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Simulation model of production processes at the new automotive manufacturing plant

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Abstract. The organisation of large-scale production is one of the most challenging tasks. The correct location of production and auxiliary sites and the optimal movement of material flow are the key to the future success of the enterprise. Before starting the construction of the enterprise, it is necessary to develop a production model with the definition of optimal parameters of the facility and its components. One of the methods of building a model of a real object is simulation modelling. Based on expert data, the data of a manufacturing facility was prepared, focusing on the expected cycle times for various assembly steps, lorry unloading processes and warehouse operations. These estimates served as input data for the simulation model by the software Anylogic. By conducting experiments with the simulation model, the optimal operating parameters of the facility elements were achieved.

Keywords: *simulation modeling, optimization, production process, agent modeling, production logistics*.

1. Introduction

Modern manufacturing is becoming increasingly complex and dynamic, requiring flexible and efficient tools for process analysis, planning, and optimization [1].

Optimization of production and logistics processes directly affects the competitiveness of enterprises. In modern conditions, cost reduction, minimization of downtime, improvement of resource utilization, and improvement of the overall efficiency of the enterprise are important success factors [2-3].

Simulation plays a key role in achieving these goals, allowing you to create virtual copies of production systems and analyze their work without risking real operations [4]. It helps to identify bottlenecks, test various scenarios, and assess the impact of changes on enterprise performance. Based on the simulation model, a digital twin of a real object, production company, logistics and other business processes of production is created [5-6]. In the context of growing competition and accelerated digital transformation, simulation modeling is becoming an integral element of strategic production management.

Simulation modeling allows not only to assess the current state of the system, but also to develop strategies for its improvement. The use of such methods in logistics and production helps to increase the accuracy of forecasting, improve coordination between departments and increase the overall reliability of production processes [7-8].

This study aims to develop and implement a simulation model of production processes at the new Manufacturing plant to optimize logistics processes and increase the efficiency of the enterprise.

Simulation is a method of creating a virtual model of a real-world system to analyze its behavior under various conditions. Simulation helps to replicate production processes, material flows, and logistics networks in manufacturing and logistics without disrupting actual operations [9]. Simulation solves real-world problems safely and intelligently. It is a convenient tool for analysis: it is clear, and easy to understand, and verify. In various fields of business and science, simulation modeling helps to find optimal solutions and provides a clear understanding of complex systems. Bits instead of atoms: Simulation is an experiment on a reliable digital representation of any system. Unlike physical modeling, such as creating a building layout, simulation modeling is based on computer technology using algorithms and equations. The simulation model can be analyzed in dynamics, as well as viewed with animations in 2D or 3D [10].

Computer modeling is used in business when conducting experiments on a real system is impossible or impractical, most often because of its cost or duration.

The ability to analyze a model in action distinguishes simulation from other methods, such as using Excel or linear programming. The user studies the processes and makes changes to the simulation model during operation, which allows for a better analysis of the system and a quick solution to the task.

2. Materials and methods

The organizational structure of the new automobile manufacturing plant consists of: Body Painting Workshops, a Plastic Coloring Shop, three Welding Workshops, three Assembly Shops, Component Warehouse. Warehouse, Treatment Plants, Engineering Networks. The components of the plant and their location are shown in Figure 1.

In simulation modeling, input data represents the real-world information used to define the system being modeled. This data serves as the foundation for the simulation, determining how the model behaves under different conditions. The input data can include various parameters such as (Table 1):

– Operational data: Processing times, service rates, production speeds.

– Resource availability: Number of workers, machines, or vehicles.

– Demand patterns: Customer orders, market fluctuations, or supply chain variability.

– Environmental conditions: Temperature, traffic flow, or weather impact.

– Statistical distributions: Random variations in arrival times or process durations.

– Historical data: Past performance records and trends.

Figure 1. Multi-brand plant

Properly collecting and processing input data ensures the simulation accurately reflects real-world scenarios, making it a crucial step in the modeling process.

Table 1. Information about truck arrival

Parameter	Value	Description
Number of trucks per day	20 pieces	Truck arrival rate
First truck arrival time	09:00 AM	Initial arrival
Truck speed	40 km/h	Speed from TSW to factory
Dock availability	14 docks	Number of unloading docks
Unloading time per Truck according to real experience	20-45 minutes	Time needed per truck
Working hours	(9:00-13:00, 14:00-18:00)	Factory working hours

The Role of Data Accuracy in Model Reliability. The accuracy of input data directly impacts the reliability and validity of a simulation model.

2.1 Sources of Data Collection

Primary sources

Production Forecast and Operational Insights. As the production process at automotive manufacturing plant is yet to commence, direct production reports are not available. However, insights were gathered through expert interviews with factory workers and managers from automotive manufacturing plant, automotive manufacturing plant and manufacturers from China, providing valuable predictions regarding workflow efficiency, time allocation, and logistical challenges.

A time-motion study was conducted based on these expert insights, focusing on the expected cycle times for different assembly stages, truck unloading processes, and warehouse operations. These estimates serve as a foundation for simulation modeling, allowing for adjustments once real-time production data becomes available.

Additionally, potential bottlenecks were identified in areas such as truck unloading schedules, material handling, and workforce distribution. These preliminary findings will be tested and refined through simulation experiments, ultimately contributing to the optimization of production workflows at automotive manufacturing plant.

Secondary sources

The Semi-Knocked Down (SKD) assembly process plays a critical role in automotive manufacturing, balancing cost efficiency and production flexibility. A review of academic literature highlights key strategies for optimizing SKD assembly, including lean manufacturing principles, just-in-time (JIT) logistics, and digital twin simulations to improve efficiency and minimize bottlenecks. Studies also emphasize the importance of ergonomic workstation design and material flow optimization to reduce cycle times.

2.2 Logistics and Material flow data

Transportation from TSW to plant

Trucks transporting SKD components arrive from the Temporary Storage Warehouses (TSW), covering a specified distance to the manufacturing plant. These trucks travel at an average speed of 40 km/h, ensuring a steady and predictable flow of materials into the facility. The travel distance, combined with potential road conditions and external factors, may slightly affect arrival accuracy, which will be considered in the simulation model.

Table 2. Duration from TSW (1,2) to plant

TSW 1 (about 10 km)	duration (149 min)
Passing the checkpoint and the road to the container yard	00:05
Finding and removing the desired container	00:29
Loading the container onto the truck (richstacker operation)	00:06
Departure from the TSW	00:05
The road to AMMK (40 km/hr)	00:18
Unloading at the AMK	01:00
The road to the TSW (40 km/hr)	00:15
Passing the checkpoint and the road to the container yard	00:05
Removing an empty container	00:06

The table presents a time breakdown of the logistics process between Temporary Storage Warehouse (TSW 1) and automotive manufacturing plant. It details each step involved in transporting a container, from retrieval at TSW to unloading at AMMK and the return trip of the truck.

Table 3. A detailed time breakdown of the logistics process

TSW 2 (about 75 km)	duration (266 min)
Passing the checkpoint and the road to the container yard	00:06
Finding and removing the desired container	00:13
Loading the container onto the truck (richstacker operation)	00:05
Departure from the TSW	00:06
The road to AMMK (50 km/hr)	01:30
Unloading at the AMK	01:00
The road to the TSW (60 km/hr)	01:15
Passing the checkpoint and the road to the container yard	00:05
Removing an empty container	00:06

The table 3 provides a detailed time breakdown of the logistics process between Temporary Storage Warehouse (TSW 2) and automotive manufacturing plant. It outlines each step involved in transporting a container over a longer distance (75 km) compared to TSW 1 (10 km).

The simulation model represents the production and logistics flow at the automotive manufacturing plant. The layout is designed to simulate the key stages of semi-knocked down (SKD) vehicle assembly, starting from truck arrival and unloading to the final vehicle testing area. Below are the main components of the model:

Entrance & Waiting Area: Trucks arrive from the Temporary Storage Warehouse (TSW) and queue up in the Waiting Area before being directed to available unloading docks.

Unloading Area: The Unloading Docks section includes 18 docks where trucks unload car parts. Trucks are assigned to the nearest available dock to ensure efficiency.

Forklift Zones: There are designated areas for Forklifts, which transport parts from the unloading docks to the storage area and assembly lines.

Storage Area: Components are temporarily stored here before being moved to the assembly line. It includes a bay system to optimize space usage.

Assembly Line: This area follows a U-shaped conveyor layout where the main assembly steps take place:

Test Ride Area: After assembly, vehicles are moved to the Test Ride area to ensure quality control before final delivery.

This model simulates the real-time logistics and production processes to identify bottlenecks and propose improvements for plant efficiency. Forklifts and trucks operate as agents within the AnyLogic agent-based simulation environment [11-14].

Table 4 are shown the assembly process data.

Table 4. Detailed data about the duration of assembly

Body assembly	Seats	60 seconds
	Front Door	50 seconds
	Rear Door	50 seconds
	Side mirrors	40 seconds
Chassis assembly	Engine	80 seconds
	Gear box	70 seconds
	Wires	40 seconds
Final Assembly	Merging body with chassis	90 seconds
Check	Checking the geometry of body	180 seconds
	Checking for leakproofness	300 seconds
	Installation the battery	90 seconds
	Refueling with gasoline	120 seconds

Anylogic model is shown in Figure 2.

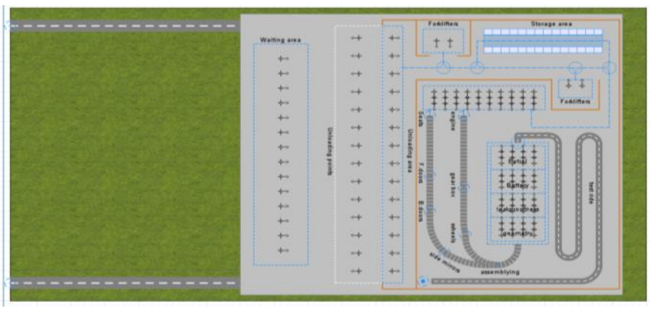

Figure 2. Interpretation of the plant in the Anylogic program

3. Results and discussion

Figure 3 are results based on the simulation model in AnyLogic for the SKD (Semi Knocked Down) car manufacturing process at automotive manufacturing plant.

The simulation model successfully replicates the key logistics and production processes at the automotive manufacturing plant, focusing on truck unloading, part storage, assembly line operations, and final test rides. The results demonstrate the efficiency of the current SKD (Semi Knocked Down) workflow while identifying opportunities for further optimization.

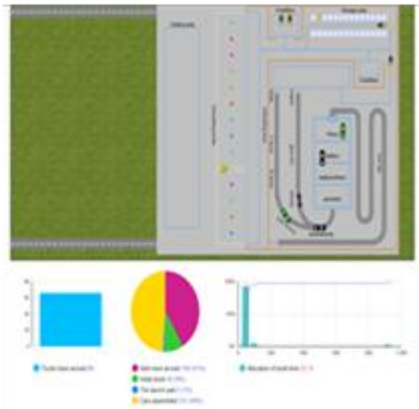

Figure 3. Simple layout of plant automotive manufacturing plant in simulation

Key outcomes from the simulation include:

– 219 cars were assembled during the simulation period, which represents 48% of the total throughput.

– 195 sets of components arrived (42%), indicating a stable supply chain with room to increase unloading speed or storage capacity.

– A total of 65 trucks delivered goods, with unloading distributed between 18 docks and supported by 5 forklifts.

– Initial stock accounted for 9%, suggesting a lean inventory strategy.

– The launch pad used 1%, revealing low queuing and good production flow.

In this simulation (Figure 4), the «Allocation of Build Time» refers to the percentage of total simulation time during which the assembly stations were actively engaged in building cars. Specifically, the value 59.59% indicates that more than half of the total operational time was utilized for productive assembly processes, including engine installation, gearbox mounting, wheel attachment, side mirrors, battery placement, and quality checks (geometry, leakproofness, etc.).

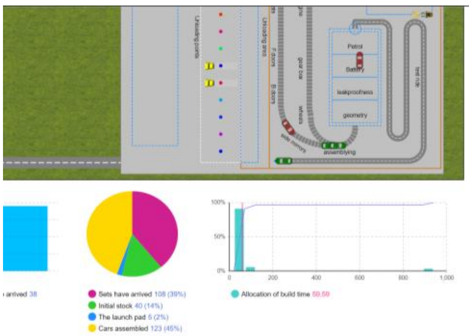

Figure 4. Allocation of Build time

The model illustrates the effectiveness of the current setup but also points toward potential improvements:

– Adding more forklifts or optimizing their routes could reduce idle times and increase unloading efficiency.

– Reducing bottlenecks at specific assembly stages could improve car throughput.

– Adjusting truck arrival schedules might reduce peak-time congestion at unloading docks.

Overall, the simulation provides valuable insights into the factory's logistics and operational performance, serving as a powerful decision-making tool for optimizing production and supply chain activities.

3.1. Case studies and efficiency analysis

Case Study 1: The Impact of Defective Incoming Parts on Manufacturing Efficiency at automotive manufacturing plant.

Introduction In modern automotive manufacturing, production efficiency and continuous workflow are critical to meeting delivery targets and maintaining quality standards. At automotive manufacturing plant, the assembly of vehicles depends heavily on the timely delivery of high-quality components from external suppliers. However, the presence of defective incoming parts presents a significant challenge to production stability. This case study explores how defective parts affect the assembly line and proposes mitigation strategies through simulation modeling.

Problem Statement Although automotive manufacturing plant does not produce the components used in car assembly, it bears the consequences of receiving defective items. Faulty parts—such as engines, gearboxes, wheels, or doors—can lead to line stoppages, delayed vehicle output, and resource inefficiencies. Without an effective strategy to handle these defects, overall manufacturing performance suffers.

Objectives:

– To quantify the impact of defective incoming parts on production output;

– To analyze delays and idle times caused by defective parts;

– To evaluate mitigation strategies such as safety stock and rwork lines;

– To simulate the scenarios using AnyLogic modeling software.

Methodology The research utilizes a simulation-based approach. Using AnyLogic, a digital twin of the assembly line is developed with realistic process times and component flows. Defective parts are modeled using probabilistic functions (e.g., assigning a 5% defect rate for specific parts). The simulation includes the following elements:

– Quality inspection upon part arrival

– Quarantine and rejection of defective items

– Delay in car assembly due to missing parts

– Use of buffer stock where available

– Rework or wait zone for partially assembled vehicles

Simulation Parameters

– Number of vehicles produced per day: 100

– Defect rate per component: 3–5%

– Number of critical components: engine, gear box, wheels, doors, side mirrors

– Time to detect defect: 1–2 minutes per item

– Delay due to unavailability of replacement: 30–90 minutes

– Safety stock: 10% of daily demand for critical parts

As a result, there are three types of scenarios and key findings (Figure 6).

The analysis demonstrates that defective incoming parts significantly hinder production flow. The presence of a well-managed buffer system and a dedicated rework zone can mitigate these disruptions. However, increasing buffer size adds inventory costs, and rework lanes require additional space and personnel. Thus, a balanced strategy that includes strict supplier quality control, accurate defect prediction, and lean buffer usage is ideal.

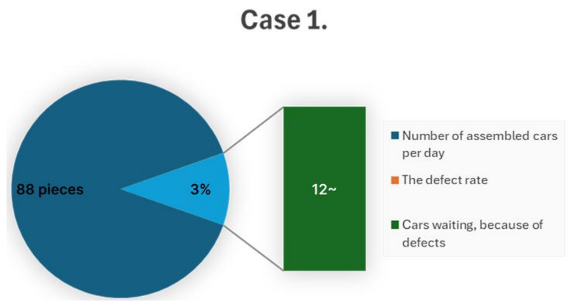

Figure 5. Case 1

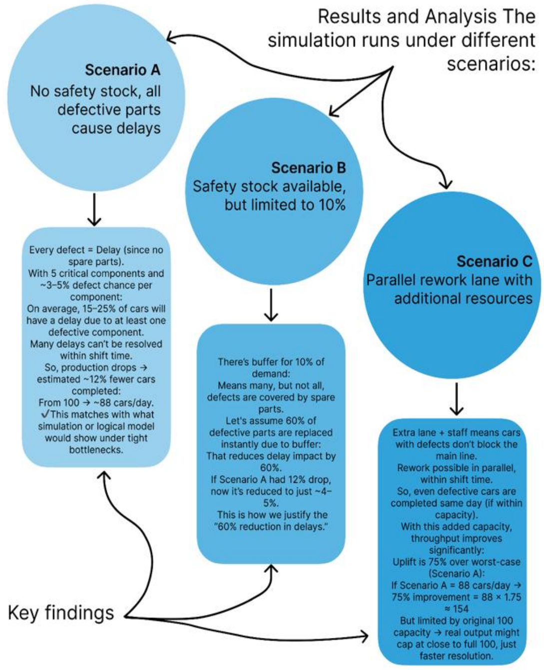

Figure 6. Scenario A, B and C

Automotive manufacturing plant, while not directly responsible for part production, must incorporate quality control mechanisms within its manufacturing operations. By leveraging simulation tools like AnyLogic, the company can forecast delays, evaluate corrective actions, and enhance operational resilience. This case underlines the importance of anticipating supply chain issues and integrating real-time response strategies in modern automotive manufacturing.

Case Study 2: Production Based on Forecast vs Real Demand – A Strategic Manufacturing Dilemma.

Introduction One of the strategic challenges in modern manufacturing is aligning production with market demand. At automotive manufacturing plant, production volumes are planned based on forecasted data provided by dealerships. However, when actual customer demand significantly deviates from forecasts, it can result in either overproduction or underproduction. This case study investigates the implications of such discrepancies on manufacturing efficiency and inventory management.

Problem Statement Producing vehicles based on dealership forecasts assumes a level of predictive accuracy that often does not materialize. When actual sales lag behind expectations, unsold inventory accumulates, tying up resources and increasing holding costs. Conversely, if demand exceeds production, stockouts may occur, leading to customer dissatisfaction and missed sales opportunities.

Objectives:

– To compare forecasted versus actual demand

– To measure the impact of demand deviation on production and inventory

– To identify strategies for improving forecast accuracy and responsiveness

– To simulate production responsiveness using AnyLogic

Methodology A simulation model is created using AnyLogic to replicate the production process based on forecasted input. Actual sales data is then introduced with varying degrees of deviation. Key performance indicators such as stock levels, production rates, and fulfillment rates are monitored across multiple forecast accuracy scenarios:

– High Accuracy (±5%);

– Medium Accuracy (±15%);

– Low Accuracy (±30%).

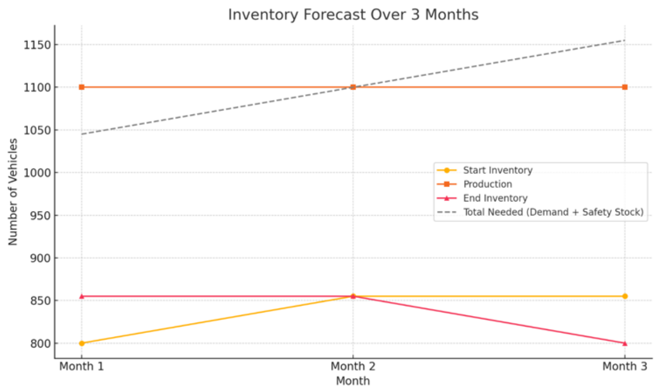

Figure 7. Forecast for next three months

Table 4. Forecast for next three months

Month	Forecasted Demand	Safety Stock (10%)	Total Needed	Projected Inventory (Start)	Production	End Inventory
1	950	95	1,045	800	1,100	855
2	1,000	100	1,100	855	1,100	855
3	1,050	105	1,155	855	1,100	800

– Forecast horizon: Monthly, updated quarterly;

– Production lead time: 2 weeks;

– Maximum warehouse capacity: 1,000 vehicles;

– Average daily production: 50 vehicles;

– Safety stock policy: 10% above forecast.

Results and Analysis The simulation revealed:

– High accuracy forecasts led to balanced inventory and efficient resource use;

– Medium accuracy caused 18% overproduction and 10% under-fulfillment in some months;

– Low accuracy resulted in severe mismatches, including warehouse overflow and production slowdowns due to limited storage;

– Dynamic forecast adjustments (monthly updates) improved alignment by 22%.

Forecast-driven production can be efficient when the data is reliable. However, in volatile markets, dependency on forecasts alone may expose the manufacturing system to inefficiencies. A hybrid model—combining rolling forecasts with real-time sales data—can improve responsiveness. Lean principles such as just-in-time (JIT) or build-to-order (BTO) may further reduce the risk of overproduction.

4. Conclusions

Production planning based solely on predicted demand presents risks in accuracy-sensitive manufacturing environments. By integrating demand tracking, dynamic forecast updates, and flexible production capabilities, automotive manufacturing plant can reduce mismatches and improve overall operational performance. Simulation modeling proves to be a valuable tool in identifying optimal demand-management strategies.

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Автомобиль зауытының өндірістік процесінің имитациялық моделі

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Аңдатпа. Ірі өндірісті ұйымдастыру-күрделі міндеттердің бірі. Өндірістік және қосалқы учаскелердің дұрыс орналасуы және материалдық ағынның оңтайлы қозғалысы кәсіпорынның болашақ табысының кепілі болып табылады. Кәсіпорынның құрылысын бастамас бұрын, объектінің және оның компоненттерінің оңтайлы параметрлерін анықтай отырып, өндіріс моделін жасау қажет. Нақты объектінің орналасуын құру әдістерінің бірі-Имитациялық модельдеу. Сараптамалық мәліметтер негізінде әртүрлі құрастыру кезеңдері, жүк көліктерін түсіру процестері және қойма операциялары үшін күтілетін цикл уақытына назар аударатын өндірістік объектінің деректері дайындалды. Бұл бағалаулар Anylogic ортасында Имитациялық модельге кіріс ретінде қызмет етті. Модельдеу моделімен эксперименттер жүргізе отырып, объект элементтерінің оңтайлы параметрлеріне қол жеткізілді.

Негізгі сөздер: *имитациялық модельдеу, оңтайландыру, өндіріс процесі, агенттерді модельдеу, өндірістік логистика.*

Имитационная модель производственного процесса автомобильного завода

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Аннотация. Организация крупного производства является одним из сложных задач. Правильное расположение производственных и вспомогательных участков и оптимальное движение материального потока является залогом будущего успеха предприятия. Перед тем, как начать строительство предприятия, необходимо разработать модель производства с определением оптимальных параметров объекта и его составляющих. Одним из методов построения макета реального объекта является имитационное моделирование. На основе экспертных данных было проведена подготовка данных производственного объекта, в котором основное внимание уделялось ожидаемому времени цикла для различных этапов сборки, процессов разгрузки грузовиков и складских операций. Эти оценки служили входными данными для имитационной модели в среде Anylogic. Проведя эксперименты с имитационной моделью, были достигнуты оптимальные параметры работы элементов исследуемого объекта, что необходимо для производственной логистики.

Ключевые слова: *имитационное моделирование, оптимизация, производственный процесс, агентное моделирование, производственная логистика.*

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