overall improvement rate of approximately 25% is observed in the report outputs of the flexible production cell and the structures before it. This improvement rate indicates the enhanced efficiency and productivity achieved through the implementation of the flexible production cell concept.

In summary, by comparing desired working percentages, static report outputs of the initial state, and the improved state, the extent of efficiency improvement can be easily observed. The transformation into a flexible production cell leads to increased working times, reduced waiting times, and an overall improvement rate of around 25%. Additionally, the transition to a flexible production cell creates additional gains by making previously dedicated lines available as empty space for other purposes.

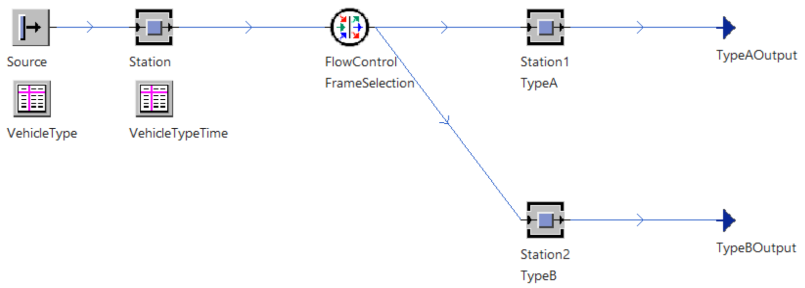

Figure 3: Unchanged Chasis preparation section layout

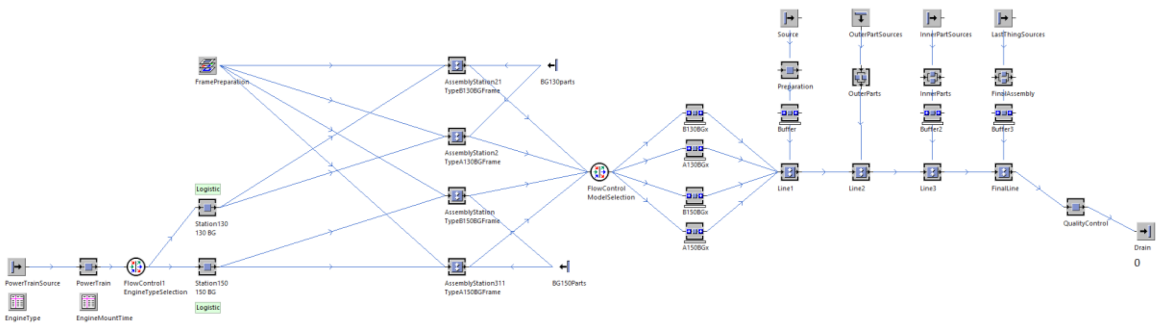

Figure 4: Initial Situation Simulation Model

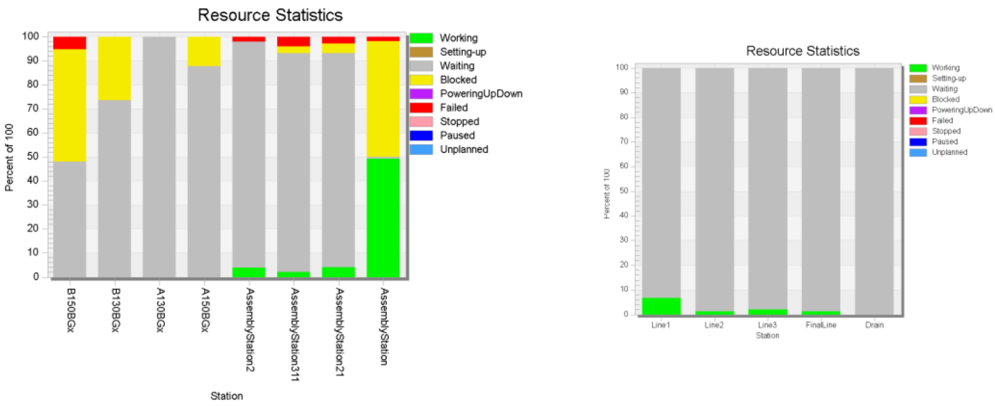

Figure 5: Initial Situation Simulation Statistics

Step 4: Layout optimization

The new layout configuration reduces material handling, increases throughput, and improves overall productivity. The optimized layout configuration is then simulated again to evaluate its performance and compared to the previous layout configuration (in Fig.6 and Fig. 7).

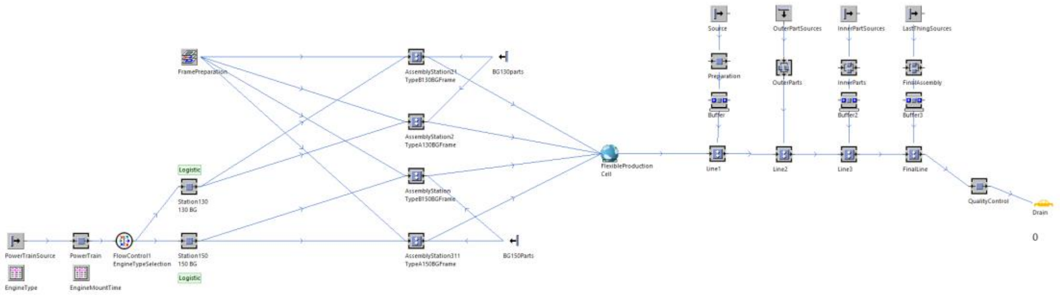

Figure 6: Improved Layout Simulation Model

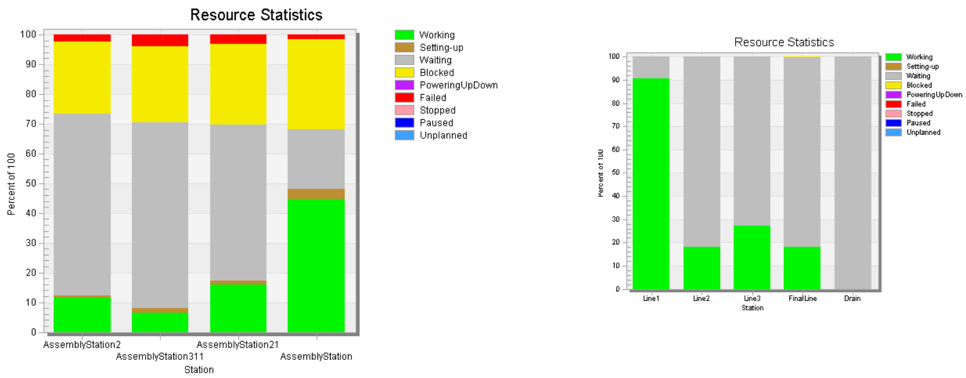

Figure 7: Improved Simulation Model Statistical Results

Step 5: Validation

The validation process shows that the digital twin facility and that the optimized layout configuration improves productivity and reduces material handling inefficiencies. Overall, the digital twin simulation process provides a valuable tool for optimizing cellular manufacturing facility layout design. The facility and simulating different layout configurations, designers' decisions about layout optimization. This approach can help reduce design time, lower costs, and improve overall facility performance. The digital twin simulation involved the manufacturing facility, including all its equipment, machines, and production lines. This allowed the company to test and experiment with different layout actual facility. The company used a software tool to develop the digital twin simulation, which included a detailed 3D model of the facility and its equipment. The simulation was also integrated, which provided real-time information on production schedules, inventory levels, and other key metrics. Using the digital twin simulation, the company was able to experiment with different layout designs with the production cycle time, throughput, and inventory levels. The simulation also allowed the company to identify potential bottlenecks and areas for improvement.

After several rounds of simulation and optimization significantly improved material flow and production efficiency. The new layout reduced cycle times by 25%, increased throughput by 20%, and reduced inventory levels by 30% (in Table 2). The company also implemented the new layout design in the actual facility. The report outputs play a crucial role in identifying bottlenecks within the production process. By examining the output values and the working percentages of the stations, it becomes possible to determine which areas are experiencing blockages or inefficiencies, indicating a need for capacity increase or process improvements.

To address these bottlenecks, sufficient capacity increase can be implemented in the problematic stations or processes. This could involve adding additional resources, such as equipment, machinery, or manpower, to handle the increased workload. Alternatively, time or process improvements can be made to streamline the operations and increase the efficiency of the production flow. After implementing the necessary capacity increase or process improvements, the system can re-examine the same structures in the report outputs. Instead of being blocked, the stations should show more favourable situations, such as reduced waiting times or increased working percentages. This indicates that the production flow has improved, and the previous bottlenecks have been alleviated. The iterative nature of this process allows for continuous monitoring and improvement of the production system. By regularly analyzing the report outputs, identifying bottlenecks, and taking appropriate actions, it is possible to optimize the production process, enhance efficiency, and maximize throughput.

Table 2: Optimized simulation results

Object	Working	Set-up	Waiting	Blocked	Powering up/down	Failed	Stopped	Paused	Unplanned	Portion
A130BGx	0.00%	0.00%	45.86%	54.14%	0.00%	0.00%	0.00%	0.00%	0.00%	
A150BGx	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
AssemblyStation	31.81%	0.00%	66.36%	0.02%	0.00%	1.81%	0.00%	0.00%	0.00%	
AssemblyStation2	23.53%	0.00%	22.19%	52.19%	0.00%	2.08%	0.00%	0.00%	0.00%	
AssemblyStation21	5.10%	0.00%	91.95%	0.00%	0.00%	2.94%	0.00%	0.00%	0.00%	
AssemblyStation311	2.62%	0.00%	93.23%	0.00%	0.00%	4.14%	0.00%	0.00%	0.00%	
B130BGx	0.00%	0.00%	99.88%	0.12%	0.00%	0.00%	0.00%	0.00%	0.00%	
B150BGx	0.00%	0.00%	94.81%	0.00%	0.00%	5.19%	0.00%	0.00%	0.00%	
BG130parts	0.00%	0.00%	0.04%	89.83%	0.00%	10.13%	0.00%	0.00%	0.00%	
BG150Parts	0.00%	0.00%	0.00%	89.56%	0.00%	10.44%	0.00%	0.00%	0.00%	
Buffer	0.00%	0.00%	0.57%	99.43%	0.00%	0.00%	0.00%	0.00%	0.00%	
Buffer2	0.00%	0.00%	0.36%	99.64%	0.00%	0.00%	0.00%	0.00%	0.00%	
Buffer3	0.00%	0.00%	0.37%	99.63%	0.00%	0.00%	0.00%	0.00%	0.00%	
Drain	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
FinalAssembly	0.92%	0.00%	33.56%	65.52%	0.00%	0.00%	0.00%	0.00%	0.00%	
FinalLine	1.75%	0.00%	98.21%	0.04%	0.00%	0.00%	0.00%	0.00%	0.00%	
InnerPartSources	0.00%	0.00%	0.39%	99.61%	0.00%	0.00%	0.00%	0.00%	0.00%	
InnerParts	0.00%	0.00%	33.57%	66.43%	0.00%	0.00%	0.00%	0.00%	0.00%	
LastThingSources	0.00%	0.00%	0.39%	99.61%	0.00%	0.00%	0.00%	0.00%	0.00%	
Line1	8.75%	0.00%	91.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Line2	1.75%	0.00%	98.25%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Line3	2.62%	0.00%	97.38%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
OuterPartSources	0.00%	0.00%	0.13%	99.87%	0.00%	0.00%	0.00%	0.00%	0.00%	
OuterParts	0.33%	0.00%	32.90%	64.82%	0.00%	1.94%	0.00%	0.00%	0.00%	
PowerTrain	6.81%	0.00%	0.03%	88.47%	0.00%	4.69%	0.00%	0.00%	0.00%	
PowerTrainSource	0.00%	0.00%	0.06%	99.94%	0.00%	0.00%	0.00%	0.00%	0.00%	
Preparation	2.78%	0.00%	0.43%	96.79%	0.00%	0.00%	0.00%	0.00%	0.00%	
QualityControl	1.75%	0.00%	96.18%	0.00%	0.00%	2.07%	0.00%	0.00%	0.00%	
Source	0.00%	0.00%	0.63%	99.37%	0.00%	0.00%	0.00%	0.00%	0.00%	
Station130	1.79%	0.00%	24.25%	73.96%	0.00%	0.00%	0.00%	0.00%	0.00%	
Station150	2.85%	0.00%	66.87%	30.27%	0.00%	0.00%	0.00%	0.00%	0.00%	

In summary, the system you described integrates 3D visualization to monitor a production area in detail, capture real-time values, monitor the system during active operation, and provide instantaneous visualization of report outputs. This technology can enhance operational efficiency, facilitate proactive maintenance, and contribute to the overall optimization of the production processes.

5. Conclusion

In conclusion, the digital twin simulation was an effective tool for optimizing the layout of the cellular manufacturing facility. The simulation allowed the company to evaluate different layout configurations and identify the optimal layout that improved the productivity, efficiency, and flexibility of the production process. The simulation also identified several process improvement opportunities that helped the company to further improve their production process. The digital twin simulation can help identify potential bottlenecks and optimize the facility's layout to reduce cycle times, minimize waiting times, and increase throughput. By integrating the digital twin simulation with other manufacturing technologies such as IoT sensors, machine learning algorithms, and predictive analytics, the facility's performance can be continuously monitored and improved.

Finally, the digital twin simulation technology used in this study can be further improved by incorporating more detailed models of the production processes, equipment, and material handling systems. This would allow for more accurate and realistic simulations, leading to better layout designs and more significant improvements in manufacturing performance.

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