Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 33 No. 3 (2023)

Implementation of Industry 4.0 and Digital Manufacturing Practices in Indian Manufacturing Industries Using Discrete Event Simulation (DES)

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Article History:

***Received**: 13-06-2023*

***Revised**: 11-08-2023*

***Accepted**: 21-09-2023*

Abstract:

Industry 4.0 and digital manufacturing have emerged as significant areas of research in recent years. According to several reputed research papers, Industry 4.0 is a new industrial revolution that involves the integration of cutting-edge technologies such as the Simulation (Discrete Event Simulation), Internet of Things (IoT), artificial intelligence (AI), and big data analytics into the manufacturing process. Smart manufacturing, on the other hand, is the implementation of these technologies in the manufacturing sector to increase efficiency, reduce waste, and improve product quality. The research suggests that Industry 4.0 and smart manufacturing have the potential to revolutionize the manufacturing industry by enabling companies to achieve higher levels of automation, productivity, and agility. The Indian manufacturing industry has witnessed substantial growth in recent years, becoming a significant contributor to the country's economic development. To maintain its competitive edge in the global market and meet the increasing demand for innovative and cost-effective products, the industry has been actively adopting digital manufacturing practices. In this context, Industry 4.0, characterized by the integration of cyber-physical systems, Simulation, the Internet of Things, and data analytics, offers new opportunities for enhancing efficiency and productivity. This research paper presents a comprehensive study on the successful implementation of digital manufacturing practices in the Indian automobile industry through the use of simulation approaches, in alignment with Industry 4.0 principles. The study aims to identify the key challenges faced by the industry and proposes viable solutions to harness the full potential of digitalization. The paper delves into the critical aspects of simulation techniques, such as discrete event simulation and virtual manufacturing, and their role in optimizing manufacturing processes, reducing lead times, and enhancing product quality. The results of this study indicate that the integration of digital manufacturing practices with Industry 4.0 principles has resulted in significant improvements across the entire value chain of the Indian automobile industry. Reduced production costs, increased production flexibility, and enhanced product quality have been observed as the key outcomes of this strategic alignment.

Keywords: Industry 4.0, Digital Manufacturing, Simulation, DES, Plant Simulation.

1. Introduction: Industry 4.0, also known as the Fourth Industrial Revolution, is the latest technological advancement that has revolutionized the manufacturing industry. This concept of Industry 4.0 is a combination of various advanced technologies such as the Internet of Things (IoT), cloud computing, artificial intelligence, and machine learning. Smart manufacturing, on the other hand, is the application of Industry 4.0 technologies in manufacturing processes to improve productivity, quality, and efficiency. The integration of these advanced technologies in the manufacturing industry has led to a new era of automation, which has transformed traditional manufacturing processes into smart and digital manufacturing processes. The adoption of Industry 4.0 technologies in manufacturing has opened new opportunities for businesses to optimize their production and supply chain management systems. This paper aims to explore the concept of Industry 4.0 and digital manufacturing, their applications, benefits, and challenges. The paper will also discuss the potential impact of Industry 4.0 on the future of manufacturing and the global economy. The study will provide insights into how Industry 4.0 technologies can help businesses to achieve operational efficiency, cost savings, and sustainable growth in the competitive market. Industry 4.0, also known as the Fourth Industrial Revolution, is a term used to describe the current trend of automation and data exchange in manufacturing and other industries. It represents a new era of industrial production that integrates advanced technologies, such as the simulation, Internet of Things (IoT), Artificial Intelligence (AI), Robotics, and Big Data, to create smart factories and supply chains. Industrial revolutions have restructured manufacturing, boosting efficiency, productivity, and technology. Each industrial revolution formed the global economy, forcing manufacturing industries to adapt and innovate to remain competitive. The First Industrial Revolution (Industry 1.0), starting in the late 18th century, introduced mechanization and steam power, transforming production and shifting economies from agrarian to industrial [1, 2]. The Second Industrial Revolution (Industry 2.0), in the late 19th century, was driven by innovations like electricity and the internal combustion engine, leading to mass production and the rise of assembly line manufacturing, transforming industries and boosting the economy [3, 4]. Industry 3.0 is the Third Industrial Revolution, which occurred in the mid-20th century. Industry 3.0, also known as the Digital Revolution, was marked by the introduction of computers and automation [5]. Industry 3.0 improves precision and efficiency and leads to computer-aided design (CAD) and computer-aided manufacturing (CAM). Industry 4.0, the Fourth Industrial Revolution of the 21st century, involves digital tech convergence, the Internet of Things (IoT), artificial intelligence (AI), and data analytics [6–8]. It encourages machines and products to collaborate in real-time, resulting in efficient and autonomous manufacturing processes. Industry 4.0 offers a range of advantages, including enhanced efficiency in manufacturing processes, leading to cost savings. It enables data-driven decision-making with the support of IoT and data analysis, allowing for informed choices and maintenance. Moreover, Industry 4.0 enables product personalization without compromising efficiency and ensures real-time visibility. It also contributes to sustainability by reducing energy consumption and enhancing waste management, aligning with environmental goals. Delmia V5 is versatile software for modeling, simulating, and optimizing production processes in manufacturing and other industries [9]. Manufacturing Interactive Application" was introduced by Dassault Systèmes as part of its broader suite of software solutions. The V5 version of DELMIA was released in the early 2000s, which was an innovative milestone in DELMIA's development. DELMIA V5 brings efficiency, quality, and cost savings to Indian manufacturing. Delmia V5 is used in industries to enhance manufacturing, offering features like process planning and robotic programming crucial for Industry 4.0 [10, 11]. Digital manufacturing processes generate huge amounts of data from sensors, equipment, and production lines [17, 18]. Some papers focused on implementing virtual manufacturing in an automobile assembly line. This assembly line handles the construction of the frame, axle, engine, cabin body, and trim components onto the chassis. The primary objective was to synchronize the conveyor system's speed (Takt Time) with that of the Electrified Monorail

Hoist System. The study explored various combinations of process parameters to achieve different production rates while ensuring a seamless material handling process. Using 3D simulation with Delmia Quest software, the study identified process planning flaws and optimized equipment motion, preventing crashes and traffic jams on the assembly line. CATIA® was employed for assembly line design and Delmia QUEST for real-time simulation. The study aimed to enhance assembly line production, reduce manufacturing costs, minimize idle time, and boost productivity. As a result, operator loading increased by 8%, accompanied by a shift increase of 5 vehicles [22]. The discrete manufacturing shows the complete activities in simulation form to understand the product flow. Discrete manufacturing shows clearly the process inefficiencies and errors in the work flow which gives the clear picture about the each and every function in the organization. Manufacturing Systems provide one of the most important applications of simulation. Simulation has been used successfully as an aid in the design of new production facilities and as well to evaluate suggested improvements to existing systems for the further improvement in manufacturing process [25]. The simulation and visualization of projected execution solutions offer the opportunity to detect manpower bottlenecks as well as inefficient equipment or worker utilization [26]

The framework is supported by an architecture that connects manufacturing and machine tool data (digital shadow), the discrete event simulation model and the optimization engine, allowing for a variety of functionalities to plan and manage the production system [27]. the companies that have adopted the technology, 79% answered that discrete-event simulation facilitates the decision-making process [28].

DES (Discrete-Event Simulation) is a tool suitable for the study of manufacturing systems and improves overall efficiency. The manufacturing system can be modelled in a simulation environment to study the different options for improving the system both to predict the effect of changes to an existing system as well as a tool to predict performance of new systems [29]. Tecnomatix Plant Simulation can be used to improve the effectiveness and profitability of a facility by finding out the solution increasing throughput and utilization of resource and facility [30]

1.1 Pillars of Industry 4.0:

The nine pillars of Industry 4.0 include:

1.1.1 ***Interoperability:*** The ability of machines, devices, sensors, and people to connect and communicate with each other through the internet.

1.1.2 ***Information transparency:*** The ability to gather and analyze data in real-time to optimize production processes and improve decision-making.

1.1.3 ***Decentralized decision-making:*** The ability of autonomous systems to make decisions on their own, reducing the need for human intervention.

1.1.4 ***Technical assistance:*** The use of smart technologies, such as augmented reality and virtual reality, to support workers in performing their tasks.

1.1.5 ***Resource efficiency:*** The optimization of energy and resource consumption through the use of advanced technologies.

1.1.6 ***Mass customization:*** The ability to produce customized products at mass production scale, using flexible and agile manufacturing processes.

1.1.7 ***Modular production:*** The use of modular production systems that can be easily reconfigured and adapted to changing production needs.

1.1.8 ***Service orientation:*** The shift from a product-based to a service-based business model, where companies provide value-added services to customers.

1.1.9 ***Continuous optimization:*** The use of real-time data and analytics to continuously improve production processes and reduce waste.

In summary, Industry 4.0 represents a fundamental shift in the way industries operate, enabled by the integration of advanced technologies. The nine pillars of Industry 4.0 provide a framework for understanding the key elements that are driving this transformation.

2. Digital Manufacturing:

Digital manufacturing refers to the integration of digital technologies, advanced data analytics, and automation into the entire manufacturing process, from product design to production and beyond. It leverages cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and additive manufacturing (3D printing) to transform traditional manufacturing methods and enable a more efficient, agile, and interconnected manufacturing ecosystem. The advent of digital manufacturing has revolutionized the way products are conceptualized, developed, and produced. It enables manufacturers to create digital representations of physical products and simulate their behavior and performance through virtual models. This digitalization of the manufacturing process allows for improved product design, prototyping, and optimization, resulting in reduced time to market and enhanced product quality. One of the key drivers of digital manufacturing is the concept of the digital twin. A digital twin is a virtual representation of a physical product, process, or system that is connected to real-time data from sensors and devices. By analyzing the data collected from the physical counterpart, manufacturers can gain valuable insights, predict maintenance needs, and optimize production parameters to improve efficiency and productivity. Digital manufacturing also facilitates seamless communication and collaboration between various stakeholders in the manufacturing ecosystem. It enables real-time information sharing, supply chain visibility, and predictive analytics, allowing for agile decision-making and more effective coordination among suppliers, manufacturers, and customers. Moreover, digital manufacturing plays a crucial role in achieving sustainability and resource efficiency in the manufacturing sector. By leveraging data analytics and IoT-enabled sensors, manufacturers can monitor energy consumption, optimize resource usage, and reduce waste throughout the production process. Overall, digital manufacturing represents a paradigm shift in the manufacturing industry, enabling manufacturers to leverage advanced technologies and data-driven insights to achieve greater efficiency, flexibility, and sustainability. Embracing digital manufacturing practices not only enhances competitiveness but also paves the way for innovation, improved customer experiences, and the creation of new business models in the evolving global market.

Digital manufacturing through simulation can help increase the productivity of a plant in several ways:

2.1 ***Optimizing Production Processes:*** By simulating different production scenarios, smart manufacturing can identify bottlenecks in the manufacturing process, optimize the use of resources, and identify ways to improve the overall efficiency of the plant. This can help increase productivity by reducing downtime, increasing throughput, and improving product quality.

2.2.*Predictive Maintenance:* Smart manufacturing can use simulation to predict when equipment is likely to fail and schedule maintenance proactively. This helps to reduce unplanned downtime, prevent equipment failure, and increase the overall reliability of the plant.

2.3 ***Improved Training***: Simulation can provide a safe and controlled environment for training new employees or testing new processes. This helps to reduce the learning curve for new employees and ensure that they are fully trained before they begin working on the production floor.

2.4 ***Faster Time-to-Market***: Smart manufacturing can use simulation to model and test new products or production processes before they are implemented in the plant. This helps to reduce the time it takes to bring new products to market, increase the overall efficiency of the plant, and improve the quality of the final product.

In summary, smart manufacturing through simulation can help increase productivity in a plant by optimizing production processes, predicting equipment failure, improving training, and reducing time-to-market for new products.

3 Advantage of Industry 4.0 and Digital Manufacturing:

Industry 4.0 and smart manufacturing offer several advantages that can be highlighted in a research paper. Some potential advantages include:

3.3 Increased Efficiency: Industry 4.0 technologies such as the Internet of Things (IoT), automation, and artificial intelligence (AI) can help companies streamline their operations and reduce waste. This can result in higher productivity and lower costs.

3.4 Improved Quality: Smart manufacturing technologies can help companies improve the quality of their products by reducing errors and defects. Sensors and other monitoring devices can be used to detect issues in real-time, allowing for faster problem-solving and more accurate adjustments.

3.5 Customization and Personalization: Industry 4.0 technologies can enable companies to offer more personalized and customized products and services. This can lead to higher customer satisfaction and greater brand loyalty.

3.6 Flexibility and Agility: Smart manufacturing can help companies become more flexible and agile in response to changing market conditions. This is particularly important in industries where demand can fluctuate rapidly.

3.7 ***Data Analytics and Decision Making:*** Industry 4.0 technologies can provide companies with access to vast amounts of data. This data can be analysed using AI and machine learning algorithms to gain insights into customer behaviour, product performance, and other critical business factors. This can lead to more informed decision-making and better business outcomes.

3.8 ***Improved Safety:*** Smart manufacturing technologies can help companies improve the safety of their operations by automating dangerous tasks and providing real-time monitoring of hazardous conditions.

3.9 ***Reduced Environmental Impact:*** Industry 4.0 technologies can help companies reduce their environmental impact by optimizing energy usage, reducing waste, and using sustainable materials.

These are just a few of the potential advantages of Industry 4.0 and smart manufacturing that can be explored in a research paper. It is worth noting that the specific benefits will vary depending on the industry and company in question. To explain about how smart manufacturing will help to increase the efficiency of plant, we are going to use Plant Simulation Software. Technomatix Plant Simulation software is a powerful tool for simulating and optimizing manufacturing processes in a variety of industries, including automotive manufacturing. It allows engineers and plant managers to create digital models of manufacturing systems and simulate their performance under different conditions. In automotive manufacturing, this software can be used to simulate and optimize various processes, such as assembly lines, paint shops, and material handling systems. For example, it can be used to simulate the assembly of a car, from the arrival of individual parts to the final assembly of the vehicle. This can help identify bottlenecks and optimize the flow of materials and workers to increase efficiency and reduce costs. The software can also be used to simulate the operation of a paint shop, including the application of various coatings and the curing process. This can help optimize the use of resources such as paint and energy, and improve the quality of the finished product. Overall, Technomatix Plant Simulation can help automotive manufacturers improve their manufacturing processes, reduce costs, and increase productivity. By simulating various scenarios and testing different configurations, engineers and plant managers can make informed decisions and optimize their systems for maximum efficiency. This software used for simulating, analysing, and optimizing manufacturing systems. It is commonly used by engineers and researchers to study different manufacturing scenarios, evaluate different process designs, and optimize production systems. Here is an example of a case study and problem statement for our research work using Technomatix Plant Simulation:

Case Study: Process Line Optimization for a Manufacturing Company

Problem Statement: A manufacturing company is facing challenges in meeting production targets due to bottlenecks in their Processing line. The company wants to optimize their assembly line process to increase production output. Consider the plant runs for 8 Hrs. per day.

Solution: The Company can use TX Plant Simulation to build a simulation model of their assembly line process and identify bottlenecks that are causing delays in the production process. The simulation model will allow the company to analyse different scenarios, evaluate different process designs, and optimize their production system.

The following steps can be taken to optimize the assembly line process:

i. ***Building the Simulation Model:*** The first step is to build a simulation model of the assembly line process using TX Plant Simulation. The model should be based on the actual production process and include all the relevant equipment, materials, and personnel.

ii. ***Analysing the Model:*** The simulation model can be used to analyse the production process and identify bottlenecks that are causing delays in the production process. The model can also be used to evaluate different process designs and scenarios to determine the most effective solution.

iii. ***Optimizing the Production System:*** Based on the analysis and evaluation of the simulation model, the company can optimize their production system. This may involve changing the layout of the assembly line, adding or removing equipment, adjusting production schedules, or improving the training of personnel.

iv. ***Implementation:*** Once the optimized production system has been identified, the company can implement the changes and monitor the production process to ensure that the changes are effective.

v. ***Continuous Improvement:*** Simulation models can be used to test different scenarios and identify areas for improvement, allowing for continuous refinement of processes and systems.

By simulating various scenarios and testing different configurations, engineers and plant managers can make informed decisions and optimize their systems for maximum efficiency. In this paper by using TX Plant simulation software we created the model of shop floor

Table 1. Scenario 1-Machines with 95% Availability

Sr. No.	Machine Name	Processing Time in Sec	Availability in %	Number 0f Parts Produced
Source	Input	NA	95	487
1	M1	90	95	221
2	M2	90	95	220
3	M3	60	95	405
4	M4	40	95	183
5	M5	40	95	195
6	M6	90	95	318
7	M7	30	95	317
Drain	Output	NA	95	317

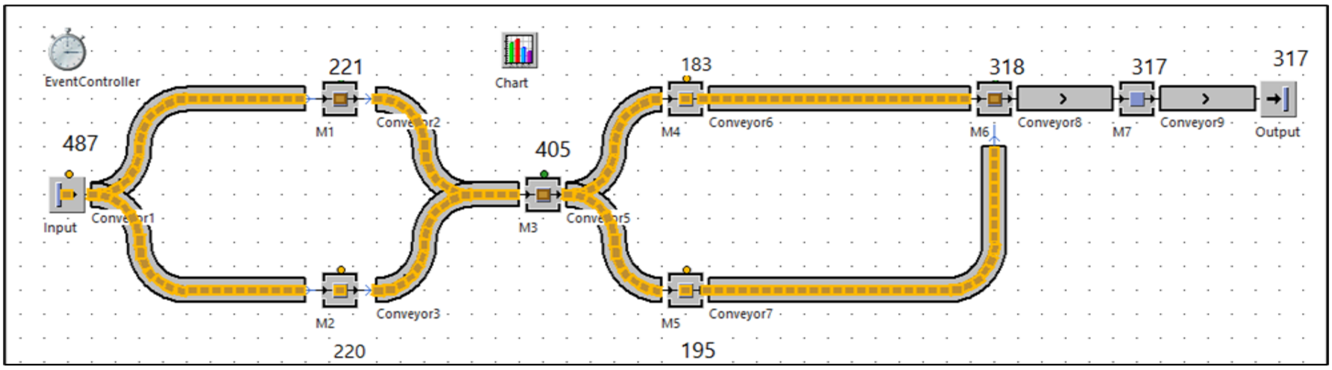
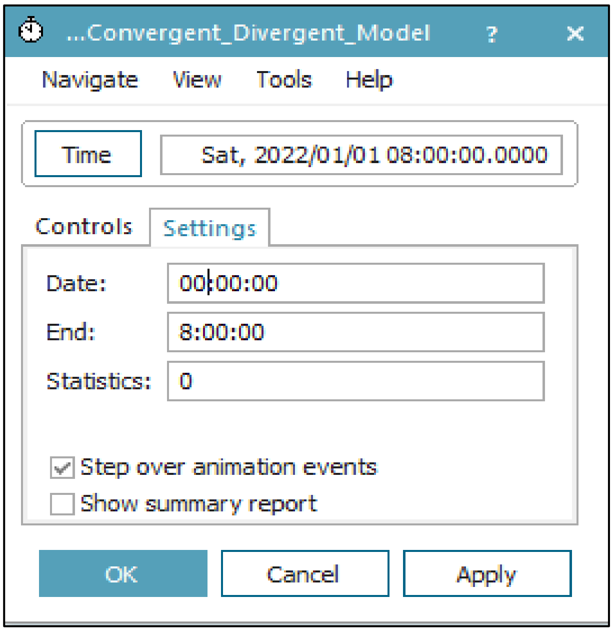


Fig.1 Simulation Model for Scenario 1 with 95% Machine Availability

Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 33 No. 3 (2023)



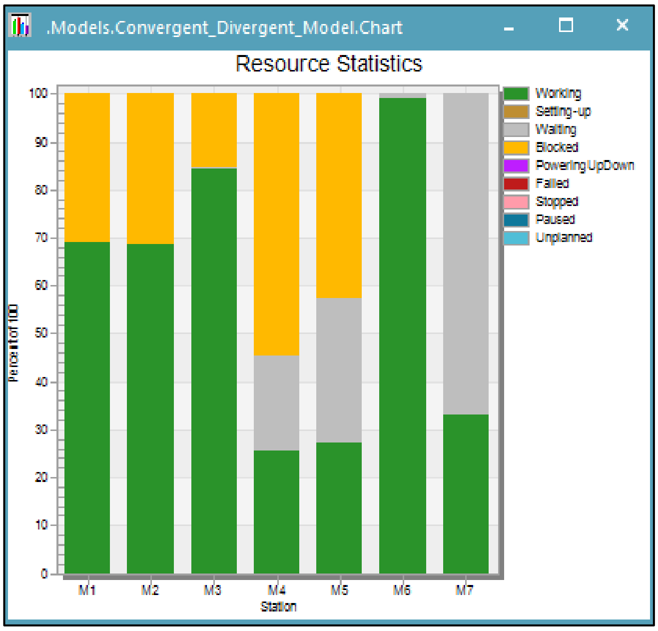


Fig. 2 Simulation Run for 8 Hours/Day

Fig.3 Resource Statistics

Table 2. State Statistics with 95% Machines Availability

Object	Working	Set-up	Waiting	Blocked	Powering up/down	Failed	Stopped	Paused	Unplanned	Portion
Conveyor	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor1	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor2	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor3	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor4	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor5	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor6	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor7	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor8	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor9	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Input	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
M1	68.90%	0.00%	0.04%	31.06%	0.00%	0.00%	0.00%	0.00%	0.00%	
M2	68.75%	0.00%	0.04%	31.21%	0.00%	0.00%	0.00%	0.00%	0.00%	
M3	84.31%	0.00%	0.38%	15.31%	0.00%	0.00%	0.00%	0.00%	0.00%	
M4	25.42%	0.00%	20.04%	54.54%	0.00%	0.00%	0.00%	0.00%	0.00%	
M5	27.08%	0.00%	30.12%	42.80%	0.00%	0.00%	0.00%	0.00%	0.00%	
M6	99.21%	0.00%	0.79%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
M7	33.02%	0.00%	66.98%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Output	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	

Table 3. Drain Statistics with 95% Machines Availability

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Part	2:29:51.3574	317	39.62	4.94%	95.06%	0.00%	3.45%	

Table 4. Scenario 2-Machines with 80% Availability

Sr. No.	Machine Name	Processing Time in Sec	Availability in %	Number 0f Parts Produced
Source	Input	NA	80	432
1	M1	90	80	193
2	M2	90	80	193
3	M3	60	80	350
4	M4	40	80	156
5	M5	40	80	167
6	M6	90	80	264
7	M7	30	80	263
Drain	Output	NA	80	262

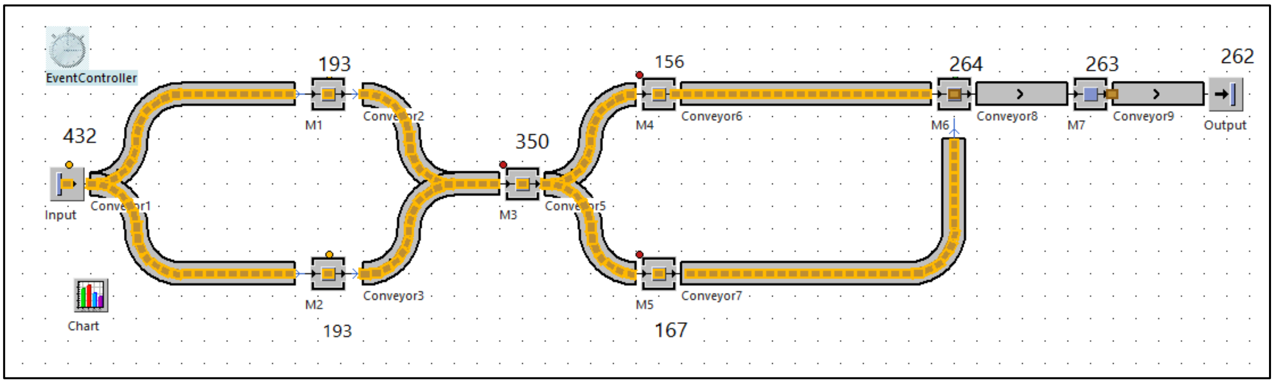


Fig. 4 Simulation Model for Scenario 2 with 80% Machine Availability

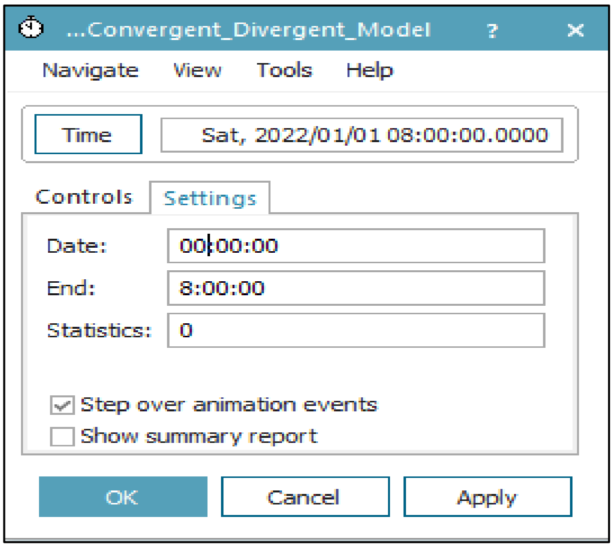


Fig. 5 Simulation Run for 8 Hours/Day

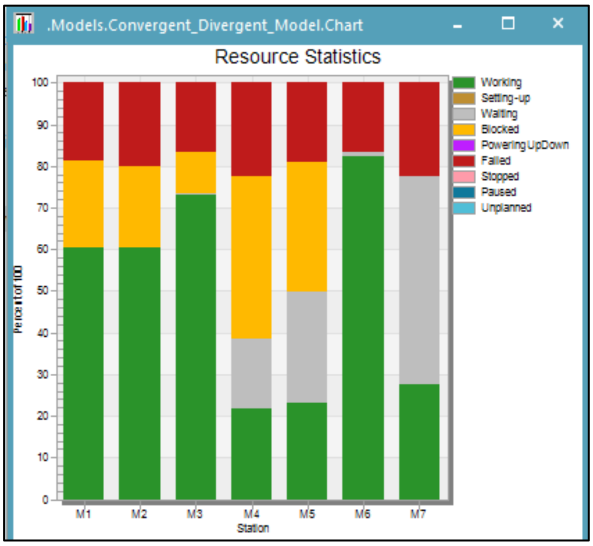


Fig. 6 Resource Statistics

Table 5. State Statistics with 80% Machines Availability

Object	Working	Set-up	Waiting	Blocked	Powering up/down	Failed	Stopped	Paused	Unplanned	Portion
Conveyor	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor1	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor2	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor3	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor4	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor5	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor6	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor7	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor8	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor9	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Input	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
M1	60.31%	0.00%	0.04%	20.87%	0.00%	18.78%	0.00%	0.00%	0.00%	
M2	60.31%	0.00%	0.04%	19.64%	0.00%	20.01%	0.00%	0.00%	0.00%	
M3	72.92%	0.00%	0.56%	9.97%	0.00%	16.55%	0.00%	0.00%	0.00%	
M4	21.60%	0.00%	17.00%	38.85%	0.00%	22.55%	0.00%	0.00%	0.00%	
M5	23.19%	0.00%	26.73%	30.89%	0.00%	19.19%	0.00%	0.00%	0.00%	
M6	82.31%	0.00%	1.07%	0.00%	0.00%	16.62%	0.00%	0.00%	0.00%	
M7	27.40%	0.00%	50.10%	0.00%	0.00%	22.51%	0.00%	0.00%	0.00%	
Output	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	

Table 6. Drain Statistics with 80% Machines Availability

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Part	2:42:34.7450	262	32.75	5.18%	94.82%	0.00%	3.18%	

Table 7. Scenario3-Machines with 80% Availability with Buffer of 100 Parts Capacity

Sr. No.	Machine Name	Processing Time in Sec	Availability in %	Number 0f Parts Produced
Source	Input	NA	80	562
1	M1	90	80	260
2	M2	90	80	256
3	M3	60	80	398
4	M4	40	80	198
5	M5	40	80	198
6	M6	90	80	264
7	M7	30	80	263
Drain	Output	NA	80	262

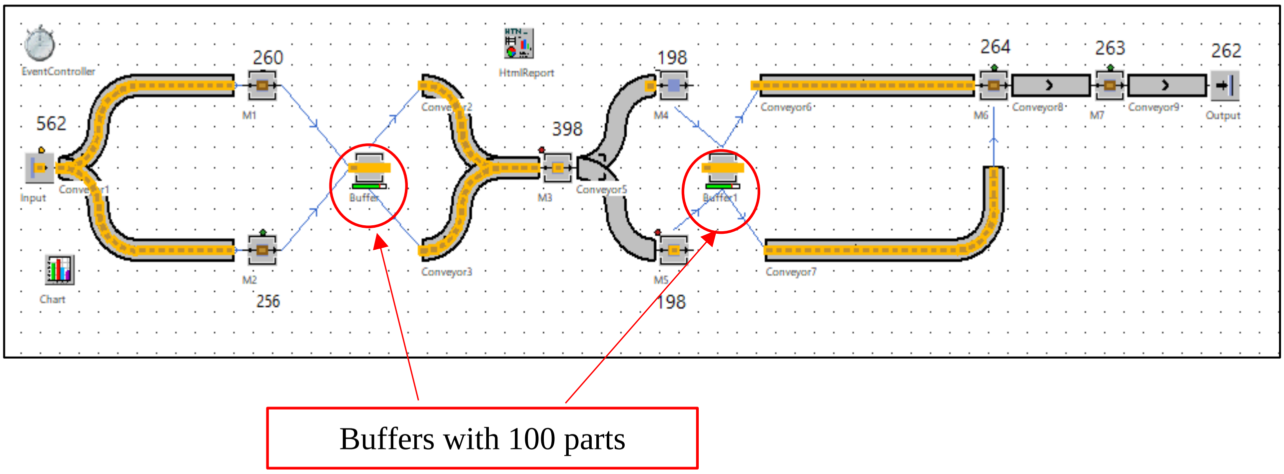
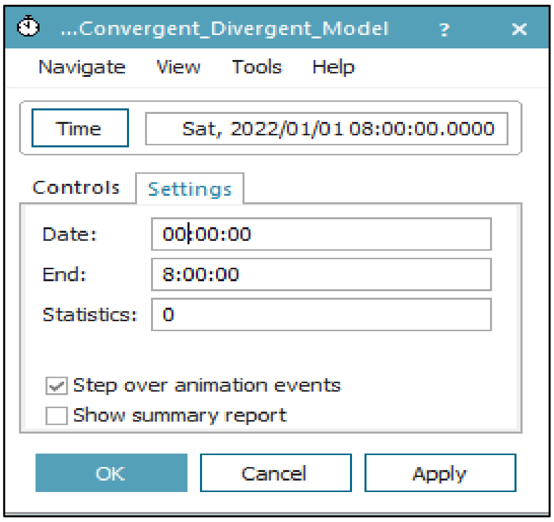


Fig. 7 Simulation Model for Scenario 3 with 80% Machine Availability with Buffer of 100 Capacity



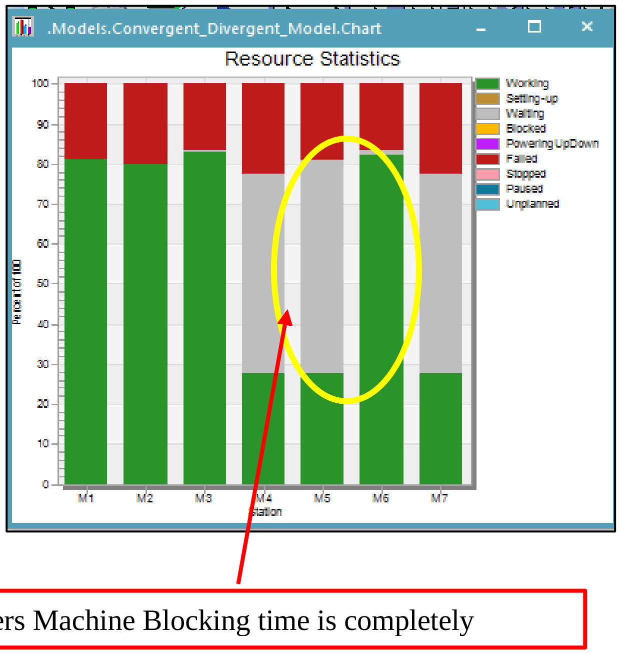


Fig. 8 Simulation Run for 8 Hours/Day

Fig. 9 Resource Statistics

Table 8. State Statistics with 80% Machines Availability with Buffer of 100 Capacity

Object	Working	Set-up	Waiting	Blocked	Powering up/down	Failed	Stopped	Paused	Unplanned	Portion
Buffer	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Buffer1	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor1	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor2	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor3	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor4	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor5	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor6	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor7	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor8	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Conveyor9	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
Input	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	
M1	81.18%	0.00%	0.04%	0.00%	0.00%	18.78%	0.00%	0.00%	0.00%	
M2	79.95%	0.00%	0.04%	0.00%	0.00%	20.01%	0.00%	0.00%	0.00%	
M3	82.89%	0.00%	0.56%	0.00%	0.00%	16.55%	0.00%	0.00%	0.00%	
M4	27.50%	0.00%	49.95%	0.00%	0.00%	22.55%	0.00%	0.00%	0.00%	
M5	27.43%	0.00%	53.38%	0.00%	0.00%	19.19%	0.00%	0.00%	0.00%	
M6	82.29%	0.00%	1.09%	0.00%	0.00%	16.62%	0.00%	0.00%	0.00%	
M7	27.38%	0.00%	50.11%	0.00%	0.00%	22.51%	0.00%	0.00%	0.00%	
Output	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	

Table 9. Drain Statistics with 80% Machines Availability with Buffer of 100 Capacity

Name	Mean Life Time	Throughput	Throughput per Hour	Production	Transport	Storage	Value added	Portion
Part	2:44:45.6003	262	32.75	4.29%	82.77%	12.93%	3.14%	

In TX Plant Simulation, a buffer is a critical element that plays a significant role in modelling and analysing production systems. Buffers are used to temporarily store or hold parts or products during the manufacturing process. They serve as a link between different stages in the production line, ensuring a smooth and continuous flow of materials. The importance of buffers in TX Plant Simulation can be summarized as follows:

1. Production Rate Control: Buffers help to balance the production rates of different workstations in the production line. By controlling the flow of parts, buffers prevent bottlenecks and overloading of downstream processes, ensuring that the system operates efficiently and at an optimal pace.

2. Absorbing Variability: Buffers act as shock absorbers for process variability. In real-world manufacturing environments, variations in processing times or supply chain disruptions can occur. Buffers provide flexibility to handle such variations and help prevent disruptions from propagating throughout the system.

3. Decoupling of Workstations: Buffers decouple workstations in the production line, making them less dependent on each other. This reduces the impact of minor delays or stoppages in one workstation from affecting the entire system, enhancing the overall system reliability.

4. Reducing Downtime: Buffers can help avoid production downtime by storing intermediate products during temporary equipment breakdowns. This allows the system to continue running even when specific workstations experience issues, minimizing production losses.

5. Synchronization: Buffers enable synchronization between different stages of production, ensuring that each workstation receives a steady supply of materials when required. This synchronization optimizes production flow and helps prevent excessive inventory build-up.

6. Improving Throughput: By optimizing the use of buffers, production managers can achieve a better throughput in the system. Properly sized buffers and their strategic placement can increase the overall productivity of the manufacturing process.

7. Resource Utilization: Buffers help optimize the utilization of resources such as machines and labor. They prevent idle time by allowing the continuous flow of parts, which reduces the need for frequent stop-start operations.
8. Inventory Management: Buffers assist in managing inventory levels effectively. By controlling the amount of buffer space allocated at different points in the production process, managers can regulate inventory and reduce carrying costs.
9. Performance Analysis: Buffers in TX Plant Simulation allow for the analysis of various production metrics, such as cycle times, lead times, and work in progress (WIP). This analysis can aid in identifying potential bottlenecks or areas for improvement.
10. What-if Scenarios: Buffers in Plant Simulation enable engineers and managers to conduct "what-if" analyses by adjusting buffer sizes and observing the impact on production performance. This capability helps in making informed decisions to optimize the production system.

Result Table:

In summary, buffers in TX Plant Simulation are essential components that contribute to the efficient functioning and optimization of production systems. They facilitate the continuous flow of materials, help manage variability, and enhance the overall performance of manufacturing processes.

Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 33 No. 3 (2023)

Table 10. Parts Produced on Each Machine with 80% Availability without Buffer and with Buffer

Sr. No.	Machine Name	Processing Time in Sec	Availability in %	Approach 1 (Without Buffer)	Approach 2 (With Buffer)
				Number 0f Parts Produced	
Source	Input	NA	80	432	562
1	M1	90	80	193	260
2	M2	90	80	193	256
3	M3	60	80	350	398
4	M4	40	80	156	198
5	M5	40	80	167	198
6	M6	90	80	264	264
7	M7	30	80	263	263
Drain	Output	NA	80	262	262

Waiting Time is completely eliminated

Conclusion: TX Plant Simulation proved to be a useful tool for identifying bottlenecks in a complex production line and proposing solutions to improve efficiency. By simulating different production scenarios, the production manager was able to make informed decisions and optimize the production process, resulting in a reduction in manufacturing time and cost, and an overall improvement in the plant's efficiency. In conclusion, Industry 4.0 and Digital Manufacturing have revolutionized the way we think about production and manufacturing. With the integration of cutting-edge technologies such as artificial intelligence, the Internet of Things, and big data analytics, Industry 4.0 has enabled businesses to achieve increased efficiency, productivity, and cost savings, while also improving the overall quality of products and services. Digital Manufacturing, a subset of Industry 4.0, has also proven to be a game-changer, providing real-time data insights to optimize production processes, reduce waste and downtime, and enhance overall product quality. These advancements have not only benefited businesses, but have also led to a more sustainable and environmentally friendly approach to manufacturing. As we move forward, the continued integration of Industry 4.0 and Digital Manufacturing technologies will be crucial for businesses to remain competitive in an increasingly digital world. It is essential that businesses adapt to these changes and invest in the necessary infrastructure and training to fully utilize the benefits of these technologies. With proper implementation and management, Industry 4.0 and Digital Manufacturing have the potential to transform the manufacturing industry for the better, leading to increased efficiency, sustainability, and profitability.

References:

[1] Akturk, C., Talan, T. and Cerasi, C.C., 2022, September. Education 4.0 and University 4.0 from Society 5.0 Perspective. In 2022 12th International Conference on Advanced Computer Information Technologies (ACIT) (pp. 577-582). IEEE.

[2] Groumpos, P.P., 2021. A critical historical and scientific overview of all industrial revolutions. IFAC-PapersOnLine, 54(13), pp.464-471.

[3] Vinitha, K., Prabhu, R.A., Bhaskar, R. and Hariharan, R., 2020. Review on industrial mathematics and materials at Industry 1.0 to Industry 4.0. Materials Today: Proceedings, 33, pp.3956-3960.

[4] Kurt, R., 2019. Industry 4.0 in terms of industrial relations and its impacts on labour life. Procedia computer science, 158, pp.590-601.

[5] Gadre, M. and Deoskar, A., 2020. Industry 4.0–digital transformation, challenges and benefits. International Journal of Future Generation Communication and Networking, 13(2), pp.139-149.

[6] Hassoun, A., Aït-Kaddour, A., Abu-Mahfouz, A.M., Rathod, N.B., Bader, F., Barba, F.J., Biancolillo, A., Cropotova, J., Galanakis, C.M., Jambrak, A.R. and Lorenzo, J.M., 2022. The fourth industrial revolution in the food industry—Part I: Industry 4.0 technologies. Critical Reviews in Food Science and Nutrition, pp.1-17.

[7] Arden, N.S., Fisher, A.C., Tyner, K., Lawrence, X.Y., Lee, S.L. and Kopcha, M., 2021. Industry 4.0 for pharmaceutical manufacturing: Preparing for the smart factories of the future. International Journal of Pharmaceutics, 602, p.120554.

[8] Shrivastava, A., Krishna, K.M., Rinawa, M.L., Soni, M., Ramkumar, G. and Jaiswal, S., 2023. Inclusion of IoT, ML, and blockchain technologies in next generation industry 4.0 environment. Materials Today: Proceedings, 80, pp.3471-3475.

[9] Banga, H.K., Kalra, P., Kumar, R., Singh, S. and Pruncu, C.I., 2021. Optimization of the cycle time of robotics resistance spot welding for automotive applications. Journal of Advanced Manufacturing and Processing, 3(3), p.e10084.

[10] Gadaleta, M., Pellicciari, M. and Berselli, G., 2019. Optimization of the energy consumption of industrial robots for automatic code generation. Robotics and Computer-Integrated Manufacturing, 57, pp.452-464.

[11] Gomez-Jauregui, V., Cue-Palencia, F., Manchado, C. and Otero, C., 2019. Education for the Industry of the Future (IoF) with the 3D Experience Platform. In Advances on Mechanics, Design Engineering and Manufacturing II: Proceedings of the International Joint Conference on Mechanics, Design Engineering & Advanced Manufacturing (JCM 2018) Springer International Publishing. (pp. 761-769).

[12] Khan, S.U. and Ali, I. (2019) 'Industry 4.0: A Survey on Smart Manufacturing and Its Future Prospects', IEEE Access, **7**, pp. 46207-46223.

[13] Lu, C., Zhang, C., Zhou, Y. and Wang, L. (2018) 'Smart manufacturing: past, present and future', Journal of Manufacturing Systems, 48, pp. 126-142.

[14] Sangwal, P.D., Jena, R.K. and Swain, S.K. (2019) 'Smart Manufacturing: An Emerging Paradigm for Sustainable Industry 4.0', IEEE Access, **7**, pp. 169413-169424.

[15] Lu, Y., Li, W., Hu, Y. and Liu, S. (2020) 'Smart manufacturing: Characteristics, technologies and enabling factors', Journal of Manufacturing Systems, **57**, pp. 32-48.

[16] Asif, R.M., Chen, N.B. and Lim, H.T. (2019) 'A review of smart manufacturing for Industry 4.0: facilitating sustainable and competitive manufacturing', Journal of Cleaner Production, **213**, pp. 1118-1130.

[17] Cohen, Y., Faccio, M., Pilati, F. and Yao, X., 2019. Design and management of digital manufacturing and assembly systems in the Industry 4.0 era. The International Journal of Advanced Manufacturing Technology, 105, pp.3565-3577.

[18] Rai, R., Tiwari, M.K., Ivanov, D. and Dolgui, A., 2021. Machine learning in manufacturing and industry 4.0 applications. International Journal of Production Research, 59(16), pp.4773-4778.

[19] Xu, L., Xu, X. and Tao, H. (2019) 'Smart manufacturing: concept, impacts and the future', International Journal of Production Research, **57(8),** pp. 2399-2416.

[20] Chen, X. and Shao, L. (2019) 'Smart Manufacturing: Current Status and Future Trends', International Journal of Advanced Manufacturing Technology, **102**, pp. 2127-2142.

[21] Jiang, J., Song, J., Cui, L. and Wang, J. (2019) 'Smart Manufacturing: From Concept to Reality', International Journal of Advanced Manufacturing Technology, **104**, pp. 3073-3089.

[22] Kumar, P., Prasad, S.B., Patel, D., Gupta, L., Nag, M.B. and Chadha, P., 2022. Production improvement on the assembly line through cycle time optimization. International Journal on Interactive Design and Manufacturing (IJIDeM), pp.1-14.

[23] Li, L., Li, Y. and Ding, L. (2020) 'Intelligent manufacturing in the context of Industry 4.0: a review', Engineering, 6(2), pp. 171-178.

[24] Wang, Y., Liu, F., Liu, C., Chen, X. and Yang, Y. (2019) 'Research on Smart Manufacturing System Based on Industry 4.0', Journal of Intelligent & Robotic Systems, 93, pp. 381-392.

[25] Dr. Dushyanth Kumar K.R. (2018) ‘Discrete Event Simulation for Digital Manufacturing Productivity’ International Journal of Science and Research (IJSR),**8(8),** pp 2280-2288.

[26] M. König, U. Beiger, H.-J. Bargstädt (2007) ‘visual simulation - an appropriate approach to support execution planning in building engineering’, 7th International Conference on Construction Applications of Virtual Reality, pp 189-197.

[27] Itziar Ricondo, Alain Porto, Miriam Ugarte,(2021) ‘A digital twin framework for the simulation and optimization of production systems’, 54th CIRP Conference on Manufacturing Systems, pp 762–767.

[28] A. Ingemansson, G.S. Bolmsjö, U. Harlin, (2002), ‘A Survey of the Use of the Discrete-Event Simulation in Manufacturing Industry’, 10th International Manufacturing Conference in China, pp 2-6.

[29] J. Banks, J. S. Carson, and B. L. Nelson, (2002), Discrete-Event System Simulation, Prentice Hall, 2nd edition.

[30] Zay Yar Myint,(2017) ‘Assembly Line Balancing and Optimization Using SIEMENS Tecnomatix Plant Simulation: A Case Study of an Electric Power Steering Column

Assembly Line', Asian Institute of Technology School of Engineering and Technology Thailand, pp 1-86.