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Optimization of Inbound Logistics of Automobile Industry Using Flexsim

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Abstract

This study focuses on optimizing inbound logistics in the automobile industry by exploring how Flex Sim software can enhance productivity in car coating and assembly processes. By evaluating both separate and integrated production setups, the study demonstrates significant gains in operational efficiency and productivity. In a setup with separate plants, producing 500 automobiles requires 73.38 hours, with an average machine efficiency of 73.24% and a yield ratio of 98.62%. Conversely, integrating coating and assembly processes in a combined plant reduces production time to 35 hours and raises machine efficiency to 85.26%, with a slight reduction in the yield ratio to 93.96%. These results suggest that while there is a minor trade-off in yield, integrating processes leads to major improvements in time and efficiency.

Keywords
Inbound Logistics Optimization, Automotive Industry, Process Integration, Flex Sim, Machine Efficiency.

1. Introduction
Over the past few years, researchers and industry experts worldwide have acknowledged the value of enhancing production lines through various simulation software. Among them, FlexSim is a powerful simulation tool. Using FlexSim, complex problems of transportation and production lines can be simulated without any difficulty. Velyka et al. (2023) analyzed the impact of varying input parameters on the output and the system behavior and found a relationship between objects in a two-stage transportation problem that accentuates that input data has a considerable influence on both the system and its output. Krynke (2021) proposes a cost-effective strategy for early-stage production planning using FlexSim simulations. By focusing on resource allocation and process selection, FlexSim allows for more informed decisions before production starts, ultimately reducing total production costs. Unlike traditional tools like Excel or MATLAB, FlexSim offers 3D visualization, providing a comprehensive view of process flows and identifying inefficiencies. The study shows that preproduction simulations help reduce the risk of equipment underutilization and enable cost-saving adjustments. The approach

is also applicable to other industries, such as logistics, offering scalability, sensitivity analysis, and enhanced decision-making through better visualization of complex data.

Modern factories must meet the dual demands of product flexibility and production cost control. Developing a new product can be costly, requiring investments in refurbishment, production planning, and logistics. FlexSim software helps streamline this process by simulating and analyzing systems in various sectors, including manufacturing, warehousing, healthcare, and logistics. By forecasting the outcomes of process adjustments, FlexSim enables improvements before implementation, lowering costs and reducing setup time for new products. This paper showcases FlexSim's capacity to model and simulate workflows, providing insights into cost savings and resource efficiency in production environments (Medan 2021).

1.1 Objectives
To remove the bottlenecks.
To increase the productivity.
To increase the yield ratio.
To increase the overall machine efficiency.

2. Literature Review
This paper investigates Discrete Event Simulation (DES) for assembly system optimization and finds that time-based and output objective functions are commonly used, allowing for reduced lead time and greater production. The most common methods include hybrid modeling, heuristic modeling, resource planning, and analytical modeling. The author concludes that the most prevalent strategy is what-if scenario analysis, and considerable variations in output occur when input parameters vary (Prajapat and Tiwari 2017).This analysis provides insights into the obstacles faced by a former export-oriented manufacturer. The manufacturer is encountering as it transitions to align with China's domestic development strategy. The study identified inefficiencies in the production of cosmetic organizers, such as irregularities in the assembly line flow and management issues. By applying FlexSim simulation alongside 6S management techniques, researchers increased the line's efficiency, achieving a balance improvement from 55.45% to 69.38%. Moreover, it boosts output from 707 to 956 units per shift. Results suggest that adopting digital tools like electronic data interchange and barcode technology, as well as optimization techniques such as 0-1 integer programming, could further enhance efficiency for similar manufacturers (Liu and Lin 2022).

The author used FlexSim simulation to optimize the manufacturing process of crankcase covers in the automobile industry. A virtual model was created to analyze the impact of varying operators and stations on efficiency in the absence of physical investment. Results show that the model minimized idle time and optimally configures Die-Casting Machines (DCM) and Vertical Milling Centers (VMC), proving useful for wide manufacturing applications (Chawla and Singari 2023). The article explores using FlexSim simulation to enhance efficiency in the steel industry, focusing on a company producing galvanized steel profiles. Weak points such as bottlenecks and downtime were identified by simulating the production process, allowing for targeted corrective actions. This model provides a digital framework for optimizing multi-process operations, ensuring flexibility, reliability, and resource efficiency. Moreover, digital tools were used to monitor environmental performance (Poloczek and Oleksiak 2023).

This analysis provides insights into using Discrete-Event Simulation (DES) to optimize complex industrial production processes, focusing on model accuracy and detail levels. Using FlexSim, iterative models of different resolutions were created, beginning with a low-detail model and refining it for accuracy. A comparison of four fidelity dimensions revealed the ideal amount of detail required to match actual production system throughput. Results show that high-detail models are useful only when enough data is available, as further refining can improve accuracy (Nigischer et al. 2023).The research utilized FlexSim modeling to address and streamline the inbound logistics process for a J e-commerce platform. Early analysis showed a range of bottlenecks and inefficiencies in the existing setup. Based on business priorities and the ESIA framework, targeted improvement strategies were then modeled and validated through simulation. This approach led to significant gains, with warehousing efficiency increasing by half. The streamlined process eliminated conveyor belt obstructions and handling steps, decreased warehouse costs, and increased on-shelf inventory by nearly 50%. Furthermore, it brings substantial improvements across the inbound logistics flow (Hu and Deng 2023).

The article develops a framework to optimize logistics distribution center layouts using FlexSim simulation software. The focus was on a small distribution center model. The center's layout and processes, including inbound and outbound logistics, were analyzed and simulated. The study identified bottlenecks that caused idle and loading times. After optimization, operational efficiency improved, and revenue increased (Wang et al. 2022).

The research examines the use of FlexSim to model and analyze production processes. The goal is to increase flexibility and improve manufacturing configurations. By simulating a workpiece's production cycle, several key insights emerged: 70 assemblies can be completed in an 8-hour shift. Operator utilization varies significantly, with Operator 1 at 95% and Operator 3 at 12%. Equipment like CNC machines is used heavily, at 92%. FlexSim's ability to predict outcomes allows for testing multiple scenarios. This helps improve flow efficiency, supports decision-making, and enables better resource allocation, ultimately leading to cost savings and improved production quality and speed (Medan and Ravai-Nagy 2022).

The author uses FlexSim in a bread production line to simulate and optimize it and aims to provide a quantitative basis for production line improvement decisions. Results identify existing issues in the bread production system. Based on these results, two improvement strategies are proposed: a short-term and a long-term solution. Both focus on maximizing cost efficiency and output. The proposed improvement schemes prove to be practical and effective, reducing design time and costs for enterprise managers (Wu et al. 2018).This paper uses FlexSim software to examine the impact of discrete plant layout on production capacity and throughput time in the manufacturing process. Optimization of the layout is done with FlexSim software. After performance evaluation over two iterations. Each iteration yielded distinct results, with the second iteration demonstrating higher productivity and improved performance. This paper ultimately presents an improved and optimized machine layout achieved through FlexSim simulation (Ashish et al. 2020).

3. Methods

3.1 Research design

This study uses a simulation-based approach to optimize inbound logistics processes of a manufacturing environment. Twice simulation model was selected for testing and refining logistics configurations in a controlled environment without disrupting real-world operations. One is a car coating model and another is the car assembly model from two different literature reviews. Also, a new simulation model is generated by combining the coating and the assembly model and comparing the discrete and combined models' operations. Flex Sim simulation software was employed here to model, analyze, and improve the inbound logistics system.

3.2 Simulation Model Development

3.2.1 Car Coating Model

In the coating model the analysis is done on the basis of production of 500 automobiles. It took 53 hours 42 minutes. The rate of product input from the welding workshop is within the normal distribution normal (50,3) (Zhang 2021).

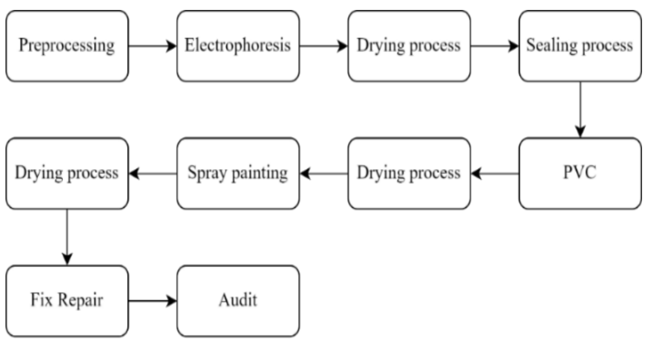

Figure 1. Painting process of the automobile production line

Table 1. Cycle Time

Production Process Machines Names	Cycle Time (CT)
Preprocessing	135s
Electrophoresis	103s
Drying process 23	130s
Sealing process	132s
PVC	153s
Drying process 24	141s
Spray painting	181s
Drying process 25	181s
Fix and Repair	222s

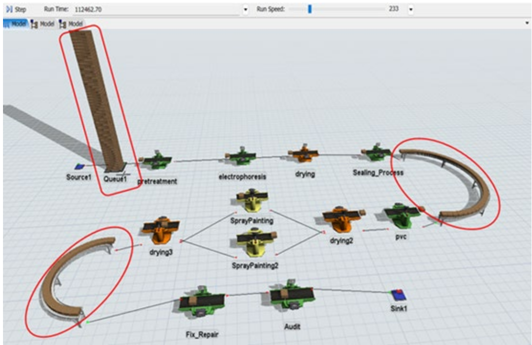

Figure 2. Coating plant before optimization

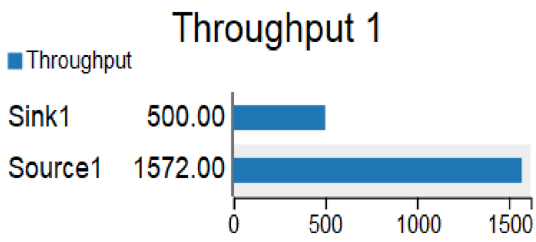

Figure 3. Inputs (Total finished products) and outputs (Finished Products)

3.2.2 Problem Identification of Coating Model

From figure 2, there is a long queue found in Queue 1 just after the Source. Queue 1 is overloaded (99.95%). Moreover, the conveyors are also overloaded. It is necessary to find the bottlenecks of the coating plant to improve the productivity of the plant.

Yield ratio (percentage) =(500/1572) *100 = 31.81% ……..(Using Figure 3)
Processing products ratio in plant line =(100 - 31.81) % = 68.19%

3.2.3 Car Assembly Model

The simulation was run until 500 cars were sent to the warehouse in 77 hour 57 minute Gong et al. (2019).

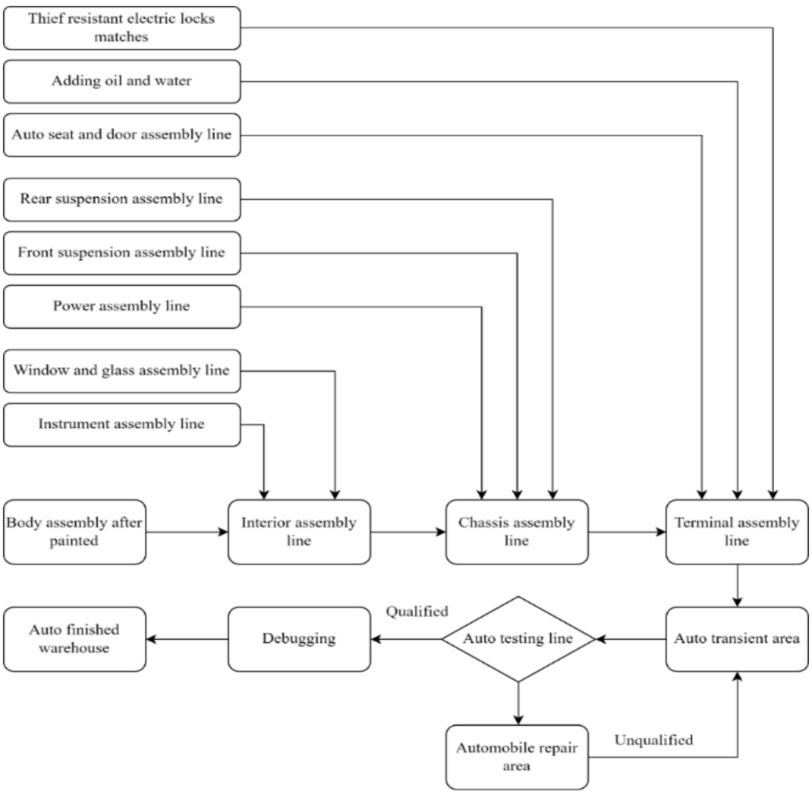

Figure 4. Automobile assembly process.

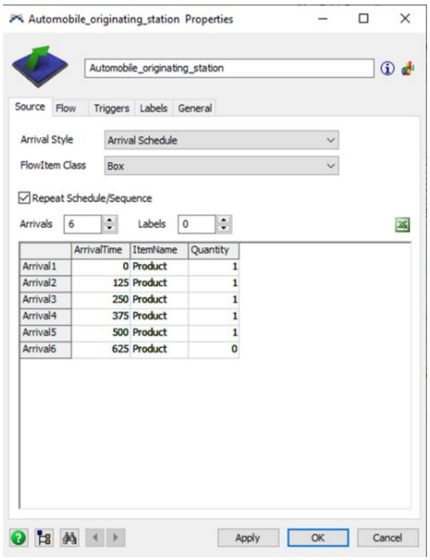

Figure 5. Source Parameter

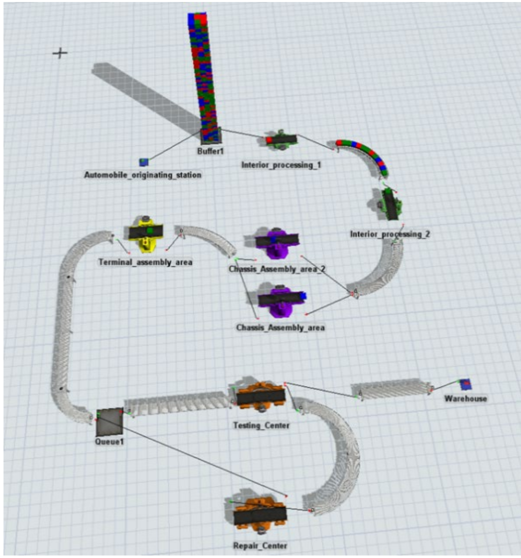

Figure 6. Simulation of car assembly plant

3.2.4 Problems found in the existing car assembly model

Initially in the automobile originating section the difference between the Arrival time is 125 seconds. Which was causing the problem in the buffer section. The bottleneck is found in buffer 1 section.

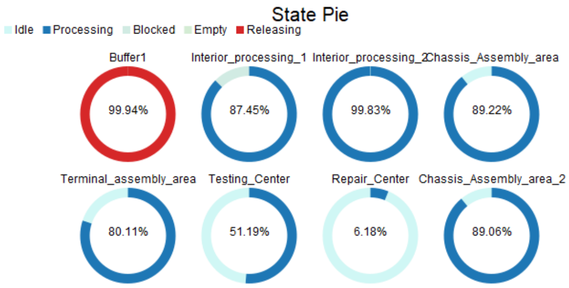

Figure 7. State Pie of car assembly plant

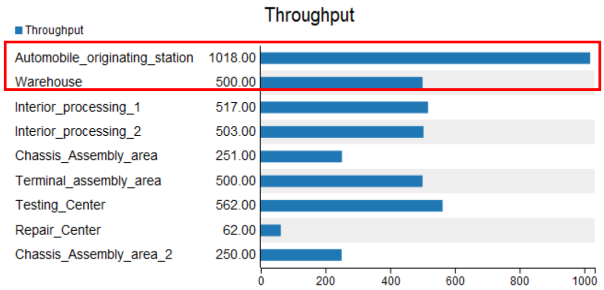

Figure 8. Output of car assembly plant

Yield ratio = (500/1080) *100 = 46.29% (Using the data of figure 8)

Processing products ratio in plant line = (100 - 46.29) % = 53.71%
Now comparing the inputs and outputs. The output is almost half of the input which is not efficient. It indicates there is a bottleneck there. This section needs to be fixed.

3.2.5 Combined Car Model

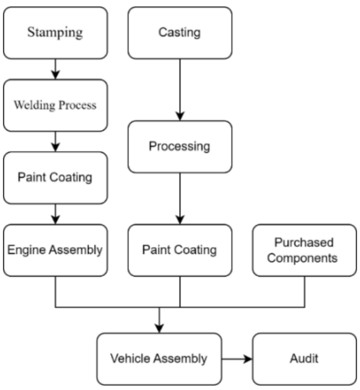

Figure 9. Vehicle manufacturing process

Table 2. First input parameters (iteration 0)

Input distribution	**Time to produce 500 automobiles in hours**	**Yield ratio (percentage)**	**Overall machine efficiency (percentage)**
Normal (180.0, 5.0)	115.325	49.65	40.39

In table 2, both optimized coating and assembly model are combined, and the objectives are to optimize the model, reduce bottlenecks and improve the floor efficiency of the plant by,

1. Implementing proper raw material input distribution in the line.
2. Placing the right machine in the right place or
3. Removing inefficient machine from the wrong place.

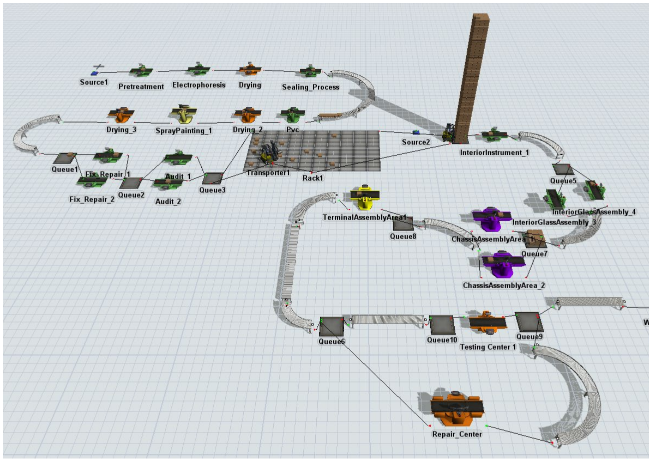

Figure 10. Simulated model of combined plant iteration 1

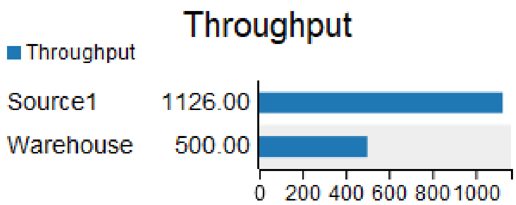

Figure 11. Data of the source and the warehouse for iteration 1

3.3 Data Analysis and Optimization

Mathematical model is the basis of data analysis which also helps to find the optimization point among the iterations.

$$\boldsymbol{Yield\ Ratio} = \frac{\Sigma_{i=1}^{n} y_i}{\Sigma_{j=1}^{m} X_i} \text{.........} (1)$$

Where:

- y_i represents the quantity of each output product.
- X_i represents the quantity of each raw material input.
- n is the total number of outputs.
- m is the total number of raw material inputs.

$$\boldsymbol{Overall\ machine\ efficiency} = \frac{\Sigma_{i=1}^{q} K_i}{\Sigma_{j=1}^{P} Z_i} \ldots \ldots \ldots (2)$$

Where:

- k_i represents the quantity of each actual production time of product.
- Z_i represents the quantity of each theoritical production time of product.
- q is the actual total time of products.
- p is the theoritical total time of products.

3.4 Steps to optimize the production process

1. Iterating the input distribution of raw materials.
2. Introducing or reducing proper machines in the right place to reduce bottlenecks.

4.Results and Discussion

4.1 Analysis and Optimization of Coating Model

For optimizing the coating industry, the bottlenecks must be removed. To find bottlenecks, iterations can help a lot. The iterations are started below:

Table 3. Parameters of iteration 1

Input distribution	Time to produce 500 automobiles in Hours	Yield ratio (percentage)	Overall machine efficiency (percentage)
Normal (50.0, 3.0)	53.712	20.55	56.52

In the research of Zhang (2021), the iteration is started from normal (50.0, 3.0) distribution.

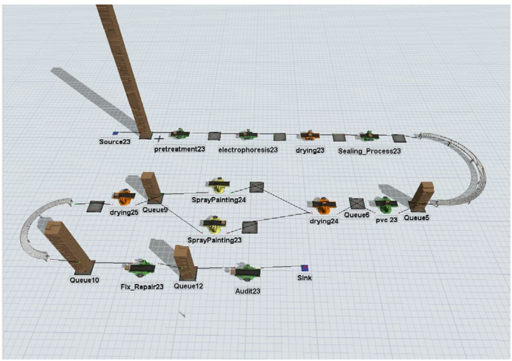

Figure 12. Scenario for the iteration 1

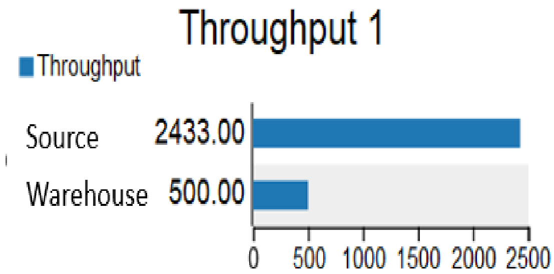

Figure 13. Data of the source and the warehouse for iteration 1

From Figure 12, bottlenecks were identified in Queue 23 (immediately after the source), Queue 5, Queue 9, Queue 10, and Queue 12. The coating process for 500 automobile bodies required 2.23 days, with a low yield ratio of 20.55%.

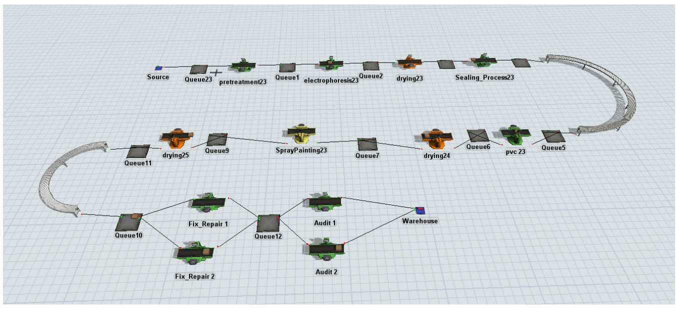

Figure 14. Scenario for the iteration 20

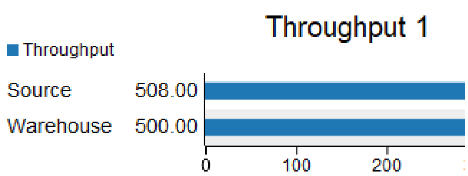

Figure 15. Data of the source and the warehouse/sink for iteration 20

In iteration 16, a fixed repair machine was introduced. In iteration 17, this fixed repair machine remained, and an additional audit machine was incorporated. From iteration 18 onward, both the fixed repair machine and the audit machine persisted, while a spray painting machine was removed. This configuration continued through iteration 23.

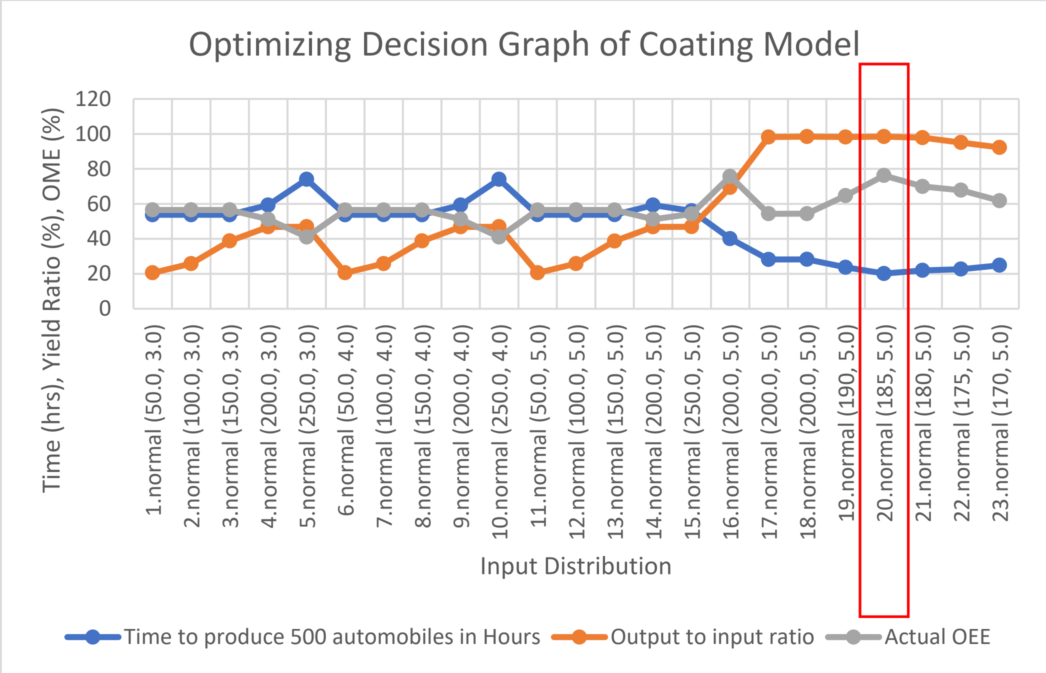

Figure 16. Optimizing Decision graph for coating model

According to figure 16, iteration 20 has the highest Overall machine efficiency (percentage) of 76.18%. Iteration 20 takes the least time to produce 500 automobiles which is 20.15 hours. Iteration 17 – 21 has similar Yield ratio. After overall comparison, iteration 20 contains the least time to produce 500 automobiles. Also, the yield ratio and the overall machine efficiency are optimum here. Thus, the parameters combination of iteration 20 can be introduced as the optimized parameters for the coating model.

4.2 Analysis and Optimization of Car Assembly Model

For optimizing the assembly industry, the bottlenecks must be removed. To find bottlenecks, iterations can help a lot. The iterations are started below:

Iteration 1.

From Gong et al. (2019) research, the iteration is started, from the interval of arrival time being 125.

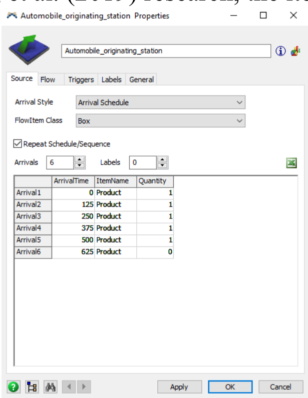

Figure 17. Production interval time setting of iteration 1.

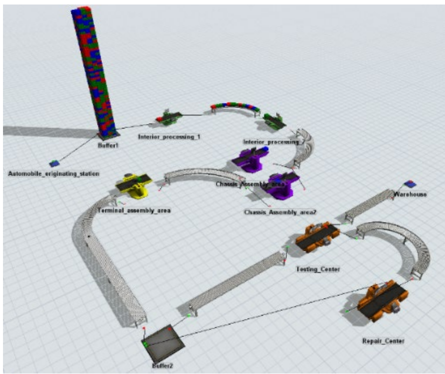

Figure 18. Simulated model of car assembly plant iteration 1

Table 4. Parameters of iteration 6

Arrival time interval in seconds	Time to produce 500 automobiles in hours	Yield ratio (percentage)	Overall machine efficiency (percentage)
500	53.23	98.81	70.30

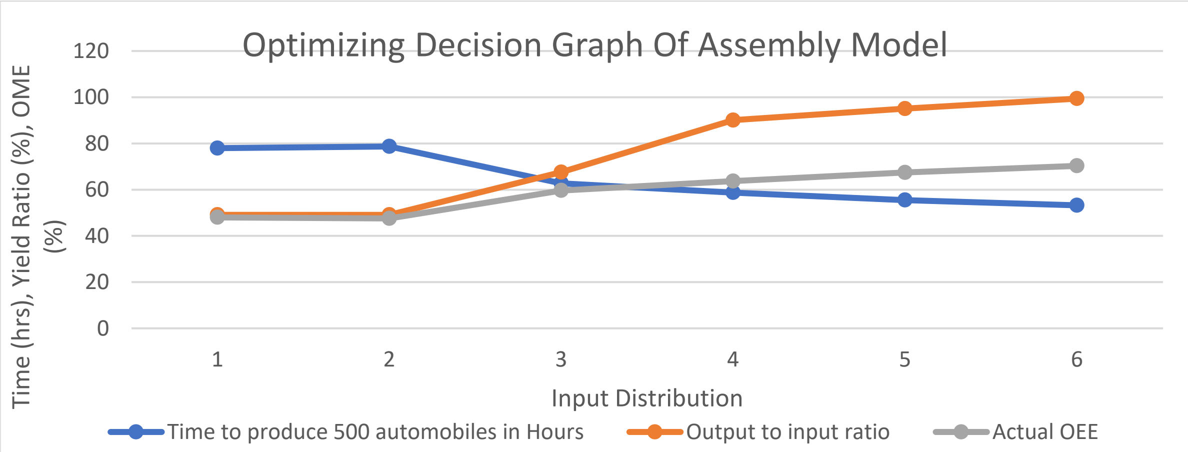

Figure 19. Optimizing Decision Graph Of Assembly Model

According to the above figure 19, iteration 6 contains the least time to produce 500 automobiles. Also, the yield ratio and the overall machine efficiency are optimum here. Thus, the parameters combination of iteration 6 can be introduced as the optimized parameters for the assembly model. When a car is produced to individual plant of coating and assembly, then, it takes 20.15 + 53.23 = 73.38 hours to produce 500 automobiles.

The overall machine efficiency becomes (70.30 + 76.18)/2 = 73.24 %
Yield ratio = (98.43 + 98.81)/2 = 98.62%

4.3 Analysis and Optimization of Combined Car Model

Both optimized coating and assembly model are combined, and the objectives are to optimize the model, reduce bottlenecks and improve the floor efficiency of the plant.

Table 5. Parameters of iteration 1

Input distribution	Time to produce 500 automobiles in hours	Yield ratio (percentage)	Overall machine efficiency (percentage)
Normal (180.0, 5.0)	115.325	49.65	40.39

Iteration (2 – 25) results are visible in the graph.

Table 6. Parameters of iteration 26

Input distribution	Time to produce 500 automobiles in hours	Yield ratio (percentage)	Overall machine efficiency (percentage)	Adding Interior Instrument	Adding Interior Glass Assembly	Adding Chassis Assembly
Normal (190.0, 3.0)	59.2450	44.56	78.25	1	1	2

Table 7. Parameters of iteration 27

Input distribution	**Time to produce 500 automobiles in hours**	**Yield ratio (percentage)**	**Overall machine efficiency (percentage)**
Normal (190.0, 3.0)	57.65240	83.06	80.33

Adding Interior Instrument	**Adding Interior Glass Assembly**	**Adding Chassis Assembly**	**Adding Terminal Assembly Area**
1	1	2	1

Table 8. Parameters of iteration 28

Input distribution	**Time to produce 500 automobiles in hours**	**Yield ratio (percentage)**	**Overall machine efficiency (percentage)**
Normal (190.0, 3.0)	36.47900	91.07	81.28

Adding Interior Instrument	**Adding Interior Glass Assembly**	**Adding Chassis Assembly**	**Adding Terminal Assembly Area**	**Adding Repair center**
1	1	2	1	1

Table 9. Parameters of iteration 29

Input distribution	**Time to produce 500 automobiles in hours**	**Yield ratio (percentage)**	**Overall machine efficiency (percentage)**
Normal (190.0, 3.0)	34.751	93.93	85.26

Adding Interior Instrument	**Adding Interior Glass Assembly**	**Adding Chassis Assembly**	**Adding Terminal Assembly Area**	**Adding Repair center**
1	1	3	1	1

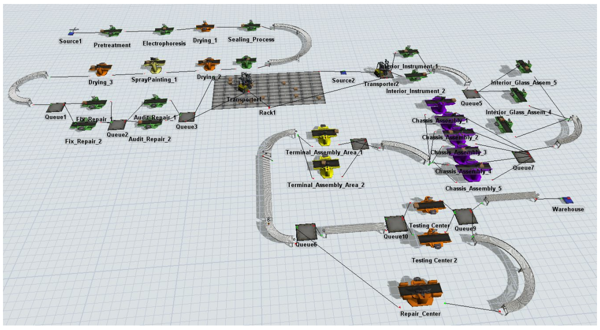

Figure 20. Simulated model of combined plant iteration 29

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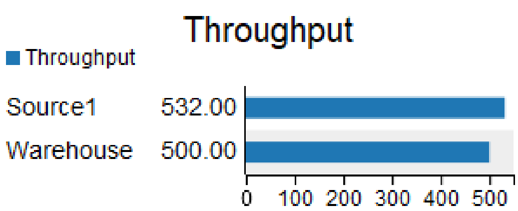

Figure 21. Data of the source and the warehouse for iteration 29

Table 10. Parameters of Iteration 30

Input distribution	Time to produce 500 automobiles in hours	Yield ratio (percentage)	Overall machine efficiency (percentage)
Normal (190.0, 3.0)	36.84200	93.96	80.32

Adding Interior Instrument	Adding Interior Glass Assembly	Adding Chassis Assembly	Adding Terminal Assembly Area	Adding Repair center
2	1	3	1	1

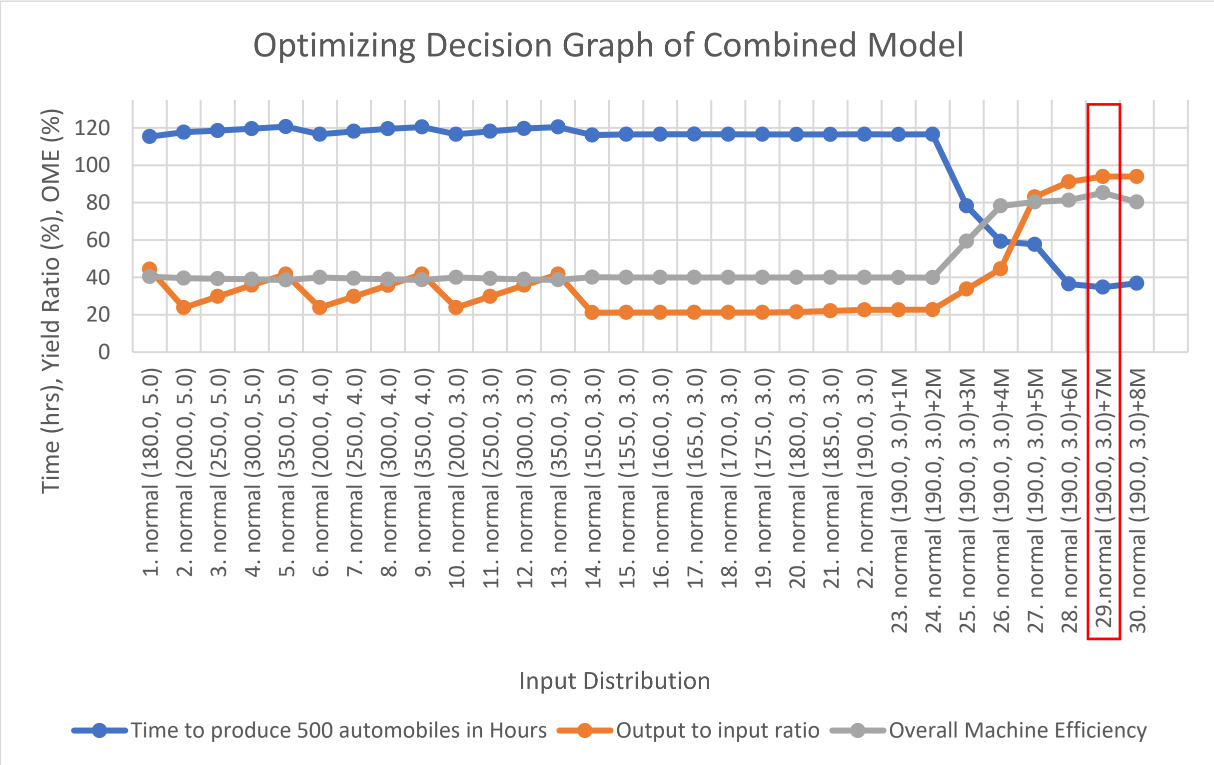

Figure 22. Optimizing decision graph (+ "X" M = adding "X" machines)

The data indicates that iteration 29 achieves the highest yield ratio, making it the optimal parameter combination based on yield percentage. Additionally, iteration 29 requires only 34.751 hours to produce 500 automobiles, the shortest production time observed, establishing it as the most time-efficient configuration. Furthermore, with an overall efficiency of 85.26%, iteration 29 also represents the highest operational efficiency. Thus, the parameter combination from iteration 29 is identified as the optimized set based on yield ratio, production time, and efficiency.

5. Conclusion

This study shows significant improvements in organizing inbound logistics for the automobile industry. FlexSim software helped to make car coating and assembly more efficient. When coating and assembly are done in separate plants, producing 500 cars takes 73.38 hours. In a combined plant, this time drops to 35 hours, saving 38.38 hours. This substantial time saving shows how combining processes can make work faster. Machine efficiency also improves from 73.24% in separate plants to 85.26% in the combined plant. While the quality rate (or yield ratio) is a bit lower in the combined setup, going from 98.62% to 93.96%, the trade-off is worth it because of the major gains in time and efficiency. These changes make production faster, more competitive, and more cost-effective. Also, according to iteration 29, it takes 35 hours to produce 500 automobiles. Thus, the production rate becomes 500/35= 14.28 ≈ 14 automobiles per hour. On 1 July 2018, Elon Musk tweeted that Tesla company had made 7000 cars in 7 days. According to it, the production rate was 7000/ (7*24) = 41.67 ≈ 41 automobiles per hour. From this data, it can be realized that our optimized production rate is realistic. In future, there is a huge scope to introduce

Machine Learning and Artificial Intelligence in this context to make the production plant more agile and optimized.

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Biographies

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