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A Digital Twin Simulation Model for Production Planning under demand uncertainty in GKN aerospace Fokker

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Abstract

This thesis studies how increases in customer demand affect production performance at Gulfstream and Dassault assembly lines at GKN Aerospace Fokker's Hoogeveen facilities and how planning decisions can be adapted to maintain system stability. The current production planning approach relies on experience and limited predictive capabilities, making it difficult to evaluate the impact of demand increases on workforce allocation, shift structures and station utilization. To address this challenge, a digital twin simulation model was developed to represent the interaction between material and information flows and capacity and planning decisions within the production system.

The study develops a digital twin integrating Discrete-Event Simulation (DES) with individual agents and Java coding to capture both the physical production processes and the planning decisions driving resource allocation. The simulation model was implemented in AnyLogic and validated using operational data from the company. Several experimental scenarios were evaluated, focusing on increased demand levels, capacity adjustments, and planning parameter variations.

The results indicate that overall system performance is highly sensitive to a limited number of bottlenecks within the production system. In particular, two Gulfstream stations are identified as critical stages that significantly influence overall performance and system stability. The developed digital twin serves as a decision support tool, enabling planners to evaluate alternative capacity configurations and planning policies prior to their implementation in practice. Overall, this project demonstrates how simulation based digital twins can facilitate data driven production planning and enhance decision making in complex aerospace manufacturing environments.

1 Introduction

1.1 Motivation

In modern manufacturing environments, the ability to effectively plan and coordinate production activities has become crucial for sustaining competitiveness. Increasing product fluctuating demand patterns and strict delivery requirements place significant pressure on production systems, often resulting in congestion, bottlenecks, and delays that propagate across multiple stages of the production process. At the same time, rising labour costs and a limited labour pool complicate the ability of companies to manage resource utilization while maintaining production targets and controlling operational costs. Consequently, effective production and workforce planning are essential to ensure that available capacity, workforce skills, and schedules remain aligned with actual production requirements. When these elements are not properly coordinated, inefficiencies at individual workstations can propagate through the system, resulting in increased lead times, delivery delays and higher costs. For manufacturing companies, understanding and anticipating these matters is fundamental for improving operational stability, managing costs, and supporting long term performance (Heuser et al., 2022; Magnanini et al., 2021; Biruk et al., 2022).

However, modern production systems are often characterized by complex interactions between resources, processes, and planning decisions. Changes in demand levels, routing policies, workforce allocation, or shift structures can significantly affect system performance, making it difficult to predict the consequences of planning decisions using traditional analytical methods. In such environments, simulation and digital twin technologies have emerged as valuable decision support tools that allow companies to analyze production system behavior under different scenarios without disrupting real operations. By representing material flows and the multiple interactions of resources (Tao et al., 2022), simulation models enable organizations to identify potential bottlenecks and evaluate alternative capacity configurations. Furthermore, the use of digital twin simulation frameworks allows for the assessment of complex planning policies to better capture system behavior before implementation (Brailsford et al., 2019).

GKN Aerospace is a global manufacturer employing more than 16,000 people across 32 production sites in 12 countries, serving leading aircraft programs worldwide. Within this network, the Hoogeveen (GKN Aerospace Fokker) facilities in the Netherlands, located on Marconi Street and Edison Street play a key role in the assembly of flight control surfaces such as rudders and elevators for the Gulfstream and Dassault programs. Although the two plants are physically adjacent, they operate as distinct production areas that must coordinate materials and capacities daily, as each site is sensitive to the events happening on either site. Fluctuations in shift structures and customer demand patterns can potentially lead to temporary bottlenecks, under or over utilized stations and late deliveries.

Addressing these challenges is important not only from an operational perspective but also for the stakeholders directly involved in daily planning and execution. Production team leaders act as the bridge between operators and schedulers, ensuring that staffing levels and skill assignments match the planned workload. Shop floor schedulers translate production plans into executable sequences, while the master planner oversees the long-term planning between demand, capacity, and workforce availability. Finally, operators experience the outcomes of these planning decisions first hand, as changes in shift configuration or task allocation affect their productivity and work rhythm. Developing a structured, data driven approach to workforce and shift planning therefore has direct implications for coordination, communication, and efficiency across all these roles, supporting both organizational and employee objectives.

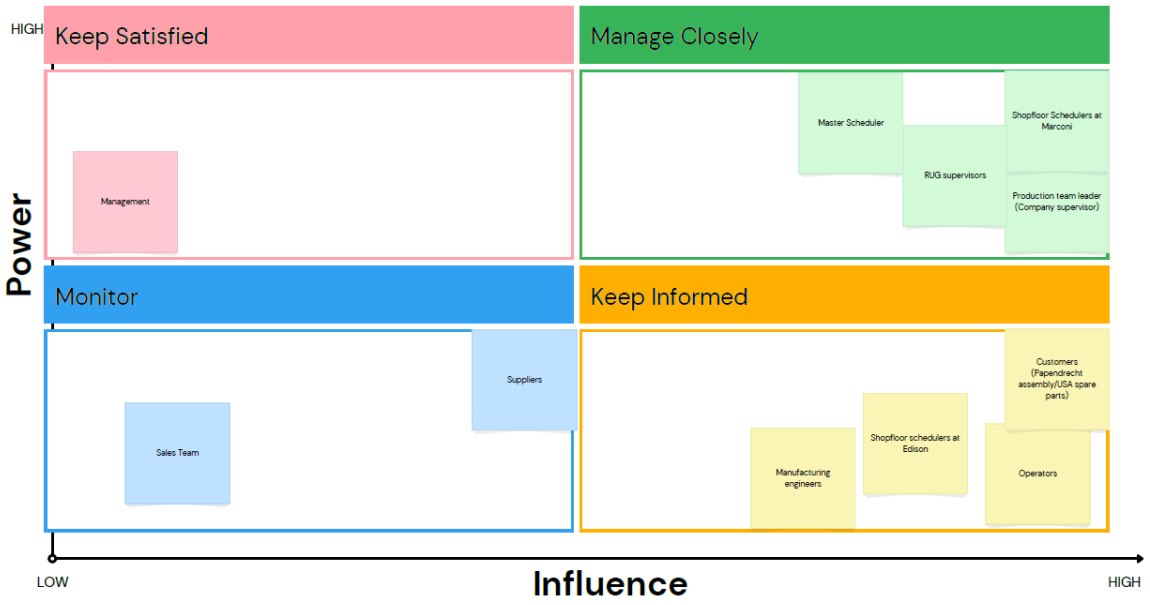


Figure 1: Stakeholder analysis diagram for this project. Axis y shows level of power while axis x shows level of influence.

The stakeholder analysis shown in Figure 1 shows the power and influence relationships surrounding the project at GKN Aerospace Fokker. The Master Scheduler, Production team leaders, and Shopfloor schedulers at Marconi fall in the *Manage Closely* quadrant, as they are directly responsible for planning, executing, and coordinating production activities. Their high influence and operational power make them key stakeholders in the model creation and validation as valuable data and resource sources. In addition, the university supervisor and the production team leader (company supervisor), are also included within the *Manage Closely* quadrant due to their high influence on the direction of the project. The university supervisor ensures that the research follows proper scientific principles and that the modelling approach meets the academic requirements of the thesis while acting as a valuable source of guidance. At the same time, the production team leader contributes with on site knowledge and practical constraints from the shopfloor. In particular, the production team leader provides guidance on how the production system operates in practice and identifies which processes and planning decisions should be represented in greater detail within the simulation model. Together,

both supervisors define requirements for the simulation model to be developed, while aiding in the scoping of the project.

The Management team, positioned under *Keep Satisfied*, holds strategic decision-making power but is less involved in daily operations. Stakeholders in the *Keep Informed* quadrant, such as Shopfloor schedulers at Edison, Operators, Manufacturing engineers, and Customers have high influence on project's practical success but limited authority, making communication and feedback essential. Finally, the *Monitor* group, which includes the Sales team and Suppliers, holds comparatively lower power and influence but remains important for context and high level understanding of the production flow. The stakeholder analysis also serves as a basis for identifying the data collection sources and its validation. Stakeholders with high operational involvement, such as the master scheduler, production team leaders, and shopfloor schedulers, provide crucial input regarding planning rules, workforce allocation, and capacity constraints. Their knowledge is used to validate both the input data and the logic implemented in the simulation model, ensuring that the model accurately represents the real production system at GKN Aerospace Fokker. In this way, the stakeholder analysis supports the identification of reliable data sources and ensures that the model reflects real practices.

From an academic perspective, efficient workforce and capacity planning have been recognized as crucial factors in manufacturing performance. Research shows that the availability and distribution of skilled labour directly influence throughput, lead time, and production stability, particularly in complex industries. Magnanini et al. (2021) demonstrated that workforce shortages or misallocations in shopfloor environments can induce delays across interconnected process stages (chains of production), as is the case at Fokker, reducing overall productivity. Their work further emphasized the value of digital twin based simulation for evaluating the operational impact of workforce availability and shift organization to resolve capacity constrained issues.

Similarly, Biruk et al. (2022) proposed a simulation based manpower planning framework capable of modelling uncertainty in workloads and resource availability, showing that stochastic approaches provide a more reliable foundation for long term staff planning and scheduling decisions than deterministic planning, especially when dealing with demand volatility. Other contributions, such as Kumar and Arora (1999), highlighted how integrated workforce scheduling across production areas can achieve substantial cost savings and reduce idle capacity by eliminating "over design" intended to absorb system variabilities.

Economic research further supports the link between workforce efficiency and cost performance: Stundziene and Baliute (2022) found a strong long term relationship between personnel costs and labour productivity across the European manufacturing sector, highlighting that the way human resources are utilized has direct financial implications on the gross operating rate and overall turnover. Overall, the literature suggests that simulation driven and data based workforce planning tools can substantially improve decision making under variable demand and constrained capacity. Despite these

advances, few works integrate shift structures, workforce allocation, and demand variability within a digital twin framework, particularly in aerospace manufacturing contexts. Addressing this gap forms the academic foundation of the present project.

1.2 Problem context

GKN Aerospace Fokker's Hoogeveen facility consists of two adjacent production sites located on Edisonstraat and Marconistraat**,** responsible for the manufacturing of rudders and elevators (left and right hand) for the Gulfstream and Dassault aircraft programs. Together, these represent two distinct production lines that share a similar production process and physical site but are operated by separate workforces assigned to each program. Although the underlying production steps are technically similar, the lines function under different shift structures: the Dassault program follows a single 40-hour shift per operator, whereas Gulfstream operates with two shifts. These differences, added to the potential fluctuation in the demand patterns, introduce significant complexity in planning and maintaining balanced utilization across lines and shifts.

At present, workforce allocation and shift planning decisions are primarily based on fixed production schedules and planner experience. While this approach is useful for stable demand, it becomes challenging when fluctuations happen. When workloads deviate from the expected or planned ones, the workforce must be reorganized to maintain productivity, creating risks of bottlenecks in some workstations.

According to company experts, the production planning at Fokker is designed yearly. In the last year and for 2026, the total demand for Gulfstream and Dassault is of 70 and 17 ship sets a year (Ship set meaning 1 rudder, 1 elevator lh and 1 elevator rh). However, for the coming 2027 year, the company expects an increase in customer demand to 100 and 20 ship sets a year, increasing notably the workload. At current times, lead times for Gulfstream finished products are in the range of 6 to 7 weeks and Dassault in 7 to 8 weeks with no orders being delivered late. This means that the company will have to adapt to the upcoming workload in order to keep performing well.

It should be noted that the demand exceeds 100 shipsets for the Gulfstream programme as it does not exclusively correspond to complete shipsets, but also includes additional component demand in the form of spare parts, which are shipped separately. This results in a higher production load than what is reflected by shipset quantities alone. Therefore the demand increased is the following:

- Dassault rudders (RUDDF): increase of 3 units (from 17 to 20)
- Gulfstream rudders (RUDDFG): increase of 57 units (from 123 to 180)
- Dassault elevator LH (ELEVLHF): increase of 4 units (from 16 to 20)
- Gulfstream elevator LH (ELEVLHFG): increase of 40 units (from 72 to 112)
- Dassault elevator RH (ELEVRHF): increase of 4 units (from 16 to 20)
- Gulfstream elevator RH (ELEVRHFG): increase of 40 units (from 72 to 112)

This challenge affects multiple levels in the organization of the production, as decisions need to be taken to adapt to the upcoming demand. Changes in one area can potentially influence others, therefore, planning inefficiencies can lead to over or under staffing,

delayed orders, and higher labour costs. Similar issues have been identified in academic studies, where limited workforce availability or rigid assignment rules cause poor system performance (Magnanini et al., 2021; Zülch et al., 2004).

To address these limitations, Fokker requires a data driven and demand adaptive planning approach that considers demand increase, workforce and capacity planning and shift structures. A simulation based digital twin provides a realistic test framework to assess different planning scenarios, anticipate bottlenecks, and recommend shift configurations that sustain delivery and lead time performance.

Category	Current Situation	Operational Consequences	Relevant Stakeholders
Planning Method	Based on internal production data and planner experience.	Limited ability to adapt to increases in demand or shift scenarios.	Master Planner, Shopfloor Schedulers
Shift Structures	Dassault lines: 1 shift; Gulfstream lines: 2 shifts.	Higher capacity at Gulfstream which leads to lower lead times compared to Dassault	Team Leaders, Production Management, Shopfloor Schedulers
Workforce Organization	Separate operator groups per program. Standard configuration for the current demand	Reduced understanding of the impacts of workforce planning when demand changes.	Team Leaders, Operators, Shopfloor Schedulers
Demand Increase	Upcoming increase in the demand for both programs	Schedule instability, overtime, or backlog accumulation.	Master Planner, Shopfloor Schedulers
Cross-site Coordination	Two adjacent sites (Edisonstraat & Marconistraat) interact through material transfers.	Potential delays due to interplay between sites	All operational stakeholders
Performance Monitoring	Mainly through lateness, workforce efficiency and average lead times per product.	Limited predictive capability to prevent deviations.	Management, Team Leaders

Table 1: Current situation at Hoogeveen facilities and their operational impacts

Therefore, and with the current situation taken into account, this study provides the following problem statement:

"GKN aerospace Fokker faces an increase in the demand for Gulfstream and Dassault programmes for the coming years. However, current planning decisions, station capacity and workforce structure is based on experience and there are no decision making support tools available in the company at the moment. Preparing for the coming demand increase, Fokker requires managerial insights on where the most demand sensitive areas in the system are and how to mitigate these effects."

1.3 Scientific and Corporate Contribution

This project contributes both to industrial practice and academic research by developing a simulation based digital twin for aerospace manufacturing. The scientific challenge addressed in this research lies in developing a simulation model that captures both physical production processes and planning logic to evaluate system behaviour under different demand and capacity scenarios. Building on simulation principles outlined by Brailsford et al. (2019) and implemented in industrial studies such as Altendorfer et al. (2013), the model integrates Discrete-Event Simulation (DES) to represent how material and information flows interact with each other.

Production planning is commonly structured as a hierarchical process, where decisions made at an overall level, such as capacity and demand planning, are linked to more detailed decisions at the level of individual orders and scheduling (Hax & Meal, 1975; Stadtler, 2005).

In particular, the study contributes to production planning research by explicitly modelling the interaction between higher level planning decisions, such as capacity and workforce allocation and the planning and execution decisions generated through the MRP logic and shopfloor scheduling. This enables the analysis of how decisions at different planning levels influence system performance.

This dual approach enables the exploration of different demand and shift scenarios, identifying the most effective configurations that sustain performance targets under increased workload. Furthermore, this modelling approach enables the systematic analysis of the interaction between planning levels, particularly how short term operational decisions, such as order releases and scheduling are influenced and constrained by tactical capacity decisions, thereby providing a structured framework to study alignment across hierarchical production planning levels.

The project operationalizes the digital twin concept (Tao et al., 2022) as a decision support tool that represents real conditions at GKN Aerospace Fokker's Hoogeveen facilities, in order to identify the most sensitive areas in production and assess mitigation strategies without disrupting real production. By combining simulation with workforce and shift planning theory (Zülch et al., 2004; Magnanini et al., 2021), the study advances current research.

In doing so, it provides an actionable model for balancing resource utilization and productivity, while demonstrating the benefits of simulation and data driven workforce and capacity planning in manufacturing environments. The project also assists GKN Aerospace Fokker Dassault and Gulfstream programmes in analysing the implications of increased demand scenarios in overall planning while identifying areas for improvement.

2 System Description and Methods

2.1 System Description and Logic

The described system is composed of two parts. There is a planning process which is equivalent to the information flow which then triggers the production process, equivalent to the material flow. Therefore, in this system, the manufacturing of products is driven by the information flow which issues production and purchase orders depending on the needs calculated by the Material Requirements Planning (MRP) integrated in Fokker's ERP system.

2.1.1 Information Flow

The information flow at GKN Aerospace Fokker's Hoogeveen facility connects customer demand with daily production planning through a hierarchical structure. Figure 2 shows how customer demand and production feedback information flows between the planning and execution levels across both the Edisonstraat and Marconistraat sites.

At the top of the diagram in Figure 2, the Sales Team receives confirmed customer demand and forecasted requirements from the given programs (Gulfstream and Dassault). This information flows to the Master Scheduler (long term planning), who assigns due dates considering current capacity and translates it into a Master Production Schedule (MPS). The MPS defines what quantities must be produced and when, serving as the primary input for the company's MRP integrated in the Enterprise Resource Planning (ERP) system. Due to the long lead times for raw material replenishment, the MPS is planned with a horizon of several years.

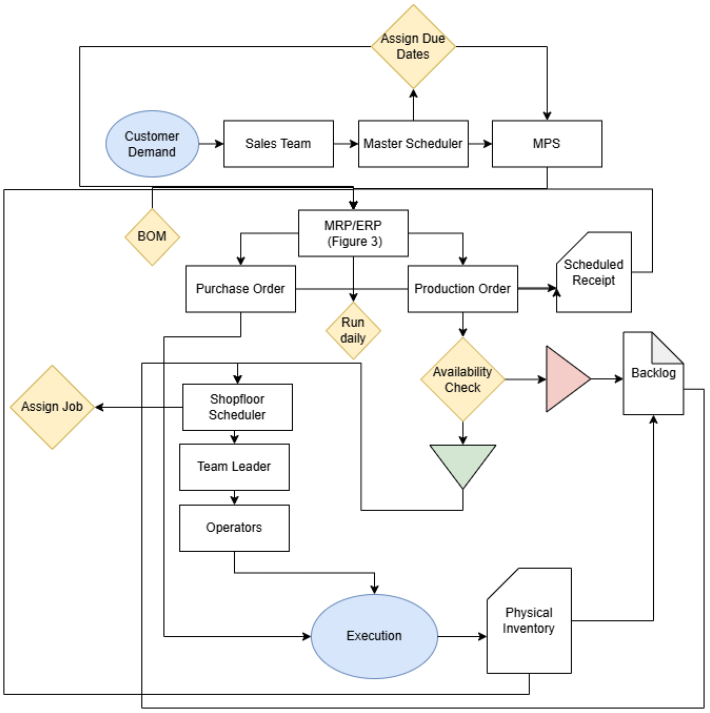


Figure 2: Information flow between planning and execution levels at Hoogeveen.

The MRP run (updated daily) performs the necessary calculations of material and finished product requirements (Figure 3). Based on the Bill of Materials (BOM) and existing inventory data, the system compares *gross requirements* for finished items with

physical *on-hand inventory*, *scheduled receipts* (already firmed orders), and *safety stock* to calculate the net requirements. Through a series of planning steps, namely, netting, lot sizing, and backward scheduling it determines *planned receipts* and *planned releases* for each product as seen in Figure 3. After the availability check, if there is a shortage identified, production orders are put on hold (backlog) until the necessary materials are available in the physical inventory. In the event of enough existing inventory then the production orders are directly sent into execution. These orders act as triggers for the material flow, instructing upstream processes or suppliers to replenish stock. At the same time the MRP issues production orders for inhouse manufactured goods.

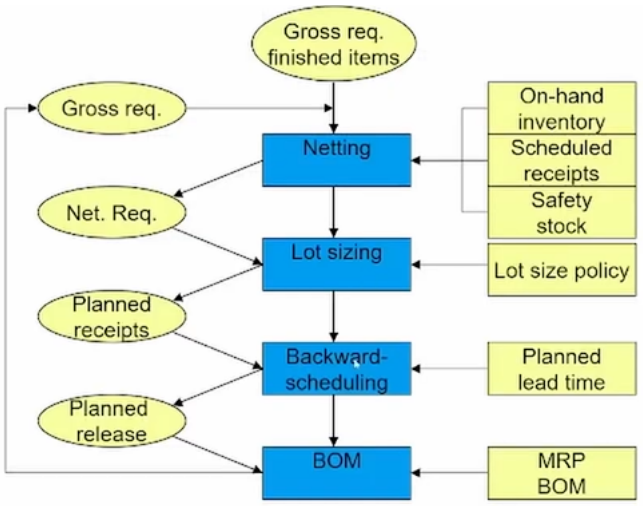


Figure 3: Material Requirements Planning (MRP) logic converting gross requirements into production and purchase orders.

Once production orders are released, responsibility shifts to the Team Leaders and Shopfloor Schedulers, who translate them into executable tasks for the operators. Shopfloor schedulers assign daily priorities and destinations (short term planning), while team leaders bridge the gap between schedulers and operators, making sure production runs smoothly. Operators then execute the tasks and report completion, updating stock and feeding performance data back into the nightly MRP update. The loop closes when finished assemblies are transferred either to the Papendrecht site for assembly or to the U.S. to be used as spare parts.

This layered information structure ensures that strategic planning (MPS and MRP) and operational execution (team leader and scheduler levels) are aligned. It also shows how the information flow directly runs the material flow as production cannot start until the MRP system releases the orders.

2.1.2 Routing

The material flow at GKN Aerospace Fokker's Hoogeveen facility describes the paths and routings that the components must take to be manufactured into final products for the Dassault and Gulfstream aircraft programs. As shown in Figure 4, production is distributed across two adjacent sites: Edisonstraat, where component (not shown in the figure for simplicity) manufacturing and intermediate final production stages occur, and Marconistraat, where final product main assembly steps and integration take place. The production system therefore consists of multiple parallel flows of structural components that converge at Marconistraat for final product assembly, forming an assembly chain.

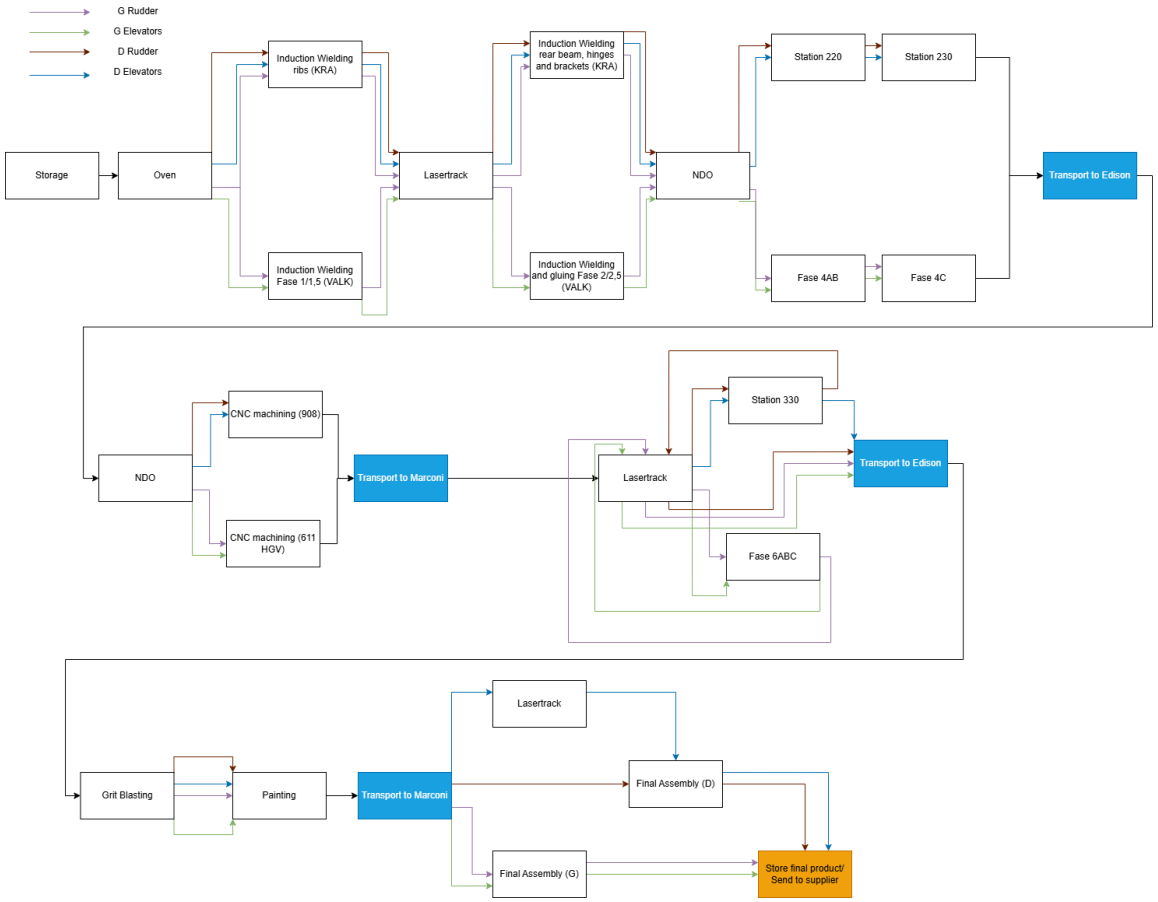


Figure 4: Diagram showcasing the material flow of Dassault and Gulfstream programs and the interplay between Marconi and Edison sites

At Edisonstraat, the manufacturing of parent components forms the foundation of the material flow. For the Dassault program, ribs, skins, and beams for both rudders and elevators are produced inhouse, while leading, trailing edges and fairing components are supplied from external suppliers. In the Gulfstream program, skins and beams are also manufactured internally, while leading and trailing edges for elevators are purchased. However, trailing edges for the rudder are produced inhouse, and ribs are mostly purchased, with only one of them being produced internally.

The production of these parent items involves several key stages: pre-cutting, lamination, autoclave curing, and debagging, followed by CNC machining (machines 908 and 611 HGV), oven processing, and manual composite finishing. Non-destructive testing (NDO)

verifies dimensional accuracy and structural integrity before releasing them to Marconi to be integrated into the final product.

In addition to component manufacturing, Edisonstraat also performs intermediate processing steps for the final products such as machining, grit blasting and painting. This bidirectional flow is essential to synchronize production between the two sites and maintain continuity in the final assembly process.

At Marconistraat, the final product assembly process begins once the parent components arrive from Edisonstraat and the different suppliers. Separate production lines exist for the Dassault and Gulfstream programs, although certain stations such as Non-Destructive Testing (NDO) and LaserTrack are shared between programs.

The induction welding stations (KRA and VALK) are dedicated to each program with KRA being used for Dassault and VALK for Gulfstream. However, KRA induction welding machines can also be used to process Gulfstream rudders when the scheduling permits it. The workflow proceeds through intermediate phases (e.g., 4AB, 4C, 6ABC, Station 220, Station 230, Station 330) before returning to inspection or laser processing steps and finally arriving at final assembly steps. After this complex process, final products are then ready to be stored and released to customers.

2.1.3 Conceptual Model

The conceptual model shown in Figure 5 integrates the information flow and material flow at GKN Aerospace Fokker's Hoogeveen facility into a system representation. The purpose of the conceptual model is to demonstrate how information generated at the planning level triggers the physical production processes executed at Edison and Marconi sites. It also defines how feedback from production closes the loop with the planning layer, supporting the digital twin logic implemented later in the simulation model.

The process begins with customer demand, received by the Sales Team and transferred to the Master Scheduler, who converts it into a Master Production Schedule (MPS). The MPS specifies the required quantities and due dates for each product of each program and acts as input to the MRP/ERP system. The MRP run calculates net material requirements based on the Bill of Materials (BOM), as shown in Figure 3. The results of this calculations generate two types of orders:

- Purchase Orders (POs) for externally sourced raw materials and components.
- Production Orders (PrOs) for internally manufactured components and products.

Purchase Orders trigger material movement from external suppliers. Production Orders are distributed between Edison shopfloor schedulers and Marconi shopfloor schedulers, who convert them into executable daily schedules and allocate available operators and resources. These schedulers, together with team leaders, determine the activation of workstations in the real manufacturing stations.

At Edison, production orders initiate the manufacturing of parent components such as skins, beams, ribs, and trailing edges. At Marconi, production orders trigger the final assembly and integration of rudders and elevators, using parent products transported from Edison and purchased components from suppliers. Both sites are interconnected by internal transport flows that carry semifinished parts and components.

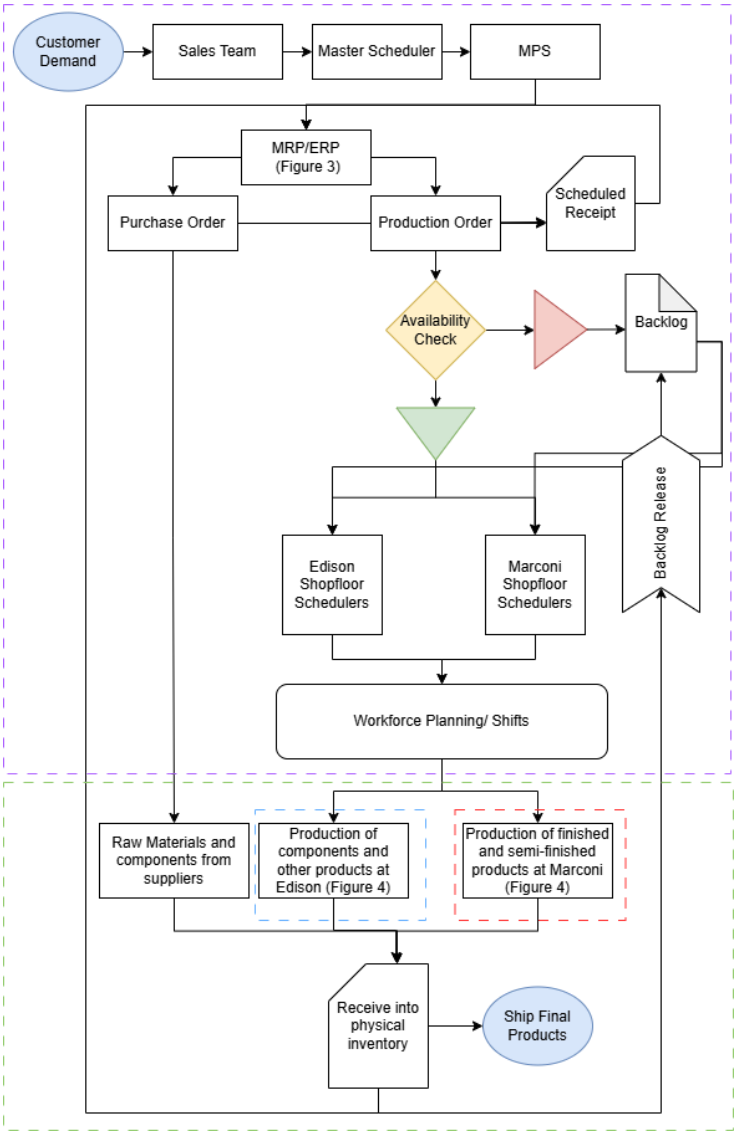


Figure 5: Conceptual model integrating material and information flows. In purple is highlighted the information flow, in green the material flow, in blue and red the actions that take place in Edison and Marconi respectively

In this way, Figure 5 illustrates the fundamental interaction between information and material flows within the system. It also highlights the critical feedback loop through which the MRP logic incorporates information from physical inventory levels and scheduled receipts (firmed orders), ensuring that planning decisions are continuously aligned with the actual state of the system rather than operating in isolation.

2.1.4 Scope of the Project

The scope of this project is limited to GKN Aerospace Fokker's Hoogeveen facilities, focusing on the production of rudders and elevators for the Dassault and Gulfstream

aircraft programs. The study encompasses the two adjacent production sites located at Edison and Marconi sites, which together form an integrated manufacturing system. Edison is modelled as the upstream facility responsible for the manufacturing of parent items such as skins, beams, ribs, and trailing edges while also being important in intermediate processes during the manufacturing of the final products. Marconi represents the downstream site where the gross of the final product assembly takes place. The model therefore captures both the flow of materials and the associated planning information that connect the two sites, defining the boundaries of this project.

Within the model, the Marconi site is represented in high detail at the workstation and shift level, as this is where most workforce allocation and scheduling decisions occur. Real capacities and processing time distributions are modelled per station based on actual data, allowing for a detailed representation of resource utilization and bottleneck analysis. In contrast, Edison remains within scope but is represented at an aggregated and lower level detail. Both the manufacturing of parent components and the intermediate processing steps related to the final product are aggregated, modelled through generalized process times derived from company data. This distinction ensures that the model accurately reflects Edison's influence on Marconi's downstream and upstream operations without introducing unnecessary complexity.

The Dassault and Gulfstream programs are modelled as independent production lines with separate workforces, although they share certain critical stations such as NDO, LaserTrack and some welding steps for the rudders which are represented as common capacity steps to capture interdependencies and queuing effects between both programs.

The BOM for each product is extensive; after consultation with Fokker teams, an aggregated BOM structure was adopted to ensure that there is no unnecessary complexity added to the model while keeping in scope the critical components. Only components identified as potential bottlenecks are modelled, while non critical products are assumed to always be available. Components in scope include rear and front beams, upper and lower skins, ribs, and leading and trailing edges and their raw materials consisting of platines and composites each with a unique product identification number.

The supply of raw materials and purchased components is also included in scope but represented in a simplified way. External supplies are modelled as transport and processing delays characterized by their lead times, rather than detailed supplier and processing operations. Materials used for in house rib production (Platine) and trailing edges, skins and beams (Composites) are explicitly included due to their long lead times, which may generate bottlenecks in upstream operations. These materials are modelled as stochastic delay processes that influence production at the Hoogeveen sites without representing external manufacturing steps.

The digital twin simulation integrates a Discrete-Event Simulation (DES) layer combined with individual agents or entities to capture the real production processes in terms of material and information flow in the physical reality. The model evaluates how alternative shift configurations, workforce allocations, and demand variations affect key

performance indicators (KPIs). The results provide quantitative insights to support decision-making at both the operational and planning levels, guiding a structured, data driven approach to workforce, shift and capacity planning that improves responsiveness to demand increases at Hoogeveen.

Category	In Scope	Out of Scope
Processes	Manufacturing of parent items and intermediate steps at Edisonstraat (aggregated); final assembly and inspection at Marconistraat	Detailed supplier manufacturing, external logistics, other products from different programs sharing capacity at Edison
Sites	Edisonstraat (aggregated; time distributions from company data); Marconistraat (detailed, real capacities and schedules per station)	Other GKN sites (e.g., Papendrecht, USA)
Resources	Machines, stations, workforce, jigs detailed at Marconi	Workforce and real capacity at Edison
Data	Processing times, transport times, BOM (aggregated), lot size, safety times,lead times, capacities, workforce skills, shift structures, etc	Other data relative to other programs that might share resources with the programs in scope. Workforce data at Edison.
Materials & Supply	Raw materials (platine, composites) and components mentioned earlier	Non critical components and materials
Simulation	DES digital twin model with shared resource logic	Processes outside Hoogeveen
BOM	Aggregated BOM including rear and front beams, upper and lower skins, ribs, leading and trailing edges; parameters include quantities, lead times, lot size, safety times, processing times,etc	Full detailed BOM structure for all products which are not identified as potential bottlenecks.

Table 2: Categories in scope for this project

2.2 Project Objective

Based on the insights gathered from GKN Aerospace Fokker's Hoogeveen facility, the main challenge lies in the absence of a systematic approach for coordinating workforce and capacity planning across Marconi site. Existing planning depends on fixed schedules and experience, which limit flexibility under different demand scenarios and increase the likelihood of production bottlenecks.

The primary goal of this project is to design and implement a digital twin simulation model that integrates production flow, workforce planning, and information flow to analyse and improve the overall performance of the rudder and elevator manufacturing processes at Hoogeveen. At the same time, the project aims to advise the company on how to react to increased demand scenarios, providing information on how the effects of demand uncertainty can affect performance at different steps in the production process.

Following the SMART framework, which emphasizes objectives that are *Specific, Measurable, Achievable, Relevant,* and *Time-bound* (Doran, 1981; Locke & Latham, 2002; Lawlor, 2012) the project objectives are given to ensure methodological clarity,

feasibility, and traceability of the outcomes. The SMART approach provides a structured base for defining measurable targets while maintaining alignment with Fokker's goals.

SMART criteria	Goals
Specific	Develop a digital twin simulation model in AnyLogic that couples the information and material flows of the Edison and Marconi sites (keeping Marconi more detailed), integrating different decision variables to assess their impact in overall performance.
Measurable	Quantitatively evaluate improvements in lead times, lateness, utilization and policy levers across realistic demand scenarios.
Achievable	Provide recommendations on what the optimal parameter configurations are for each tested scenario.
Relevant	Support Fokker's strategic goal of improving efficiency and planning accuracy by providing a decision support tool. At the same time, the model will aid the company in identifying areas at the planning and execution layers sensitive to demand variations.
Time-bound	The design project along with the model will be delivered by mid March 2026.

Table 3: SMART goals of the design project

In order to address the design objective and the project goals shown in Table 3 the following main research question is presented:

How do increases in customer demand affect overall system performance at GKN Aerospace Fokker's Hoogeveen facilities, and how can workforce, shift, station capacity and other planning levers be adjusted to mitigate these effects?

This research question tackles the SMART objectives presented earlier, providing a base and clear path towards the model design and implementation.

2.3 Methods

Due to the complexity of the production system and the interaction between multiple resources, analytical approaches are often not enough to capture the dynamic behaviour of the system. Simulation modelling allows the representation of complex production processes and enables the evaluation of different scenarios without affecting the real production system. By testing alternative capacity configurations and planning parameters within a virtual environment, simulation provides a decision support tool for identifying bottlenecks and improving production performance (Ragazzini et al., 2024; Raheem et al., 2024).

This project follows a quantitative, simulation and parameter variation methodology combining operations management principles with modelling. The research adopts a digital twin simulation approach integrating Discrete-Event Simulation (DES) and

entities or agents to capture both the physical production processes and workforce dynamics and information layer at GKN Aerospace Fokker's Hoogeveen facilities. The model enables the assessment of how planning parameters and capacity allocation influence production performance under increasing demand scenarios. The overall methodological framework built upon modeling and digital twin principles described by Brailsford et al. (2019), Altendorfer et al. (2013), and Tao et al. (2022).

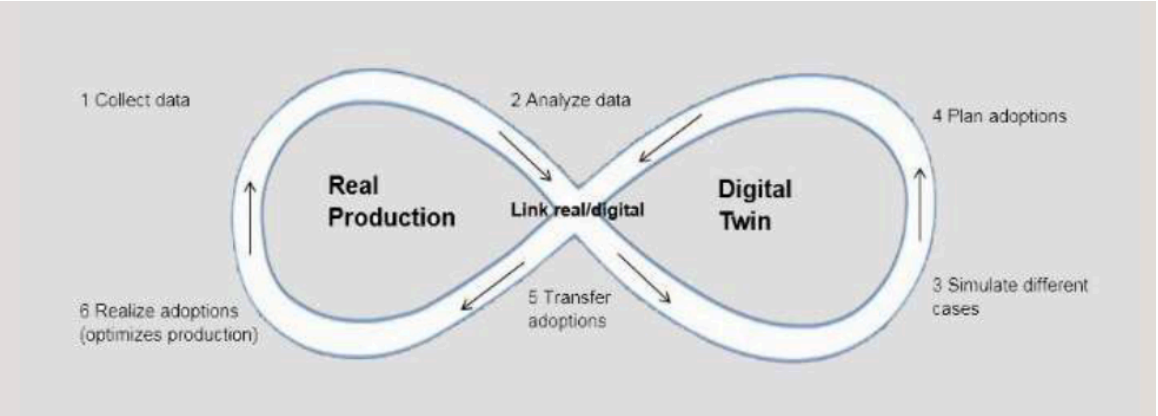


Figure 6: Digital twin from creation to implementation in reality

The methodological process is divided into five main design phases, ensuring traceability and methodological rigor, following guidelines for simulation studies proposed by Robinson (2008) and Sargent (2013):

1. System Analysis and Data Collection: Mapping of the material and information flows at Edisonstraat and Marconistraat, including identification of critical processes, resources, and potential bottlenecks. Collection of data from the processes (processing times, lead times, lot size, safety times, etc) and workforce information (shift calendars, availability, and skills).
2. Model Design and Conceptualization: Conceptual definition of the simulation model to be implemented, integrating material and information flows.
3. Model Implementation: Development of the model in AnyLogic, linking material and planning layers. Implementation of data gathered in step 1 and logic designed in step 2.
4. Validation and Verification: Validation follows an iterative approach combining validation, data comparison, and scenario testing, consistent with the procedures recommended by Altendorfer et al. (2013) ,Tao et al. (2022) and Sargent et al. (2013) for digital twin applications. Verification ensures internal consistency of the simulation model logic, inputs and outputs.
5. Scenario Experimentation and performance results: Execution of experiments testing different scenarios under increased customer demands. Impact of decision variables on system performance assessed through selected KPIs.

3 Model Development

3.1 System analysis and Data Collection

According to literature in simulation and model analysis, a clear definition of the models inputs and outputs is key to ensure that the simulations results are valid and interpretable (Law et al, 2015)

During the system analysis and data collection phase of the project, input and output analysis were performed to define the parameters of the simulation model close to reality while identifying required data to drive the simulation model behavior. Additionally, performance indicators were also identified in order to evaluate the models accuracy.

The data collection was performed by approaching key members of Fokker identified in the stakeholder analysis shown in Figure 1. Firstly, a reconnaissance kind of approach was applied, interviewing different components of the crew to achieve a general idea of how the production process was being carried out at the Hoogeveen facilities. Later on, this information helped identify those colleagues who could provide empirical data valuable for the model regarding the processes on scope. After gathering all the data, different meetings were held to gain insights on its validity and identify additional data that could have been under the radar.

3.1.1 Input Analysis

Input analysis focuses on identifying and characterizing all parameters that influence the behavior of the production system. These inputs are collected from historical data, planning parameters, and system specifications. Here, there is also a distinction to be made, the input analysis and consequent data gathering was performed taking into account two layers: planning parameters and material or physical flow.

a) Planning parameters

<u>Customer Demand</u>

Customer demand data was requested from the master planner, according to the information obtained on site, the demand is distributed weekly according to production capacity and other constraints, which is then added to the MPS (see figure 2).

Therefore, different excel files were provided by the company containing the customer demand and yearly production planning for both Gulfstream and Dassault programs with the following parameters:

- Type of product
- Quantity of product (Units)
- Due date (Weeks)

<u>Lot sizes, safety stocks and planned lead times (MRP parameters)</u>

According to the MRP design followed in Figure 3, the identified necessary data was lot size policies, with quantity per item in the BOM, planned lead times for purchased and

produced items and safety stocks per item in the BOM. Additionally, the planned lead times per production steps were also necessary to gather in order to apply the backward scheduling step in the MRP. The data was gathered through meetings with shop floor schedulers for Gulfstream and Dassault programmes, after storing all this information, the given data was cross checked in Fokker's ERP system, to ensure that it was veridic.

The data gathered included the following parameters:

- Lead times for produced and purchased items: per product per production step
- Safety times for produced and purchased items: per product per production step
- Measured real lead times per product for benchmarking and further validation
- Safety stocks per item
- Lot size policy and quantity for produced and purchased items

Amount of Gulfstream rudders sent to Dassault welding station

Another important parameter is the amount of Gulfstream rudders sent to the Dassault welding machine (KRA) per week. As explained in previous sections of this report, the Dassault welding robot is capable of processing Gulfstream rudders, this was identified as a key parameter during interviews with both the Master planner and the shop floor schedulers, where they acknowledged be an important policy lever in their weekly production planning.

The data gathered from this interview included:

- Gulfstream rudder production split logic
- Current quantity of Gulfstream rudders sent to Dassault welding machine per week (KRA)

Operators per step, shifts and time schedules

For the workforce planning layer, data was gathered from the shop floor schedulers. As it is one of the cornerstones of this project, workforce allocation logic and working hours for both programs were a key input.

The data gathered in this case includes:

- Number of shifts
- Time schedules
- Skill matrices
- Number of operators per production step

b) Material and process flow

Bill of Materials (BOM)

In the case of this project, the bill of materials is of the utmost importance. After meetings with members of Fokker such as production team leaders and master scheduler, critical materials and components were identified as bottleneck prone. Therefore, for the

aggregated BOM there were 17 levels identified for each final product. From raw material and components purchased from suppliers and inhouse produced components to the final products were mapped, while identifying at which step in the material flow those components were used for more accuracy. At the same time, quantities necessary per production step were identified through interviews with manufacturing engineers and operators, while double checking in the Fokker ERP system. This data collection process delivered the most crucial materials, according to Fokker experience, of both programs and all 6 final products. Common materials throughout programs and products were also identified.

In the end, the data gathered in this step was:

- Crucial materials and components per product and necessary quantities, per program
- Production step were materials and components are used
- Products built inhouse (At edison) and purchased from supplier

Routings

As the simulation model aims to represent reality with the highest accuracy possible, it was crucial to map the material flow in Edison and Marconi sites. In the case of Marconi (detailed modelling) the routing data was gathered by holding spontaneous interviews with operators at the floor level. Next, the information gathered from operators was compared with the routings at the ERP system. However, for some production steps, the ERP system steps were not fully in line with what the operators were doing. Therefore, additional interviews with operators were necessary to map the real routings clearly. In the case of the Edison (aggregated modelling) site, the routings were provided solely by the ERP system. The final assembly routings can be seen in Figure 4.

Capacity

At Marconi site, the jobs are carried out in jigs, where operators fix the product to work on it, therefore, station capacity is identified to be the number of jigs per production step. In this case, on site analysis and station inspection was necessary to identify the number of jigs available for each station step and product.

These inspections provided a key piece of data, as the number of jigs per step are crucial to the model.

Processing, drying and transport times

The processing times are key when modelling the time it takes for a product to be completed. As almost all production steps are performed by the operators by hand, the stochasticity of the jobs is identified as a crucial piece of information for the model.

In this case, the processing time data was provided by an engineer at Fokker, whose task was to measure the efficiency of each production step at the Gulfstream and Dassault production lines in the Marconi site. The data was provided in an excel sheet, divided by operations according to the ERP routing. As mentioned earlier, the ERP and real routings

differed in some steps, therefore, additional handling of the data was required. The operations which were identified as belonging to only one physical step in reality were summed and aggregated. Additionally, the data was different for both programs, with Gulfstream having an average of 200 samples per product per production step and Dassault having an average of 10 to 20 samples per product per production step.

In order to achieve the highest possible accuracy in the representation of processing times, stochastic time distributions were fitted to empirical data. The inclusion of stochastic processing times is widely recommended in discrete event simulation studies, as it allows the model to capture variability observed in real production systems rather than relying on deterministic averages (Law et al., 2015)

To this end, a distribution fitting procedure was performed using a custom Python script (see Annex A). The script imports real processing time data and evaluates candidate probability distributions by combining visual inspection and statistical goodness of fit measures, following best practices in simulation input modeling (Banks at al., 2010)

The empirical data was first cleaned to remove invalid and non positive observations. Additionally, the data was visualized in a two axis diagram, where the horizontal axis represents processing time and the vertical axis represents probability density. This histogram served as the empirical reference against which candidate theoretical distributions were compared.

The distribution fitting procedure was applied exclusively to the Gulfstream program, as this program provided a sufficiently large number of observations to support statistically credible distribution fitting. In contrast, the Dassault program showed limited data availability, which did not show reliable statistical results. In line with common practice under data scarcity conditions, processing times for the Dassault program were therefore modeled using triangular distributions, defined by minimum, maximum, and most likely processing times derived from the historical raw data.

For the Gulfstream data, a wide range of candidate distributions was evaluated, including lognormal, gamma, Weibull, exponential, logistic, and their truncated variants, as well as bounded distributions such as beta and triangular. The selection of these candidates was guided by the requirement that processing times must be non negative and by their common use in modeling manufacturing processes (Spearman & J et al., 2014)

Each candidate distribution was fitted using maximum likelihood estimation (MLE). Two quantitative criteria were then employed to assess goodness of fit:

1. Akaike Information Criterion (AIC), used to compare candidate distributions by balancing how well they fit the data against how complex they are. Lower AIC values indicate models that achieve a good fit without unnecessary complexity.

2. Kolmogorov Smirnov (KS) statistic, which measures the maximum deviation between the empirical and theoretical cumulative distribution functions.

The combined use of AIC and KS statistics is well established in the simulation literature as a robust approach to input distribution selection (Law A.M et al.,1983.).

In addition to quantitative metrics, visual validation was performed by overlaying the fitted probability density functions onto the empirical histogram graph. This step allowed the assessment of distributional characteristics such as skewness, tail behavior, and the location of the mode, which are not always fully captured by numerical indicators alone.

The final choice of processing time distributions was based on a combination of:

- Statistical goodness-of-fit (AIC and KS)
- Visual fit with empirical data
- Possibility of implementation within Anylogic

Through this multi criteria approach different distributions were identified as fit for all the stations and processes in the system, these distributions are:

- Gamma
- Lognormal
- Logistic
- and Triangular for those processes were the number of samples was not big enough

Apart from the processing time distributions which conform the stochastic part of the model, data on drying and transport times between Edison and Marconi sites and when in the process they are applied was also gathered from operators and manufacturing engineers.

3.1.2 Output Analysis

Output analysis defines the set of performance indicators used to evaluate the behavior and effectiveness of the simulation model. According to simulation methodology literature, the selection of appropriate output measures is crucial to ensure that simulation results are meaningful and aligned with the objectives of the study (Law et al., 2015).

The output variables selected in this project were chosen to assess operational performance, planning accuracy, and model validity. These outputs enable both the evaluation of the current system and the comparison across different scenarios.

a) Lead Time Performance

Lead time related outputs were defined to analyze the behavior of the production system and identify critical or bottleneck prone elements. The simulation measures:

- average lead time per production step per product, including backlog time, measured from production order release to its completion
- average lead time per station
- average lead time per final product
- average backlog time per product
- average number of backlogged orders per station

Including backlog and queue time in lead time measurements allows the model to capture waiting effects caused by upstream or downstream congestion, which is essential for identifying bottlenecks. These outputs support both system analysis and comparison with planned lead times used in the MRP logic. Additionally, average lead times allow for a further analysis and comparison with real performance metrics provided by Fokker, aiding in the validation of the model.

b) Delivery performance

Delivery related outputs were defined to assess the system's ability to meet customer due dates. The following indicators were considered:

- percentage of late final product deliveries
- service level (1-pctLateDeliveries)

These outputs provide a direct measure of customer delivery performance and are used to evaluate the impact of planning parameters, capacity constraints, and backlog accumulation on meeting due dates.

c) System Dynamics and Capacity Performance

To evaluate overall system behavior and production stability, the simulation tracks:

- Work in progress (WIP) per station
- Total throughput per station
- Jig and operator utilization per station

WIP is used as an indicator of congestion and flow efficiency, while throughput reflects the effective production rate of the system. At the same time, utilization levels of jigs and operators allow for a detailed analysis of possible bottlenecks in the system. Together, these outputs support the analysis of capacity utilization and the identification of constrained production steps.

3.2 Model Design and Conceptualization

Building upon the system scope, boundaries, gathered data and conceptual model defined in earlier sections of this project, this chapter focuses on the logical design of the simulation model. The objective is to describe how the planning layer, including order releases, and physical production interact with each other, independently of software implementation details. The emphasis is placed on the logic followed that is implemented in Anylogic at a later stage.

3.2.1 Planning logic and MRP design

The planning logic implemented in the simulation model follows the classical MRP framework illustrated in Figure 3. The model transforms customer demand into production and purchase orders through a sequential process consisting of gross requirement, netting, lot sizing, backward scheduling, and BOM explosion. The mathematical formulation of the netting procedure is based on the MRP standard equations (Segersted et al., 1996).

Demand Conversion and Gross Requirements

The planning process starts with customer demand, which is defined for final products over time. This demand is directly translated into gross requirements for final products, forming the primary input to the MRP calculation for the highest BOM level.

Projected Inventory

For each item and planning period t, the model computes the projected inventory by using initial inventory, scheduled receipts, and gross requirements as inputs. The projected inventory balance before considering further planned supply is calculated as:

$$l_t^{before} = l_{t-1} + x_t - d_t$$

where:

- l_{t-1} is the projected on-hand inventory at the end of the previous period
- x_t represents scheduled receipts in period t
- d_t represents gross requirements in period t

Net Requirements with Safety Stock

Safety stock levels are incorporated into the netting logic. If the projected inventory balance after satisfying gross requirements falls below the safety stock level ss, a net requirement is generated to restore inventory to the safety stock threshold. The net requirement in period t is calculated as:

$$x_{t,net} = max(0, ss - l_t^{before})$$

If the projected inventory remains above the safety stock level, the net requirement is zero. This approach ensures that planned supply decisions are driven not only by demand satisfaction but also by inventory policies.

Lot Sizing and Planned Receipts

When a net requirement is identified, the lot sizing step determines the quantity of material to be ordered or produced.

For lot-for-lot sizing, the planned receipt equals the net requirement:

$$pr_t = x_{t,net}$$

For fixed order quantity (FOQ) policies with order size Q, planned receipts are rounded up to the nearest multiple of Q:

$$pr_t = Q(\frac{x_{t,net}}{Q})$$

This ensures that any shortage relative to the safety stock level is covered while respecting the predefined lot sizing policy.

Projected On-Hand Inventory Update

Once the planned receipt quantity has been determined, the projected on-hand inventory at the end of period t is updated as:

$$l_t = l_t^{before} + pr_t$$

The resulting inventory balance becomes the starting inventory for the subsequent planning period. This recursive inventory update is applied across all planning time buckets, enabling the generation of a complete projected on-hand inventory profile over the planning horizon.

Backward Scheduling and Planned Releases

Planned receipts generated through the lot sizing step are converted into planned releases through backward scheduling. Planned lead times are used to shift planned receipts backward in time, determining the release time in which production or purchase orders must be initiated to meet the required due date.

Multi-Level BOM Explosion

Following the determination of planned releases for final products, the MRP logic proceeds with the BOM explosion. The planned release of a parent item generates gross requirements for its direct child components according to their usage quantities:

$$d_{t,child} = Planned\ release_{t,parent} \times Usage\ quantity$$

This process is applied iteratively across all BOM levels. At each level, the same sequence of netting, lot sizing, backward scheduling, and inventory projection is executed, enabling consistent multi-level planning.

Rolling Horizon Planning

The MRP logic in the simulation model is executed using a rolling horizon approach. Rather than generating a single static production plan for the entire simulation period, the planning process is periodically executed over a fixed planning horizon as time progresses.

At the beginning of each planning run, the planning horizon is shifted forward, and the MRP calculations are repeated using updated system information. This includes the current simulation time, the physical on hand inventory for each item, and the quantities of material that are already in the pipeline due to previously released production and purchase orders which are then converted to scheduled receipts.

Horizon Advancement and Replanning

For each planning run, customer demand within the MRP horizon is converted into gross requirements, after which netting, lot sizing, backward scheduling, and BOM explosion are performed as described in the previous sections. Planned releases are generated for future periods within the horizon, however, they are not released until its release time arrives.

This rolling mechanism allows the model to continuously update planning decisions in response to changes in inventory levels and inbound material, while maintaining a consistent planning structure. The replanning is carried out in each MRP run and all requirements are calculated for all time buckets in the MRP horizon.

Planning and MRP Outputs

The previously explained steps calculate the following variables for all periods in the MRP horizon, these variables are also recalculated for each daily MRP run:

- gross requirements
- net requirements
- planned releases

- planned receipts
- projected on-hand inventory per product, obtained through BOM explosion.

These variables are then used to drive production by the MRP and later on serve as a crucial output to make sure that the MRP is correctly implemented.

3.2.2 Bill of materials (BOM) design and routing

The conceptual design of the BOM and routing logic implemented in the simulation model follows the data driven modeling approach proposed by Hübl et al., 2011 in which product structures and routing information are represented through structured master data rather than hard coded model logic (Hübl et al., 2011)

In this project, the material structure is represented through two different master datasets which complement each other: one for inhouse produced items and one for purchased items. This separation reflects the different planning and execution behavior of produced and purchased components while maintaining a unified planning framework.

Master Dataset for Produced Items (BOM)

The BOM master dataset defines the structure of all inhouse produced items, including final products and semifinished or intermediate products and components. Each line in this dataset represents a parent–child relationship and specifies the quantity of child items required to produce one unit of the parent item.

In addition, the BOM dataset embeds routing information by identifying the station at which the transformation of components into the parent item occurs. This design allows routing logic to be derived dynamically from the dataset during execution while providing a clean way of varying parameters for future configurations.

The produced items BOM includes the following attributes:

- parent item and child item identifiers
- input quantity and output quantity
- production station or machine group
- planned lead time
- safety time
- safety stock
- lot size quantity (FOQ)
- processing time distribution type and parameters (minimum, maximum, mode,parameter 1, parameter 2)
- drying time
- transport time

This improved representation based on the one designed by Hübl et al. 2011 enables consistent application of planning parameters, routing logic, and execution behavior across all production levels.

Master Dataset for Purchased Items

Purchased items are represented in a separate purchased items master dataset, reflecting the fact that these items do not undergo internal production routing but are instead supplied externally.

This dataset defines:

- purchased item identifiers
- planned procurement lead times
- safety times
- safety stock levels
- lot size quantities
- transport or delivery delay parameters.

Purchased items do not consume internal production capacity and therefore do not include routing or station related attributes. However, they are fully integrated into the planning logic through netting, lot sizing, and scheduled receipts, and they directly affect material availability for inhouse production orders as they are represented as inputs in the BOM dataset.

Integration of Produced and Purchased Master Data

Although produced and purchased items are stored in separate master datasets, both are processed consistently within the MRP logic. During the BOM explosion, planned releases of produced items generate gross requirements for both produced and purchased child components. The MRP produces planned purchase orders for supplied components, while generating planned production orders for inhouse produced items.

This separation of master data improves model clarity and flexibility, allowing changes to procurement parametrization or production structure without affecting the planning or execution logic.

Role in Planning and Execution Integration

Together, the produced items BOM dataset and the purchased items dataset form the structural backbone of the simulation model. They enable multilevel requirement propagation during planning and drive material consumption, routing, and timing during execution.

This dual dataset approach supports scalable model design, while ensuring that the distinct characteristics of produced and purchased components are represented accurately.

3.2.3 Order release and backlog logic

This subsection describes how planned releases generated by the MRP planning layer are translated into production and purchase orders, and how backlog is represented in the model.

Planned Order Release

Planned production and purchase orders are released into the material flow layer at their respective planned release periods, as determined by the backward scheduling step of the MRP logic. At the time of release, each order becomes eligible for execution.

Material Availability Check

Upon release, each production order goes through a material availability check to verify whether all required child items, as defined by the BOM, are available in inventory. This check ensures that production can only start when the necessary components are physically present.

If all required child items are available in sufficient quantities, the production order is allowed to proceed to its designated production step and begin execution according to the defined routing and resource constraints.

Backlog Representation

If one or more required child items are not available at the time of order release, the production order cannot start processing and is placed in the backlog. Backlogged orders remain waiting until the required child items become available.

Once the missing components are received or produced and inventory levels are sufficient, the backlogged production order is released into the material flow. This mechanism allows the model to represent material related waiting times and backlog accumulation.

3.2.4 Execution logic and material flow

This subsection describes the execution layer of the model, focusing on how production orders flow through the system, interact with resources, and consume material once they are released from the planning layer.

Production Order cycle

Production orders enter the execution layer at their planned release times. Upon release, each order becomes a physical entity that progresses through the production system according to the routing and resource constraints. An order remains in the system until all required production steps have been completed, at which point it exits the execution layer as a product which is then added to physical inventory.

Routing and Process Flow

Each production order follows a defined routing logic that specifies the order of production steps required for completion. The routing logic reflects the actual manufacturing process and determines the sequence of stations that an order must visit according to Fokker's real processes.

For sites modeled in detail, individual production steps are explicitly represented, while for aggregated sites, multiple physical operations are combined into a single step.

VALK vs KRA Weekly Split Logic

As mentioned throughout the thesis, Gulfstream rudders can be processed either in the dedicated Gulfstream welding station at Marconi (VALK) or alternatively in the Dassault welding station (KRA). Therefore, a weekly split logic is introduced in the conceptual model to determine how many rudders are routed to each welding location.

This split is defined as a planning parameter representing the number of Gulfstream rudders assigned to KRA routing per week, while the remaining demand is processed at VALK. The purpose of this mechanism is to capture the flexibility available in the system and to evaluate its impact on workload distribution, resource utilization, and overall production lead times.

From a modelling perspective, this logic is implemented at the order release stage, where each released rudder order is assigned a routing based on the predefined weekly allocation. By varying this split across scenarios, the model enables the analysis of trade offs between relieving congestion at VALK and increasing workload at KRA, as well as the resulting effects on both Gulfstream and Dassault products.

Workforce Allocation and Capacity Constraints

Execution is constrained by the availability of materials in the inventory, available jigs and human resources. At each production step, an order must seize the required operator, before processing can begin. However, jigs need to be available for an operator to be seized. Therefore, if there are no jigs available at a given time, an operator cannot be seized and therefore the order waits in a queue until qualified workforce is available. This modelling decision represents a dual capacity logic in the model, where capacity is given by workforce availability and jig availability.

Queueing and Waiting Behavior

If the required jigs or operators to complete a job are busy, production orders wait in queues associated with their respective production steps. Queueing behavior represents capacity induced waiting and contributes to WIP accumulation.

In addition to capacity related waiting, orders may also experience waiting due to material unavailability, as described in the backlog logic, allowing for a realistic behavior of the model.

Material Consumption Logic

Material consumption is modeled to ensure consistency between planning and execution. Required components are deducted from inventory when a production order starts processing. Consumption follows a logic where all required components must be available for the operation to begin, and once the job has begun, the inputs necessary in terms of materials are deducted from the physical inventory.

This approach prevents partial consumption and ensures that inventory levels remain physically consistent throughout the simulation.

Order Completion and Inventory Update

Upon completion of a production step, the finished product quantity is credited to the physical inventory. This inventory update then may trigger the release of backlogged orders that were waiting for materials to arrive. This logic links material flow outcomes to downstream processes and material availability.

3.2.5 Interaction between information and material flows

With the planning layer already explained, this subsection describes how information flows generated by the planning layer interact with the physical material flow within the model as seen in Figure 5. The interaction between these two layers is essential to ensure consistency between planning decisions and material execution.

Order Translation from Planning to Execution

Production and purchase orders generated by the MRP logic are transferred to the material flow layer at their respective planned release times. At this point, orders are translated from planning into physical entities that interact with resources, inventories, and material flow logic.

This mechanism establishes a clear interface between the information driven planning layer and the material driven execution layer.

Initialization of On hand Inventory

At the beginning of each MRP run, the starting on hand inventory for each item is initialized by reading the corresponding physical inventory state from the material flow. This inventory represents the actual material available at the start of the planning horizon and serves as the baseline for both planning calculations and material availability checks.

By initializing inventory explicitly at the start of MRP each run, the model ensures consistency between the planning inputs and the physical inventory state used during execution.

Representation of Scheduled Receipts

In addition to starting inventory, the model takes into account scheduled receipts, which represent material quantities that are already in the material flow due to orders released prior to the current planning run after the horizon is rolled. These scheduled receipts are populated by aggregating inbound quantities from previously released production and purchase orders that have not yet been completed or received.

Scheduled receipts are treated as planning inputs within the MRP logic and influence net requirement calculations and projected inventory levels. At the material flow level, the same quantities are seen as material arrivals when the corresponding orders complete, ensuring alignment between planned and physical material flows.

Consistency Between Planning and Execution Layers

The described interaction ensures that information flows and material flows remain consistent throughout the simulation. Planning decisions are based on a combination of starting inventory and expected inbound material, while execution outcomes determine actual material availability and order completion.

3.2.6 Decision variables

In order to support scenario analysis and evaluate alternative planning and different configurations, a set of decision variables was defined within the model. These variables represent configurable policy levers that influence system behavior and performance and can be adjusted to assess their impacts.

The decision variables were selected based on their relevance to production planning and capacity management at Fokker and are grouped into capacity and resource decisions, crossprogram allocation decisions, and planning policy decisions. Customer demand is treated as an external input; however, alternative demand profiles are used as scenario cases to evaluate the robustness of the system under different demand conditions.

Category	Decision Variable	Description
Capacity & Resources	Number of jigs per phase	Defines station capacity by limiting the number of jobs that can be processed simultaneously per production phase.
Capacity & Resources	Number of shifts	Determines available working time per day or week for each production area
Capacity & Resources	Shift time schedules	Defines start and end times of shifts and the working calendar.
Capacity & Resources	Number of assembly operators	Workforce capacity available for assembly operations per production phase.
Capacity & Resources	Number of welding operators	Workforce capacity available for welding operations.
Capacity & Resources	Oven maximum capacity	Maximum number of kits or items that can be processed in a single oven batch.
Capacity & Resources	Oven waiting time	Maximum waiting time before starting the next oven batch when forming a batch.
Cross-program allocation	Number of rudders sent to KRA per week	Controls the weekly allocation of Gulfstream rudders to the Dassault welding station (KRA).
Planning policy (MRP)	Planned lead times and safety times	Planned production or procurement lead times used in backward scheduling. Safety time buffers are also added to the base planned lead times.
Planning policy (MRP)	Safety stock levels	Inventory buffers maintained per item to protect against shortages.
Planning policy (MRP)	Lot size quantity (FOQ)	Fixed order quantity applied during the lot sizing step of the MRP logic.
External scenario input	Customer demand	Demand profiles used as external inputs; varied across scenarios to test system robustness.

Table 5: Decision and external variables considered for the model

3.2.7 Assumptions and simplifications

To balance model realism with time and data availability, a number of assumptions and simplifications were introduced in the model. These assumptions are consistent with the objectives of the study and common practice in discrete-event simulation modeling. They should be considered when interpreting the outcomes of the simulation.

Category	Assumption / Simplification	Description
Materials	Materials outside the BOM are always available	Only materials explicitly included in the bill of materials are modeled. Auxiliary materials not part of the BOM are assumed to be always available and therefore do not constrain production.
Transport	Transport availability is not explicitly modeled	Truck and transport resource availability are not modeled as capacity constraints. Transport is represented as a fixed delay time between processes.
Downstream processes	Edison downstream processes are aggregated	Upstream processes at the Edison site are modeled using measured in-house lead times rather than explicit capacity and routing logic, due to limited information on capacity and throughput. All processes are also aggregated into one single step.
Workforce scope	Workforce modeled only at Marconi	Workforce availability and allocation are explicitly modeled only for the Marconi site, where management requires managerial insights..
Workforce flexibility	Workforce assigned to predefined stations	Operators are assigned only to production stations corresponding to their standard functions.
Workforce availability	No sick leave/ no downtimes	Workforce availability follows predefined shift schedules; sick leave, absenteeism, and unplanned absences are not modeled. Downtimes not modelled due to data being unavailable.
Setup times	Setup times included in processing times	Setup activities are incorporated into processing time distributions and are not modeled as separate events.
Quality	No rework or scrap	Quality losses, rework loops, and scrap are not explicitly modeled; all processed items are assumed to meet quality requirements.

Table 6:Assumptions and simplifications in the model

3.3 Validation and verification

Once the conceptual model is translated into the Anylogic software, verification and validation are essential steps in the further development of the simulation model to ensure that it is both correctly implemented and representative of the real system it aims to represent. Verification focuses on confirming that the simulation model accurately reflects the underlying conceptual model, while validation assesses whether the model provides a realistic enough representation of the real production system for the intended purpose.

Figure 7 shows the relationship between the physical reality being modeled, the conceptual model, and the computer simulation model, highlighting the iterative nature of the modeling and validation process. The figure emphasizes that model credibility is not established through a single activity, but rather through continuous and iterative processes between analysis and modeling, computer programming, and experimentation, with data validity playing a central role throughout the process.

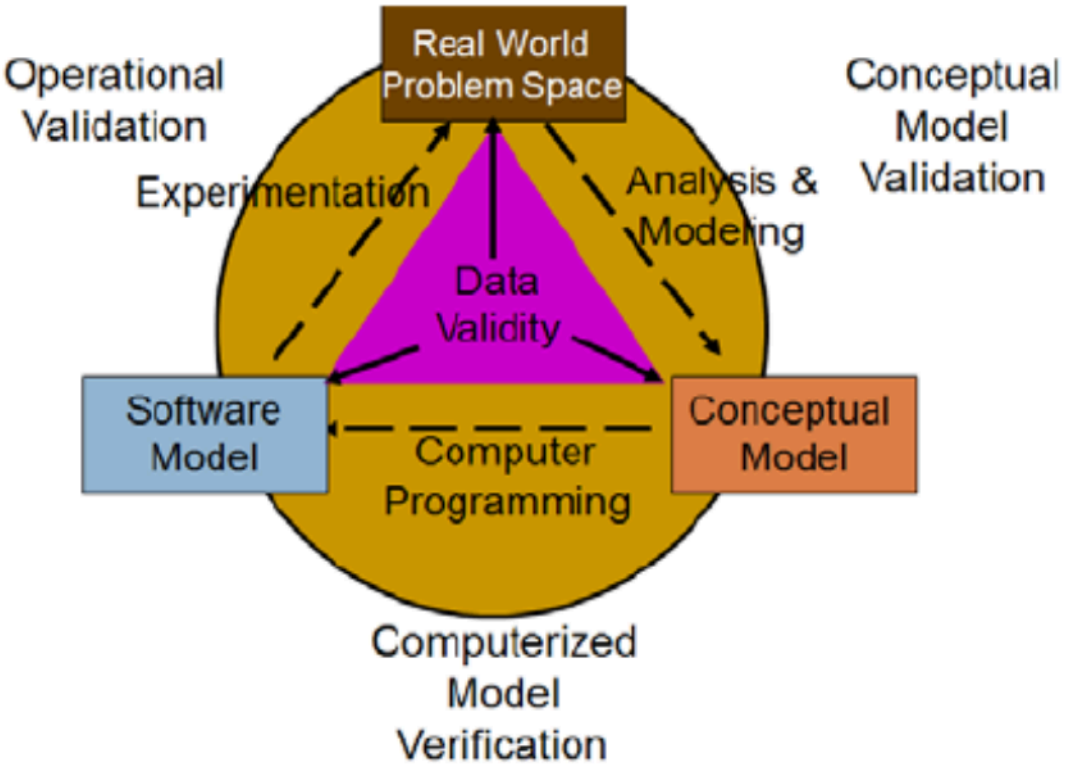


Figure 7 : Validation and verification process (Sargent et al.,2013)

Conceptual model validation concerns the correctness and completeness of the assumptions, system boundaries, and logical relationships defined during the analysis and modeling phase. This step ensures that the conceptual model captures the essential behavior of the physical production system at Fokker. Computerized model verification, in contrast, focuses on confirming that the conceptual model has been correctly translated into the simulation logic, free of programming errors and undesired behavior within Anylogic.

Operational validation is performed through experimentation with the simulation model, where model outputs (selected KPIs) are compared against the real system performance. This comparison allows the assessment of whether the model reproduces key performance indicators, such as production lead times and delivery performance, with an acceptable level of accuracy. Given the stochastic nature of the modeled system, statistical techniques are required to account for variability in simulation outcomes.

In this study, verification and validation are conducted following the structure depicted in Figure 7. First, conceptual model validation and computerized model verification are addressed to ensure correct implementation. Subsequently, operational validation is performed through simulation experiments using multiple independent replications, allowing performance measures to be evaluated using confidence intervals. This approach ensures that the simulation model is both technically sound and suitable for supporting decision making within Fokkers environment.

3.3.1 Data Validity

Since the quality of simulation outputs is heavily influenced by the quality of its inputs, ensuring data validity is crucial for both verification and validation.

In this study, data validity was addressed by systematically collecting and processing production data from the studied manufacturing system at Fokker, including routing information, processing times, demand data, capacities and planning parameters. Processing time data were analyzed using statistical fitting techniques to identify coherent probability distributions, therefore capturing the stochasticity seen in the real system. Where data were unavailable, assumptions were made in accordance with Fokker and University experts to ensure credibility. Furthermore, the data obtained from Fokker's informatic systems or experienced members of the workforce was cross-checked with each other, ensuring that the data provided was aligned.

By establishing data validity early in this study, the risk of taking mistaken or unnecessary assumptions through the conceptual and computerized models was minimized.

3.3.2 Conceptual model validation

Conceptual model validation focuses on determining whether the representation of the system accurately portrays the structure, logic, and behavior of the real production process. This includes the validation of system boundaries and scope, information and material flows, resource interaction and relationships and model assumptions.

The conceptual model of the production system was developed through process mapping for the information and material flows, analysis of production routings in comparison with reality and discussions with company experts. Validation was performed by reviewing the conceptual model with stakeholders in an iterative way to confirm that the modeled process including all its logic and rules reflect real practice. Special attention was paid to the representation of material flows, resource constraints, and planning logic, such as order releases and capacity (jigs and workforce).

This step ensured that the conceptual model provides an accurate abstract model of the real system while not making it too complex.

3.3.3 Computerized model verification

Computerized model verification addresses if the conceptual model has been correctly translated into a simulation model. The verification process focuses on identifying programming errors, incorrect logic implementation, and unwanted model behavior.

Verification of the computerized model was conducted through code reviews, debugging (mainly for MRP array calculations), and use of traces and prints in the Anylogic console. Outputs, such as inventory levels, number of purchase and production orders released, workforce use,etc were carefully reviewed to ensure consistency with what the expected behavior is. In this case, the verification was also iterative, the model was built in blocks, namely information and material flows, which were then splitted in sub blocks namely, gross requirement array filling, net computation, machine routing, production order filtering, etc. After the completion of each block or sub block it was made sure that the logic implemented was valid, therefore, preventing errors to be carried to the next block.

These verification activities confirmed that the simulation model operates as intended and implements the logic defined in the conceptual model, therefore providing a strong base for validation experiments.

3.3.4 Confidence intervals and Output analysis

Due to the stochasticity of discrete event simulation models, individual simulation runs may produce different outcomes even under identical input conditions. To take into account this variability, performance measures must be estimated using multiple independent replications (with different simulation seeds) and analyzed using statistical techniques. In this study, confidence intervals are employed to quantify the uncertainty of the model output performance measures (Law et al., 2015) .

Let Xi represent the observed value of a performance measure obtained from replication i, with n independent replications. The sample mean is computed as:

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

The samples standard deviation is given by:

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n} (X_i - \overline{X})^2}$$

The standard error of the mean is:

$$SE = \frac{S}{\sqrt{n}}$$

Student's t distribution confidence interval:

$$\overline{X} \pm t_{\alpha/2,n-1} \cdot SE$$

In this study, a 95% confidence level (α=0.05) is used, following common practice in simulation output analysis. This approach allows the model performance metrics to be expressed as a range rather than a single number estimate. At the same time, the simulation of each scenario will perform 10 replications with different seeds per configuration, allowing for a wider range of stochasticity in the experiment outcomes and ensuring that the results are not influenced by a single random outcome of the simulation.

3.3.5 Operational validation

As a final validation step, operational validation analyses if the simulation model selected performance metric outputs are close to real system performance. This is achieved by comparing model outputs with Fokker provided performance data from the real production system.

In this case, the data available in the company is total production lead time per finished product per programme and service level or percentage of late orders.

Operational validation was performed by conducting simulation experiments under standard configurations, using ten independent replications with random seeds. The main performance indicators used to validate the simulation model are production average lead times per production step, average total production lead time per final item and percentage of late deliveries. The mean and corresponding 95% confidence interval were computed for each. These results were then compared against empirical site data.

The model is considered operationally valid if the observed system performance is within or close enough to the confidence intervals produced by the simulation model. The results of this comparison are presented in tables, providing a quantitative assessment of the model's validity.

The setup of the validation experiment uses the standard planning and operational configuration as are currently parametrized in the company. In the case of the customer demand external input, the chosen one is that relative to the performance metrics gathered from Fokker, which is 70 and 17 ship sets for Gulfstream and Dassault programs respectively.

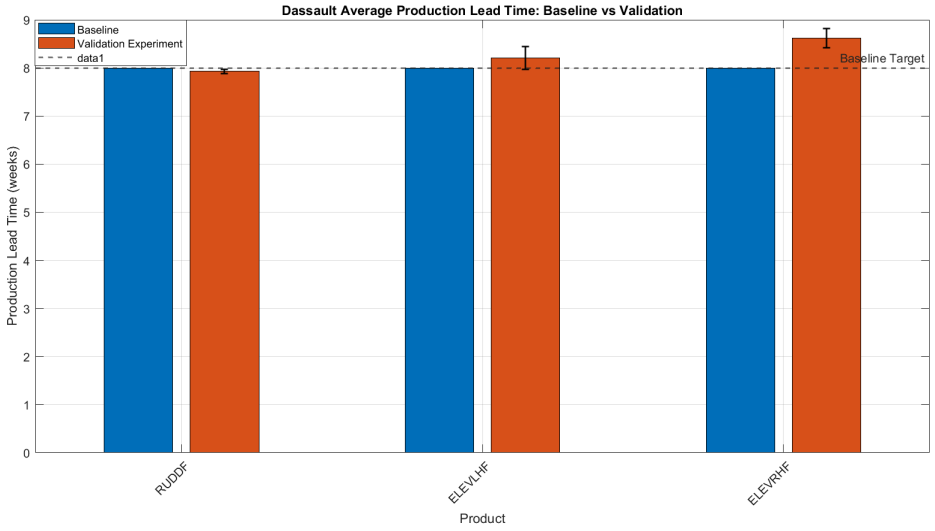


Figure 8: Average production lead time for Dassault products: Comparison between baseline and validation experiment results

Operational validation was performed by comparing simulated performance metrics under baseline conditions with empirical production data provided by Fokker. The baseline scenario reflects the current operational configuration (70 Gulfstream and 17 Dassault shipsets per year), with ten independent replications, a simulation horizon of 1000 days, and a warm up time of 380 days.

For the Dassault Rudder, the simulated average total production lead time was 7.93 weeks with a 95% confidence interval of [7.885, 7.975]. The company reports an observed production lead time between 7 and 8 weeks. The simulated mean is within this empirical range. The narrow confidence interval (0.045 weeks) indicates high statistical precision of the estimate.

For the Dassault LH Elevator, the simulated mean lead time was 8.21 weeks (95% CI: [7.97, 8.45]). Although slightly above the upper bound of the reported 7–8 week interval, the confidence interval overlaps with the real system range, which indicates that there is not a huge statistical deviation.

For the Dassault RH Elevator, the simulated mean lead time was 8.62 weeks (95% CI: [8.42, 8.82]). While this estimate is slightly above the empirical upper bound of 8 weeks,

discussions with company experts confirmed that production lead times may fluctuate above 8 weeks, therefore the results given by the model are within acceptable limits.

In addition to lead time comparison, delivery performance was validated. Both the real system and the simulation model show a service level of 100% (0% late orders) under the baseline demand configuration. This confirms that the model correctly reproduces the real production stability.

Overall, the simulation outputs reproduce empirical lead time performance with small deviations and consistent service level across runs. Given that observed real world data are reported as ranges rather than precise point estimates, and considering the stochasticity of the production system, the model is considered operationally valid for decision support purposes.

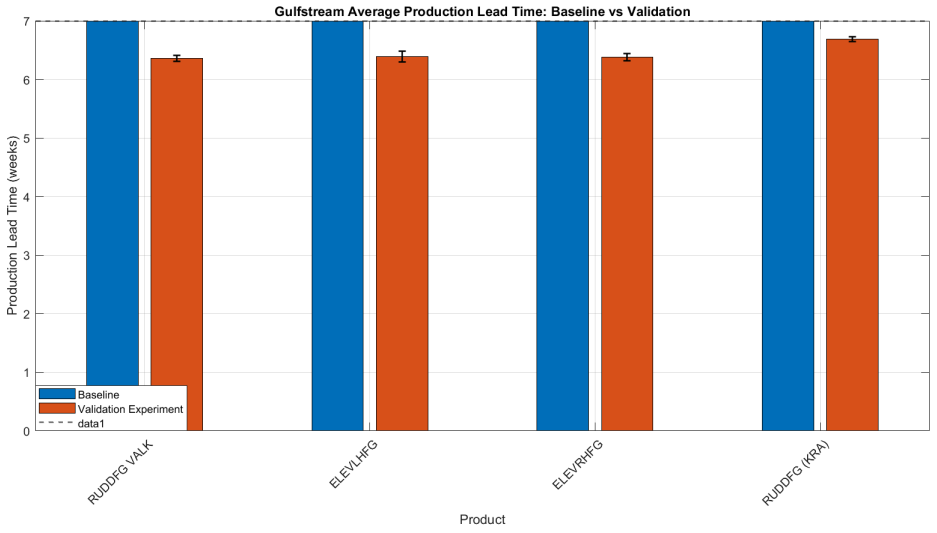


Figure 9:Average production lead time for Gulfstream products: Comparison between baseline and validation experiment results

Under the standard routing, the simulated average total production lead time for the Gulfstream Rudder was 6.36 weeks (95% CI: 0.0468). For the Gulfstream LH and RH Elevators, the simulated mean lead times were 6.39 weeks (95% CI: 0.0916) and 6.38 weeks (95% CI: 0.0585), respectively.

When applying the additional rudder routing configuration (rudders sent through Dassault Welding line), the simulated average lead time for the Gulfstream Rudder increased slightly to 6.69 weeks (95% CI: 0.0402).

All simulated mean values fall within the empirical lead time range reported by the company (6–7 weeks). Additionally, the confidence intervals are small (0.040–0.092 weeks), indicating high statistical precision of the simulation estimates. The close alignment between simulated and observed lead time ranges confirms that the model accurately reproduces the current operational regime of the Gulfstream production system.

In addition, the model reproduces the observed delivery performance of the current system: across all baseline replications, the percentage of late deliveries was 0% for Gulfstream finished products, consistent with the reported service level in practice.

Overall, the baseline results demonstrate that the model is valid and captures the current stable operational performance for the Gulfstream programme with lead time performance aligned to empirical values and correct service level, supporting its use for scenario analysis and decision support.

Finally, it is important to note that differences in data availability affect validation accuracy across programmes. Gulfstream processing time distributions were fitted on larger datasets, whereas Dassault processing time data were available only in limited sample sizes per step. As a result, Dassault processing times were modeled using simplified distributions, which increases input uncertainty and may reduce accuracy for Dassault lead time estimates. This limitation is reflected in wider confidence intervals for Dassault outputs and should be considered when interpreting small deviations from reported lead time ranges. Nevertheless, the model remains suitable for the project objective.

4 Scenario Experimentation and Performance Results

Once the model has been verified and validated for the intended purpose, it is time to perform experiments. This section shows the experiments conducted using the simulation model developed throughout the study, in order to analyze the performance of the production system under increased demand level, operational configurations and planning parameter settings. The goal of these experiments is to evaluate the behavior of the production system when demand increases, identify potential bottlenecks and assess improvement policies through both operational and planning layers.

All experiments were performed using a simulation horizon of 1000 days, including a warmup period of 380 days in order to allow the system to reach a steady state. For each experimental configuration, 10 independent replications were carried out using different random seeds. The results presented in this section correspond to the average values obtained across replications, and confidence intervals are computed for all key performance indicators.

Due to computational limitations caused by the number of possible parameter combinations, planning parameters are varied using percentual factors applied to the baseline values instead of testing every possible parameter value individually. This approach allows evaluating the sensitivity of the system to planning decisions while keeping the total number of simulation runs feasible with the available computational power.

The experiments are performed in a three stage structure. First, the system is evaluated under increased demand levels while maintaining the original configuration in order to observe its performance and identify bottleneck sources. Second, capacity adjustments are tested at the identified bottlenecks in order to evaluate potential improvements in the material flow. Finally, once feasible capacity configurations are identified, planning parameters such as planned lead times, safety stock levels, and lot sizes are varied to analyze their impact on system performance. All available decision making parameters are shown in Table 5.

4.1 Experimental Design

The experimental design is structured in three stages. Each stage focuses on a different layer of the production system and builds on the results of the previous one.

In the first stage, demand levels are increased while maintaining the current or initial configuration used in the operational validation experiment. The objective of this experiment is to show how the production system behaves under higher workload conditions and to identify stations that become capacity constrained.

In the second stage, the results of the demand experiment are used to identify bottleneck sources. Capacity adjustments are then tested at these stations in order to identify potential improvements in the material flow. These adjustments include changes in the number of shifts, additional working days or hours, number of jigs per step and number of operators per step, as well as weekly production split of Gulfstream rudder between both welding machines.

Finally, in the third and final stage, planning parameters are varied in order to assess their impact on performance once the material flow constraints have been addressed. The parameters considered include planned lead times, safety stock levels, and lot sizes. These parameters influence the behavior of the MRP system and therefore affect order release timing, inventory levels, and backlog occurrences.

By structuring the experiments in this way, it is possible to identify improvements achieved through capacity changes from those resulting from planning adjustments.

4.2 Demand Increase Experiment

The first experiment shows the performance of the system under increased demand while maintaining the standard configuration of the production system. All operational parameters, including the number of operators, shifts, routing configurations, and planning parameters remain unchanged.

Dassault Rudder

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	RUDDF	11	55,70	53,04	34,0	0,56	0,13	0,15	0,37	28,10	0,5547	0,4197	#NUM!	0,0804	0,0042	0,0055	0,0060	0,2146
Oven Wait	1	Agg2	-	-	-	RUDD7	10	60,04	56,38	34,0	0,00	5,22	0,00	0,00	692,00	0,4197	0,3966	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Oven max kits	6	Lasertrack	1	4	2	RUDD61	4	57,38	56,57	34,0	0,43	1,79	0,60	0,30	2055,10	0,3966	0,3872	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Demand 100 ss/20ss		Station 330	1	2	1	RUDD6	9	60,57	55,54	34,0	0,60	0,23	0,21	0,37	26,00	0,3872	0,3539	#NUM!	0,1322	0,0075	0,0082	0,0060	#NUM!
Schedules 6-15		Lasertrack	1	4	2	RUDD51	4	56,54	55,94	34,0	0,43	1,79	0,60	0,30	2055,10	0,3539	0,3661	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs 10		Agg1	-	-	-	RUDD5	8	60,94	55,62	33,0	0,00	5,02	0,00	0,00	689,50	0,3661	0,9550	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds Random		station 230	1	2	1	RUDD4	7	59,63	56,67	33,0	1,18	0,17	0,16	0,20	27,50	0,9530	0,3144	#NUM!	0,1341	0,0075	0,0105	0,0044	0,3577
leadFactorProd 1 Overall results		station 220	1	2	1	RUDD3	6	58,67	57,12	33,0	0,16	0,07	0,09	0,20	27,00	0,3144	0,3130	#NUM!	0,0957	0,0025	0,0029	0,0044	#NUM!
leadFactorPurch 1 LatePct 65,56		NDO	1	2	1	RUDD21	5	59,12	58,12	33,0	0,76	0,96	0,42	0,21	686,90	0,3130	0,2879	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
ssFactorProd 1 Total Avg lead 128,99		Welding KRA	1	2	1	RUDD2w1	45	60,12	58,20	34,0	0,69	0,09	0,10	0,57	27,00	0,2879	0,4539	#NUM!	0,0543	0,0033	0,0035	0,0049	#NUM!
ssFactorPurch 1 CI 0,6711		Welding KRA	1	2	1	RUDD2w	34	60,20	60,06	34,0	0,32	0,05	0,05	0,57	27,10	0,4539	0,8535	#NUM!	0,0541	0,0039	0,0028	0,0049	0,2146
lotSizeFactorProd 1 Prod Lead 7-8 weeks		Welding KRA	1	2	1	RUDD2	44	62,06	62,14	32,0	0,68	0,04	0,02	0,57	27,60	0,8835	0,8843	#NUM!	0,1416	0,0060	0,0014	0,0049	0,4745
lotSizeFactorPurch 1 SimTime 1000 days		Lasertrack	1	4	2	RUDD12	4	63,21	63,40	32,0	0,43	1,79	0,60	0,30	2055,10	0,8831	0,9902	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
safetyTimeFactorComponent 1 WarmUp 380 days		Welding KRA	1	-	1	RUDD1	3	65,54	61,93	32,0	2,19	1,21	0,59	0,59	254,60	0,6878	0,2672	#NUM!	0,0596	0,0258	0,0061	0,0061	0,4745
		Oven	-	-	2	DOvenKitRUDDdas	2	63,21	61,73	32,0	0,74	1,26	0,00	0,00	673,30	0,2672	0,2734	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Dassault LH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	ELEVLHF	15	56,94	54,35	35,0	0,62	0,14	0,15	0,37	29,20	0,5642	0,2788	#NUM!	0,0894	0,0040	0,0050	0,0060	0,2861
Oven Wait	1	Agg2	-	-	-	ELEVLH71	4	55,35	54,51	35,0	0,43	1,79	0,60	0,30	2055,10	0,4640	0,2540	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Oven max kits	6	Lasertrack	1	4	2	ELEVLH7	10	61,51	54,81	34,0	0,00	5,22	0,00	0,00	692,00	0,4409	0,7195	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Demand 100 ss/20ss		Station 330	1	2	1	ELEVLH6	14	56,88	53,11	34,0	0,74	0,20	0,19	0,37	28,40	1,1521	0,2988	#NUM!	0,1138	0,0056	0,0054	0,0060	0,3505
Schedules 6-15		Lasertrack	1	4	2	ELEVLH51	4	54,11	53,51	34,0	0,43	1,79	0,60	0,30	2055,10	0,5187	0,2888	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs 10		Agg1	-	-	-	ELEVLH5	8	58,51	52,20	34,0	0,00	5,02	0,00	0,00	689,50	0,4679	0,2779	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds Random		station 230	1	2	1	ELEVLH4	13	56,20	54,87	33,0	0,88	0,14	0,13	0,20	28,00	0,4824	0,2284	#NUM!	0,0793	0,0040	0,0043	0,0044	#NUM!
leadFactorProd 1 Overall results		station 220	1	2	1	ELEVLH3	12	56,98	56,75	33,0	0,12	0,08	0,09	0,20	27,00	0,3864	0,8625	#NUM!	0,0828	0,0029	0,0037	0,0044	#NUM!
leadFactorPurch 1 LatePct 79,62		NDO	1	2	1	ELEVLH21	5	58,79	59,32	33,0	0,78	0,96	0,42	0,21	686,90	1,0674	0,6299	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
ssFactorProd 1 Total Avg lead 127,07		Welding KRA	1	2	1	ELEVLH21w	47	61,32	59,33	33,0	0,97	0,11	0,10	0,57	26,60	1,0929	0,2718	#NUM!	0,1232	0,0051	0,0026	0,0049	0,3505
ssFactorPurch 1 CI 0,3836		Welding KRA	1	2	1	ELEVLH2w	38	61,33	60,26	33,0	0,45	0,05	0,05	0,57	26,90	0,4714	0,3299	#NUM!	0,0849	0,0032	0,0013	0,0049	0,2146
lotSizeFactorProd 1 Prod Lead 7-8 weeks		Welding KRA	1	2	1	ELEVLH2	46	62,26	61,53	33,0	0,55	0,03	0,03	0,57	26,90	0,5726	0,3645	#NUM!	0,0885	0,0038	0,0022	0,0049	0,2146
lotSizeFactorPurch 1 SimTime 1000 days		Lasertrack	1	4	2	ELEVLH12	4	62,53	62,23	33,0	0,43	1,79	0,60	0,30	2055,10	0,8326	0,2878	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
safetyTimeFactorComponent 1 WarmUp 380 days		Welding KRA	1	-	1	ELEVLH1	3	64,23	61,52	33,0	2,19	1,21	0,59	0,59	254,60	0,4996	0,2748	#NUM!	0,0596	0,0258	0,0061	0,0061	0,4745
		Oven	-	-	2	DOvenKitELHdas	2	62,52	61,13	33,0	0,74	1,26	0,00	0,00	673,30	0,4770	0,2695	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Dassault RH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	ELEVRHF	19	59,22	56,60	35,0	0,65	0,14	0,15	0,37	29,20	0,4416	0,2755	#NUM!	0,1235	0,0064	0,0070	0,0060	0,2861
Oven Wait	1	Agg2	-	-	-	ELEVRH71	4	57,60	56,72	35,0	0,43	1,79	0,60	0,30	2055,10	0,4782	0,2715	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Oven max kits	6	Lasertrack	1	4	2	ELEVRH7	10	63,72	56,28	34,0	0,00	5,22	0,00	0,00	692,00	0,4713	0,6228	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Demand 100 ss/20ss		Station 330	1	2	1	ELEVRH6	18	58,42	55,21	34,0	0,89	0,21	0,18	0,37	28,80	1,0046	0,2403	#NUM!	0,1070	0,0046	0,0055	0,0060	0,2861
Schedules 6-15		Lasertrack	1	4	2	ELEVRH51	4	56,21	55,55	34,0	0,43	1,79	0,60	0,30	2055,10	0,4171	0,2944	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs 10		Agg1	-	-	-	ELEVRH5	8	60,55	54,23	34,0	0,00	5,02	0,00	0,00	689,50	0,5111	0,2876	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds Random		station 230	1	2	1	ELEVRH4	17	58,23	56,11	33,0	0,92	0,14	0,12	0,20	28,00	0,4902	0,7606	#NUM!	0,1026	0,0054	0,0066	0,0044	#NUM!
leadFactorProd 1 Overall results		station 220	1	2	1	ELEVRH3	16	58,26	58,45	33,0	0,27	0,07	0,09	0,20	27,40	1,2970	1,0924	#NUM!	0,0826	0,0038	0,0035	0,0044	0,3505
leadFactorPurch 1 LatePct 73,08		NDO	1	2	1	ELEVRH21	5	60,54	60,03	33,0	0,76	0,96	0,42	0,21	686,90	1,7518	0,8469	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
ssFactorProd 1 Total Avg lead 130,91		Welding KRA	1	2	1	ELEVRH2w1	49	62,13	61,71	33,0	0,94	0,11	0,10	0,57	26,70	1,3685	0,3162	#NUM!	0,0831	0,0040	0,0032	0,0049	0,5587
ssFactorPurch 1 CI 0,5102		Welding KRA	1	2	1	ELEVRH2w	39	63,71	62,54	33,0	0,65	0,05	0,05	0,57	26,90	0,5468	0,3299	#NUM!	0,0730	0,0037	0,0032	0,0049	0,2146
lotSizeFactorProd 1 Prod Lead 7-8 weeks		Welding KRA	1	2	1	ELEVRH2	48	64,54	63,45	33,0	0,87	0,05	0,03	0,57	26,90	0,5709	0,3404	#NUM!	0,0842	0,0037	0,0012	0,0049	0,2146
lotSizeFactorPurch 1 SimTime 1000 days		Lasertrack	1	4	2	ELEVRH12	4	64,45	64,06	33,0	0,43	1,79	0,60	0,30	2055,10	0,5909	0,3457	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
safetyTimeFactorComponent 1 WarmUp 380 days		Welding KRA	1	-	1	ELEVRH1	3	66,06	61,72	33,0	2,19	1,21	0,59	0,59	254,60	0,6001	0,2823	#NUM!	0,0596	0,0258	0,0061	0,0061	0,4745
		Oven	-	-	2	DOvenKitERHdas	2	62,72	61,75	33,0	0,74	1,26	0,00	0,00	673,30	0,4553	0,2730	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Table 7:Increased demand experiment for Dassault products

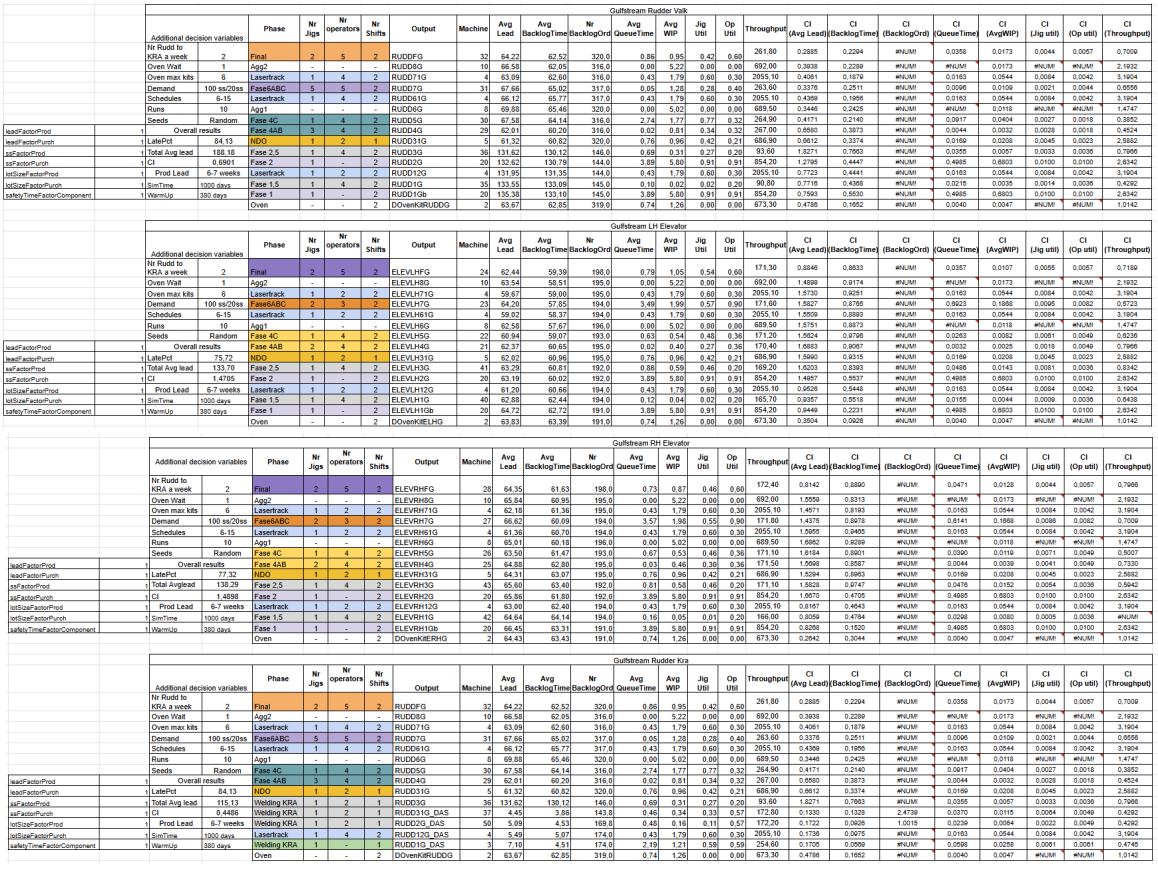
The results of the demand increase experiment reveal significant performance degradation across all Dassault products. Table 7 shows that both the average backlog time and the number of backlogged orders are already very high at the first production stage, corresponding to the oven.

For the Dassault Rudder, the average backlog time at the oven reaches approximately 56 days, with around 34 orders experiencing backlog conditions. A similar effect is observed for the LH and RH elevators, where backlog times at the initial stages of production exceed 54–56 days.

These results suggest that the production system encounters a capacity limitation upstream of the oven stage, specifically within the inhouse manufacturing processes

responsible for producing components necessary for assembly start at Marconi such as skins and beams. Since these downstream operations cannot process incoming orders at the rate required by the increased demand, queues propagate downstream through the production line, causing orders to remain blocked at the first stage of production and starving further production which at the same time also increases backlog time in subsequent production steps.

As a consequence, the total production lead time increases significantly, reaching approximately 127–131 weeks across the Dassault products, which is much higher than the empirical production lead time reported by the company (7–8 weeks). Additionally, the proportion of late orders increases substantially, with percentages ranging between 65% and 80%.



Gulfstream Rudder Valk

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	RUDDFG	32	64,22	62,52	320,0	0,86	0,95	0,42	0,60	261,80	0,2885	0,2294	#NUM!	0,0358	0,0173	0,0044	0,0057	0,7009
Oven Wait	1	Agg2	-	-	-	RUDD8G	10	66,58	62,05	316,0	0,00	5,22	0,00	0,00	692,00	0,3938	0,2289	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Oven max kits	6	Lasertrack	1	4	2	RUDD71G	4	63,09	62,60	316,0	0,43	1,79	0,60	0,30	2055,10	0,4081	0,1879	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Demand	100 ss/20ss	Fase6ABC	5	5	2	RUDD7G	31	67,66	65,02	317,0	0,05	1,28	0,28	0,40	263,60	0,3376	0,2511	#NUM!	0,0096	0,0109	0,0021	0,0044	0,6556
Schedules	6-15	Lasertrack	1	4	2	RUDD61G	4	66,12	65,77	317,0	0,43	1,79	0,60	0,30	2055,10	0,4369	0,1956	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs	10	Agg1	-	-	-	RUDD6G	8	69,88	65,46	320,0	0,00	5,02	0,00	0,00	689,50	0,3448	0,2425	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds	Random	Fase 4C	1	4	2	RUDD5G	30	67,58	64,14	316,0	2,74	1,77	0,77	0,32	264,90	0,4171	0,2140	#NUM!	0,0917	0,0404	0,0027	0,0018	0,3852
Overall results		Fase 4AB	3	4	2	RUDD4G	29	62,01	60,20	316,0	0,02	0,81	0,34	0,32	267,00	0,6580	0,3873	#NUM!	0,0044	0,0032	0,0028	0,0018	0,4524
LatePct	84,13	NDO	1	2	1	RUDD31G	5	61,32	60,82	320,0	0,76	0,96	0,42	0,21	686,90	0,6612	0,3374	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
Total Avg lead	188,18	Fase 2,5	1	4	2	RUDD3G	36	131,62	130,12	146,0	0,69	0,31	0,27	0,20	93,60	1,8271	0,7663	#NUM!	0,0355	0,0057	0,0033	0,0036	0,7966
CI	0,6901	Fase 2	1	-	2	RUDD2G	20	132,62	130,79	144,0	3,89	5,80	0,91	0,91	854,20	1,2795	0,4447	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
Prod Lead	6-7 weeks	Lasertrack	1	2	2	RUDD12G	4	131,95	131,35	144,0	0,43	1,79	0,60	0,30	2055,10	0,7723	0,4441	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
SimTime	1000 days	Fase 1,5	1	4	2	RUDD1G	35	133,55	133,09	145,0	0,10	0,02	0,02	0,20	90,80	0,7716	0,4368	#NUM!	0,0215	0,0035	0,0014	0,0036	0,4292
WarmUp	380 days	Fase 1	1	-	2	RUDD1Gb	20	135,38	133,10	145,0	3,89	5,80	0,91	0,91	854,20	0,7593	0,5530	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
		Oven	-	-	2	DOvenKitRUDDG	2	63,67	62,85	319,0	0,74	1,26	0,00	0,00	673,30	0,4788	0,1652	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Gulfstream LH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	ELEVLHFG	24	62,44	59,39	198,0	0,79	1,05	0,54	0,60	171,30	0,8846	0,8833	#NUM!	0,0357	0,0107	0,0055	0,0057	0,7189
Oven Wait	1	Agg2	-	-	-	ELEVLH8G	10	63,54	58,51	195,0	0,00	5,22	0,00	0,00	692,00	1,4899	0,9174	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Oven max kits	6	Lasertrack	1	2	2	ELEVLH71G	4	59,67	59,00	195,0	0,43	1,79	0,60	0,30	2055,10	1,5730	0,9251	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Demand	100 ss/20ss	Fase6ABC	2	3	2	ELEVLH7G	23	64,20	57,85	194,0	3,48	1,99	0,57	0,90	171,60	1,5627	0,8765	#NUM!	0,5923	0,1958	0,0095	0,0062	0,5723
Schedules	6-15	Lasertrack	1	2	2	ELEVLH61G	4	59,02	58,37	194,0	0,43	1,79	0,60	0,30	2055,10	1,5509	0,8893	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs	10	Agg1	-	-	-	ELEVLH6G	8	62,58	57,67	196,0	0,00	5,02	0,00	0,00	689,50	1,5751	0,8873	#NUM!	0,0118	#NUM!	#NUM!	#NUM!	1,4747
Seeds	Random	Fase 4C	1	4	2	ELEVLH5G	22	60,94	59,07	193,0	0,63	0,54	0,48	0,36	171,20	1,5824	0,9796	#NUM!	0,0263	0,0082	0,0061	0,0049	0,6236
Overall results		Fase 4AB	2	4	2	ELEVLH4G	21	62,37	60,65	195,0	0,02	0,40	0,27	0,36	170,40	1,6683	0,9067	#NUM!	0,0032	0,0025	0,0018	0,0049	0,7966
LatePct	75,72	NDO	1	2	1	ELEVLH31G	5	62,62	60,96	195,0	0,76	0,96	0,42	0,21	686,90	1,5990	0,9315	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
Total Avg lead	133,70	Fase 2,5	1	4	2	ELEVLH3G	41	63,29	60,81	192,0	0,86	0,59	0,46	0,20	169,20	1,6203	0,9393	#NUM!	0,0486	0,0143	0,0081	0,0036	0,8342
CI	1,4705	Fase 2	1	-	2	ELEVLH2G	20	63,19	60,02	192,0	3,89	5,80	0,91	0,91	854,20	1,4957	0,5537	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
Prod Lead	6-7 weeks	Lasertrack	1	2	2	ELEVLH12G	4	61,20	60,66	194,0	0,43	1,79	0,60	0,30	2055,10	0,9528	0,5448	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
SimTime	1000 days	Fase 1,5	1	4	2	ELEVLH1G	40	62,88	62,44	194,0	0,12	0,04	0,02	0,20	165,70	0,9357	0,5518	#NUM!	0,0155	0,0044	0,0009	0,0036	0,6438
WarmUp	380 days	Fase 1	1	-	2	ELEVLH1Gb	20	64,72	62,72	191,0	3,89	5,80	0,91	0,91	854,20	0,9449	0,2231	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
		Oven	-	-	2	DOvenKitELHG	2	63,83	63,39	191,0	0,74	1,26	0,00	0,00	673,30	0,3504	0,0926	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Gulfstream RH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	ELEVRHFG	28	64,35	61,63	198,0	0,73	0,87	0,46	0,60	172,40	0,8142	0,8890	#NUM!	0,0471	0,0128	0,0044	0,0057	0,7966
Oven Wait	1	Agg2	-	-	-	ELEVRH8G	10	65,84	60,95	195,0	0,00	5,22	0,00	0,00	692,00	1,5559	0,9313	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Oven max kits	6	Lasertrack	1	2	2	ELEVRH71G	4	62,18	61,36	195,0	0,43	1,79	0,60	0,30	2055,10	1,4571	0,8193	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Demand	100 ss/20ss	Fase6ABC	2	3	2	ELEVRH7G	27	66,62	60,09	194,0	3,57	1,98	0,55	0,90	171,80	1,4375	0,8978	#NUM!	0,6141	0,1988	0,0088	0,0062	0,7009
Schedules	6-15	Lasertrack	1	2	2	ELEVRH61G	4	61,36	60,70	194,0	0,43	1,79	0,60	0,30	2055,10	1,5955	0,9455	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs	10	Agg1	-	-	-	ELEVRH6G	8	65,01	60,18	196,0	0,00	5,02	0,00	0,00	689,50	1,5662	0,9299	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds	Random	Fase 4C	1	4	2	ELEVRH5G	26	63,56	61,47	193,0	0,67	0,53	0,46	0,36	171,10	1,6184	0,9901	#NUM!	0,0390	0,0119	0,0071	0,0049	0,5057
Overall results		Fase 4AB	2	4	2	ELEVRH4G	25	64,88	62,80	195,0	0,03	0,46	0,30	0,36	171,50	1,5668	0,8587	#NUM!	0,0044	0,0039	0,0041	0,0049	0,7330
LatePct	77,32	NDO	1	2	1	ELEVRH31G	5	64,31	63,07	195,0	0,76	0,96	0,42	0,21	686,90	1,5294	0,8963	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
Total Avglead	138,29	Fase 2,5	1	4	2	ELEVRH3G	43	65,60	63,40	192,0	0,81	0,58	0,46	0,20	171,10	1,5828	0,9747	#NUM!	0,0478	0,0152	0,0054	0,0036	0,5942
CI	1,4898	Fase 2	1	-	2	ELEVRH2G	26	65,86	61,88	192,0	3,89	5,80	0,91	0,91	854,20	1,5070	0,4705	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
Prod Lead	6-7 weeks	Lasertrack	1	2	2	ELEVRH12G	4	63,00	62,40	194,0	0,43	1,79	0,60	0,30	2055,10	0,8167	0,4643	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
SimTime	1000 days	Fase 1,5	1	4	2	ELEVRH1G	42	64,64	64,14	194,0	0,16	0,05	0,01	0,20	166,00	0,8059	0,4784	#NUM!	0,0298	0,0080	0,0005	0,0036	#NUM!
WarmUp	380 days	Fase 1	1	-	2	ELEVRH1Gb	20	66,45	63,31	191,0	3,89	5,80	0,91	0,91	854,20	0,8268	0,1520	#NUM!	0,4665	0,6803	0,0100	0,0100	2,6342
		Oven	-	-	2	DOvenKitERHG	2	64,43	63,43	191,0	0,74	1,26	0,00	0,00	673,30	0,2642	0,3044	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Gulfstream Rudder Kra

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	RUDDFG	32	64,22	62,52	320,0	0,86	0,95	0,42	0,60	261,80	0,2885	0,2294	#NUM!	0,0358	0,0173	0,0044	0,0057	0,7009
Oven Wait	1	Agg2	-	-	-	RUDD8G	10	66,58	62,05	316,0	0,00	5,22	0,00	0,00	692,00	0,3938	0,2289	#NUM!	#NUM!	0,0173	#NUM!	#NUM!	2,1932
Oven max kits	6	Lasertrack	1	4	2	RUDD71G	4	63,09	62,60	316,0	0,43	1,79	0,60	0,30	2055,10	0,4081	0,1879	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Demand	100 ss/20ss	Fase6ABC	5	5	2	RUDD7G	31	67,66	65,02	317,0	0,05	1,28	0,28	0,40	263,60	0,3376	0,2511	#NUM!	0,0096	0,0109	0,0021	0,0044	0,6556
Schedules	6-15	Lasertrack	1	4	2	RUDD61G	4	66,12	65,77	317,0	0,43	1,79	0,60	0,30	2055,10	0,4369	0,1956	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
Runs	10	Agg1	-	-	-	RUDD6G	8	69,88	65,46	320,0	0,00	5,02	0,00	0,00	689,50	0,3448	0,2425	#NUM!	#NUM!	0,0118	#NUM!	#NUM!	1,4747
Seeds	Random	Fase 4C	1	4	2	RUDD5G	30	67,58	64,14	316,0	2,74	1,77	0,77	0,32	264,90	0,4171	0,2140	#NUM!	0,0917	0,0404	0,0027	0,0018	0,3852
Overall results		Fase 4AB	3	4	2	RUDD4G	29	62,01	60,20	316,0	0,02	0,81	0,34	0,32	267,00	0,6580	0,3873	#NUM!	0,0044	0,0032	0,0028	0,0018	0,4524
LatePct	84,13	NDO	1	2	1	RUDD31G	5	61,32	60,82	320,0	0,76	0,96	0,42	0,21	686,90	0,6612	0,3374	#NUM!	0,0169	0,0208	0,0045	0,0023	2,5882
Total Avg lead	115,13	Welding KRA	1	2	1	RUDD3G	36	131,62	130,12	146,0	0,69	0,31	0,27	0,20	93,60	1,8271	0,7663	#NUM!	0,0355	0,0057	0,0033	0,0036	0,7966
CI	0,4486	Welding KRA	1	2	1	RUDD31G_DAS	37	4,45	3,86	143,8	0,46	0,34	0,33	0,57	172,60	0,1330	0,1328	2,4739	0,0370	0,0115	0,0054	0,0049	0,4292
Prod Lead	6-7 weeks	Welding KRA	1	2	1	RUDD2G_DAS	50	5,09	4,53	169,8	0,48	0,16	0,11	0,57	172,20	0,1722	0,0626	1,0015	0,0239	0,0064	0,0022	0,0049	0,4292
SimTime	1000 days	Lasertrack	1	4	2	RUDD12G_DAS	4	5,49	5,87	174,0	0,43	1,79	0,60	0,30	2055,10	0,1736	0,0975	#NUM!	0,0163	0,0544	0,0084	0,0042	3,1904
WarmUp	380 days	Welding KRA	1	-	1	RUDD1G_DAS	3	7,10	4,51	174,0	2,19	1,21	0,59	0,59	254,60	0,1705	0,0569	#NUM!	0,0598	0,0258	0,0061	0,0061	0,4745
		Oven	-	-	2	DOvenKitRUDDG	2	63,67	62,85	319,0	0,74	1,26	0,00	0,00	673,30	0,4788	0,1652	#NUM!	0,0040	0,0047	#NUM!	#NUM!	1,0142

Table 8:Increased demand experiment for Gulfstream products

Table 8 shows a similar scenario in the case of Gulfstream products. The simulation results show very high backlog times already at the first stage of production (Oven). For the Gulfstream Rudder, backlog times of approximately 62–65 days are shown with more than 300 backlogged orders, while the LH and RH elevators show backlog times between 58 and 63 days, with approximately 190–200 orders being backlogged.

As in the Dassault case, these results indicate that the production system becomes unstable due to the congestion in Edison component manufacturing, preventing orders from progressing through the production chain.

As a consequence, the total production lead times increase significantly, reaching approximately 188 weeks for the Gulfstream Rudder and around 134–138 weeks for the elevators, exceeding by far the lead times of 6–7 weeks reported by the company. The proportion of late orders also increases drastically, reaching values between 75% and 84%.

These results confirm that the current system configuration is unable to adapt to the increased demand level. The observed backlog propagation highlights the presence of capacity constrained steps in the Edison component manufacturing production processes, which become the focus of the capacity expansion experiments performed in the following sections.

4.3 Upstream Capacity Increase Experiment

As seen in the previous experiment section, the rate at which the production orders arrive to the upstream processes (in house component manufacturing at Edison) is much higher than the actual production rate at standard capacity, which explodes the backlog and waiting times in downstream processes happening at Marconi. For this reason, the present experiment explores how increasing capacity downstream affects the system. Note that the production of these components happens entirely at Edison which is modeled in an aggregated way, therefore detailed insights cannot be given in this project, however the experiments can point out potential capacity problems in those stages of production. In this case capacity is increased by one third.

Dassault Rudder

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	RUDDF	11	6,62	3,94	34,0	0,46	0,15	0,18	0,46	34,00	0,1513	0,1571	#NUM!	0,0462	0,0026	0,0051	0,0052	#NUM
Oven Wait	1	Agg2	-	-	-	RUDD7	10	10,94	3,28	34,0	0,00	5,60	0,00	0,00	736,50	0,1571	0,1415	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Oven max kits	6	Lasertrack	1	4	2	RUDD61	4	4,28	3,40	33,9	0,47	2,08	0,66	0,33	2235,10	0,1415	0,1413	0,2146	0,0194	0,0804	0,0078	0,0039	20,2774
Demand	100 ss/20ss	Station 330	1	2	1	RUDD6	9	7,39	2,41	34,0	0,56	0,27	0,23	0,46	33,60	0,1303	0,0966	#NUM!	0,0645	0,0023	0,0049	0,0052	0,3505
Schedules	6-15	Lasertrack	1	4	2	RUDD51	4	3,41	2,97	34,0	0,47	2,08	0,66	0,33	2235,10	0,0966	0,0880	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	RUDD5	8	7,97	1,64	33,8	0,00	5,36	0,00	0,00	735,50	0,0880	0,0758	#NUM!	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	station 230	1	2	1	RUDD4	7	5,64	2,68	9,2	2,14	0,26	0,21	0,27	33,20	0,0770	0,2686	0,5353	0,0687	0,0049	0,0020	0,0040	0,2661
Overall results		station 220	1	2	1	RUDD3	6	2,50	1,66	11,1	0,56	0,10	0,13	0,27	33,00	0,0820	0,2414	1,2975	0,0686	0,0031	0,0024	0,0040	#NUM!
LatePct	0,32	NDO	1	2	1	RUDD21	5	2,06	1,43	33,0	0,67	0,92	0,45	0,22	732,20	0,1057	0,0628	#NUM!	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	9,56	Welding KRA	1	2	1	RUDD2wr1	45	3,43	2,63	9,6	1,25	0,14	0,13	0,64	33,00	0,0628	0,1712	0,4745	0,0691	0,0036	0,0018	0,0037	#NUM!
CI	0,1559	Welding KRA	1	2	1	RUDD2w	34	2,07	1,60	13,6	0,67	0,08	0,07	0,64	34,00	0,0444	0,2198	1,5409	0,0768	0,0038	0,0020	0,0037	#NUM!
Prod Lead	7-8 weeks	Welding KRA	1	2	1	RUDD2	44	2,22	1,54	29,6	0,64	0,04	0,02	0,64	33,80	0,1538	0,1199	0,7295	0,0631	0,0036	0,0010	0,0037	0,2661
SimTime	1000 days	Lasertrack	1	4	2	RUDD12	4	2,45	2,13	30,8	0,47	2,08	0,66	0,33	2235,10	0,1150	0,1059	0,5353	0,0194	0,0804	0,0078	0,0039	20,2774
WarmUp	360 days	Welding KRA	1	-	1	RUDD1	3	4,14	0,78	32,9	2,51	1,42	0,64	0,64	271,50	0,0811	#NUM!	#NUM!	0,0635	0,0300	0,0068	0,0068	0,3577
		Oven	-	-	2	DOvenKitRUDDdas	2	1,78	0,00	32,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Dassault LH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	ELEVLHF	15	8,33	5,31	35,0	0,71	0,16	0,18	0,40	34,30	0,3436	0,2732	#NUM!	0,1189	0,0075	0,0076	0,0052	0,3278
Oven Wait	1	Agg2	-	-	-	ELEVLH71	4	6,31	5,63	35,0	0,47	2,08	0,66	0,33	2235,10	0,4741	0,2273	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Oven max kits	6	Lasertrack	1	4	2	ELEVLH7	10	12,63	4,85	34,9	0,00	5,60	0,00	0,00	736,50	0,3945	0,2382	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Demand	100 ss/20ss	Station 330	1	2	1	ELEVLH6	14	6,92	2,28	33,8	0,92	0,26	0,20	0,40	34,50	0,3848	0,1207	0,2851	0,1391	0,0078	0,0062	0,0052	0,3577
Schedules	6-15	Lasertrack	1	4	2	ELEVLH51	4	3,27	2,84	34,0	0,47	2,08	0,66	0,33	2235,10	0,2042	0,1186	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	ELEVLH5	9	7,84	1,70	29,5	0,00	5,36	0,00	0,00	735,50	0,2059	0,0998	1,6076	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	station 230	1	2	1	ELEVLH4	13	5,44	2,43	33,0	0,70	0,16	0,18	0,27	34,00	0,2069	0,0498	#NUM!	0,1151	0,0065	0,0050	0,0040	#NUM!
Overall results		station 220	1	2	1	ELEVLH3	12	4,52	3,13	8,6	1,90	0,19	0,15	0,27	33,00	0,0868	0,1740	0,9704	0,1051	0,0055	0,0023	0,0040	#NUM!
LatePct	10,33	NDO	1	2	1	ELEVLH21	5	2,14	1,61	30,0	0,67	0,92	0,45	0,22	732,20	0,2693	0,1266	1,1970	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	10,03	Welding KRA	1	2	1	ELEVLH21w	47	3,44	0,91	25,8	1,05	0,15	0,13	0,64	33,00	0,2294	0,0890	1,6562	0,0880	0,0051	0,0039	0,0037	#NUM!
CI	0,1051	Welding KRA	1	2	1	ELEVLH2w	38	2,66	2,08	8,4	1,52	0,11	0,06	0,64	33,00	0,1181	0,2545	1,4378	0,0780	0,0043	0,0026	0,0037	#NUM!
Prod Lead	7-8 weeks	Welding KRA	1	2	1	ELEVLH2	46	1,39	1,72	10,8	0,65	0,04	0,03	0,64	33,00	0,2672	0,3580	1,8041	0,0929	0,0049	0,0033	0,0037	#NUM!
SimTime	1000 days	Lasertrack	1	4	2	ELEVLH12	4	1,23	1,21	22,6	0,47	2,08	0,66	0,33	2235,10	0,2803	0,2398	2,1745	0,0194	0,0804	0,0078	0,0039	20,2774
WarmUp	360 days	Welding KRA	1	-	1	ELEVLH1	3	2,79	0,42	33,0	2,51	1,42	0,64	0,64	271,50	0,2397	#NUM!	#NUM!	0,0635	0,0300	0,0068	0,0068	0,3577
		Oven	-	-	2	DOvenKitELHdas	2	1,42	0,00	33,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Dassault RH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final assembly	1	2	1	ELEVRHF	19	8,47	5,52	35,0	0,62	0,16	0,18	0,40	34,60	0,2499	0,2016	#NUM!	0,1063	0,0051	0,0025	0,0052	0,3505
Oven Wait	1	Agg2	-	-	-	ELEVRH71	4	6,52	5,71	35,0	0,47	2,08	0,66	0,33	2235,10	0,3500	0,1841	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Oven max kits	6	Lasertrack	1	4	2	ELEVRH7	10	12,71	4,88	34,0	0,00	5,60	0,00	0,00	736,50	0,3195	0,1460	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Demand	100 ss/20ss	Station 330	1	2	1	ELEVRH6	18	6,90	2,39	33,7	0,85	0,25	0,19	0,40	34,70	0,2899	0,1357	0,4581	0,1149	0,0068	0,0074	0,0052	0,3278
Schedules	6-15	Lasertrack	1	4	2	ELEVRH51	4	3,36	2,87	34,0	0,47	2,08	0,66	0,33	2235,10	0,2351	0,1164	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	ELEVRH5	8	7,87	2,69	19,6	0,00	5,36	0,00	0,00	735,50	0,2020	0,2253	1,7870	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	station 230	1	2	1	ELEVRH4	17	5,38	2,49	33,0	0,55	0,15	0,16	0,27	34,00	0,2003	0,0783	#NUM!	0,0882	0,0066	0,0058	0,0040	#NUM!
Overall results		station 220	1	2	1	ELEVRH3	16	4,60	3,73	14,6	1,51	0,15	0,12	0,27	33,20	0,1368	0,2295	1,2876	0,0889	0,0051	0,0030	0,0040	0,2661
LatePct	4,00	NDO	1	2	1	ELEVRH21	5	3,23	2,54	28,2	0,67	0,92	0,45	0,22	732,20	0,3338	0,1374	1,2307	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	11,40	Welding KRA	1	2	1	ELEVRH2wr1	49	4,19	2,19	23,7	1,08	0,14	0,13	0,64	33,20	0,2700	0,1466	1,6012	0,0885	0,0053	0,0033	0,0037	0,2861
CI	0,2349	Welding KRA	1	2	1	ELEVRH2w	39	3,50	2,93	22,6	1,00	0,08	0,06	0,64	33,00	0,2037	0,1735	1,8709	0,0391	0,0023	0,0015	0,0037	#NUM!
Prod Lead	7-8 weeks	Welding KRA	1	2	1	ELEVRH2	48	3,56	2,88	27,3	0,95	0,06	0,04	0,64	33,00	0,3545	0,1748	1,2411	0,1033	0,0055	0,0023	0,0037	#NUM!
SimTime	1000 days	Lasertrack	1	4	2	ELEVRH12	4	3,33	2,70	32,4	0,47	2,08	0,66	0,33	2235,10	0,2757	0,1661	0,3505	0,0194	0,0804	0,0078	0,0039	20,2774
WarmUp	360 days	Welding KRA	1	-	1	ELEVRH1	3	4,65	0,42	33,0	2,51	1,42	0,64	0,64	271,50	0,2932	#NUM!	#NUM!	0,0635	0,0300	0,0068	0,0068	0,3577
		Oven	-	-	2	DOvenKitERHdas	2	1,42	0,00	33,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Table 9:Downstream capacity increase experiment for Dassault products

The results of the capacity increase at upstream component production shows a significant improvement in performance for Dassault products. As shown in Table 9, the backlog propagation observed in the demand increase experiment disappears and the production system returns to stability.

For the Dassault Rudder, the total average production lead time decreases to approximately 9.56 weeks, while backlog times at the first stage of production drops drastically. Similar improvements are observed for the elevators, where total lead times reach approximately 10.03 weeks for the LH elevator and 11.40 weeks for the RH elevator. Compared to the previous demand increase scenario, where lead times exceeded 120 weeks, these results indicate that the increase in downstream capacity effectively removes the congestion that previously propagated upstream through the production system.

An important observation concerns operator and jig utilization. Across most production stages, operator utilization remains at moderate levels, generally between 0.2 and 0.64. This indicates that the Dassault system still has a reasonable amount of available capacity even under the increased demand scenario. As a consequence, the effect of stochasticity in processing times is expected to have a limited impact on overall system stability, since production steps are not operating close to full utilization.

Gulfstream Rudder Valk

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	RUDDFG	32	36,36	34,17	320,0	0,99	1,12	0,48	0,61	292,70	1,5872	1,6196	#NUM!	0,0377	0,0204	0,0051	0,0074	2,5200
Oven Wait	1	Agg2	-	-	-	RUDD8G	10	38,21	33,09	316,0	0,00	5,60	0,00	0,00	736,50	2,8138	1,6452	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Oven max kits	6	Lasertrack	1	4	2	RUDD71G	4	34,13	33,33	316,0	0,47	2,08	0,66	0,33	2235,10	2,8586	1,6884	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Demand	100 ss/20ss	Fase6ABC	5	5	2	RUDD7G	31	38,39	35,48	317,0	0,07	1,42	0,30	0,44	294,80	2,9307	1,6755	#NUM!	0,0102	0,0118	0,0035	0,0031	2,0930
Schedules	6-15	Lasertrack	1	4	2	RUDD61G	4	36,56	36,03	317,0	0,47	2,08	0,66	0,33	2235,10	2,9132	1,6911	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	RUDD6G	8	40,13	35,03	320,0	0,00	5,36	0,00	0,00	735,50	2,9412	1,7254	#NUM!	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	Fase 4C	1	4	2	RUDD5G	30	37,13	34,12	316,0	1,68	1,47	0,85	0,36	295,40	2,9984	1,7858	#NUM!	0,0842	0,0488	0,0096	0,0026	2,3983
Overall results		Fase 4AB	3	4	2	RUDD4G	29	36,21	34,34	316,0	0,02	0,89	0,39	0,36	295,90	3,1045	1,7744	#NUM!	0,0043	0,0062	0,0041	0,0026	2,4459
LatePct	85,08	NDO	1	2	1	RUDD31G	5	35,43	34,78	320,0	0,67	0,92	0,45	0,22	732,20	3,0940	1,7674	#NUM!	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	87,60	Fase 2,5	1	4	2	RUDD3G	36	77,42	75,25	146,0	0,63	0,40	0,35	0,22	122,50	6,6570	3,8548	#NUM!	0,0356	0,0115	0,0059	0,0028	2,2451
CI	4,2374	Fase 2	1	-	2	RUDD2G	20	77,69	38,62	144,0	41,36	69,12	1,00	1,00	956,00	6,7402	2,2457	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
Prod Lead	6-7 weeks	Lasertrack	1	2	2	RUDD12G	4	39,73	39,17	144,0	0,47	2,08	0,66	0,33	2235,10	3,8995	2,2609	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
SimTime	1000 days	Fase 1,5	1	4	2	RUDD1G	35	41,38	40,90	145,0	0,14	0,05	0,03	0,22	134,10	3,9263	2,2642	#NUM!	0,0272	0,0067	0,0029	0,0028	1,5492
WarmUp	380 days	Fase 1	1	-	2	RUDD1Gb	20	43,09	0,42	145,0	41,36	69,12	1,00	1,00	956,00	3,9329	#NUM!	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
		Oven	-	-	2	DOvenKillRUDDG	2	1,42	0,00	319,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Gulfstream LH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	ELEVLHFG	24	73,53	69,97	198,0	0,80	1,04	0,53	0,61	169,40	3,1212	3,2597	#NUM!	0,0506	0,0240	0,0074	0,0074	2,1979
Oven Wait	1	Agg2	-	-	-	ELEVLH8G	10	74,16	69,56	195,0	0,00	5,60	0,00	0,00	736,50	5,6481	3,2870	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Oven max kits	6	Lasertrack	1	2	2	ELEVLH71G	4	70,75	69,89	195,0	0,47	2,08	0,66	0,33	2235,10	5,7126	3,3274	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Demand	100 ss/20ss	Fase6ABC	2	3	2	ELEVLH7G	23	75,11	69,97	194,0	2,32	1,65	0,56	0,90	169,40	5,7835	3,3879	#NUM!	0,4601	0,1530	0,0124	0,0168	2,5533
Schedules	6-15	Lasertrack	1	2	2	ELEVLH61G	4	71,17	70,62	194,0	0,47	2,08	0,66	0,33	2235,10	6,4248	3,8821	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	ELEVLH6G	8	74,86	70,01	196,0	0,00	5,36	0,00	0,00	735,50	6,4247	3,7573	#NUM!	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	Fase 4C	1	4	2	ELEVLH5G	22	73,30	71,49	193,0	0,61	0,53	0,46	0,36	169,50	6,5551	3,8485	#NUM!	0,0392	0,0149	0,0119	0,0061	2,9859
Overall results		Fase 4AB	2	4	2	ELEVLH4G	21	74,61	73,14	195,0	0,02	0,40	0,27	0,36	168,90	6,6951	3,8780	#NUM!	0,0052	0,0065	0,0066	0,0061	2,9745
LatePct	76,58	NDO	1	2	1	ELEVLH31G	5	74,54	73,47	195,0	0,67	0,92	0,45	0,22	732,20	6,7347	3,9140	#NUM!	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	133,60	Fase 2,5	1	4	2	ELEVLH3G	41	75,88	73,55	192,0	0,85	0,59	0,46	0,22	168,40	6,8296	3,9643	#NUM!	0,0407	0,0184	0,0086	0,0028	2,5225
CI	6,5688	Fase 2	1	-	2	ELEVLH2G	20	75,97	37,27	192,0	41,36	69,12	1,00	1,00	956,00	6,7003	2,1265	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
Prod Lead	6-7 weeks	Lasertrack	1	2	2	ELEVLH12G	4	38,38	37,79	194,0	0,47	2,08	0,66	0,33	2235,10	3,8972	2,1312	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
SimTime	1000 days	Fase 1,5	1	4	2	ELEVLH1G	40	39,92	39,55	194,0	0,16	0,06	0,02	0,22	180,50	3,7090	2,1243	#NUM!	0,0218	0,0063	0,0009	0,0028	2,0547
WarmUp	380 days	Fase 1	1	-	2	ELEVLH1Gb	20	41,73	0,42	128,0	41,36	69,12	1,00	1,00	956,00	3,8995	#NUM!	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
		Oven	-	-	2	DOvenKillELHG	2	1,09	0,00	191,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Gulfstream RH Elevator

Additional decision variables		Phase	Nr Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	ELEVRHFG	28	73,56	70,61	198,0	0,77	0,88	0,46	0,61	170,50	3,0187	3,0796	#NUM!	0,0398	0,0145	0,0058	0,0074	2,5241
Oven Wait	1	Agg2	-	-	-	ELEVRH8G	10	74,85	69,95	195,0	0,00	5,60	0,00	0,00	736,50	5,3007	3,1971	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Oven max kits	6	Lasertrack	1	2	2	ELEVRH71G	4	71,20	70,38	195,0	0,47	2,08	0,66	0,33	2235,10	5,5498	3,1383	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Demand	100 ss/20ss	Fase6ABC	2	3	2	ELEVRH7G	27	75,67	70,36	194,0	2,44	1,66	0,55	0,90	171,10	5,4491	3,7649	#NUM!	0,5736	0,1994	0,0157	0,0168	2,9745
Schedules	6-15	Lasertrack	1	2	2	ELEVRH61G	4	71,63	70,96	194,0	0,47	2,08	0,66	0,33	2235,10	6,5345	3,8122	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	ELEVRH6G	8	75,27	70,40	196,0	0,00	5,36	0,00	0,00	735,50	6,8262	3,8489	#NUM!	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	Fase 4C	1	4	2	ELEVRH5G	26	73,75	71,56	193,0	0,69	0,53	0,46	0,36	170,40	6,6600	3,7931	#NUM!	0,0393	0,0098	0,0098	0,0061	2,9356
Overall results		Fase 4AB	2	4	2	ELEVRH4G	25	75,00	73,03	195,0	0,03	0,46	0,29	0,36	170,30	6,6257	3,8107	#NUM!	0,0043	0,0071	0,0055	0,0061	2,9155
LatePct	76,84	NDO	1	2	1	ELEVRH31G	5	74,55	73,38	195,0	0,67	0,92	0,45	0,22	732,20	6,6877	3,9055	#NUM!	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avglead	134,08	Fase 2,5	1	4	2	ELEVRH3G	43	75,92	73,73	192,0	0,73	0,56	0,46	0,22	170,10	6,8202	3,8347	#NUM!	0,0478	0,0172	0,0072	0,0028	2,8695
CI	6,5208	Fase 2	1	-	2	ELEVRH2G	20	76,26	37,14	192,0	41,36	69,12	1,00	1,00	956,00	6,7450	2,1542	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
Prod Lead	6-7 weeks	Lasertrack	1	2	2	ELEVRH12G	4	38,29	37,72	194,0	0,47	2,08	0,66	0,33	2235,10	3,7388	2,1321	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
SimTime	1000 days	Fase 1,5	1	4	2	ELEVRH1G	42	39,88	39,45	194,0	0,18	0,06	0,02	0,22	181,20	3,7105	2,1318	#NUM!	0,0139	0,0043	0,0007	0,0028	1,9928
WarmUp	380 days	Fase 1	1	-	2	ELEVRH1Gb	20	41,67	0,42	128,0	41,36	69,12	1,00	1,00	956,00	3,7113	#NUM!	#NUM!	2,1852	3,4857	#NUM!	#NUM!	12,4357
		Oven	-	-	2	DOvenKillERHG	2	1,09	0,00	191,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Gulfstream Rudder Kra

Additional decision variables		Phase	Nr. Jigs	Nr operators	Nr Shifts	Output	Machine	Avg Lead	Avg BacklogTime	Nr BacklogOrd	Avg QueueTime	Avg WIP	Jig Util	Op Util	Throughput	CI (Avg Lead)	CI (BacklogTime)	CI (BacklogOrd)	CI (QueueTime)	CI (AvgWIP)	CI (Jig util)	CI (Op util)	CI (Throughput)
Nr Rudd to KRA a week	2	Final	2	5	2	RUDDFG	32	36,36	34,17	320,0	0,99	1,12	0,48	0,61	292,70	1,5872	1,6196	#NUM!	0,0377	0,0204	0,0051	0,0074	2,5200
Oven Wait	1	Agg2	-	-	-	RUDD8G	10	38,21	33,09	316,0	0,00	5,60	0,00	0,00	736,50	2,8138	1,6452	#NUM!	#NUM!	0,0560	#NUM!	#NUM!	7,5520
Oven max kits	6	Lasertrack	1	4	2	RUDD71G	4	34,13	33,33	316,0	0,47	2,08	0,66	0,33	2235,10	2,8586	1,6884	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Demand	100 ss/20ss	Fase6ABC	5	5	2	RUDD7G	31	38,39	35,48	317,0	0,07	1,42	0,30	0,44	294,80	2,9307	1,6755	#NUM!	0,0102	0,0118	0,0035	0,0031	2,0930
Schedules	6-15	Lasertrack	1	4	2	RUDD61G	4	36,56	36,03	317,0	0,47	2,08	0,66	0,33	2235,10	2,9132	1,6911	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
Runs	10	Agg1	-	-	-	RUDD6G	8	40,13	35,03	320,0	0,00	5,36	0,00	0,00	735,50	2,9412	1,7254	#NUM!	#NUM!	0,0608	#NUM!	#NUM!	7,5588
Seeds	Random	Fase 4C	1	4	2	RUDD5G	30	37,13	34,12	316,0	1,68	1,47	0,85	0,36	295,40	2,9984	1,7858	#NUM!	0,0842	0,0488	0,0096	0,0026	2,3983
Overall results		Fase 4AB	3	4	2	RUDD4G	29	36,21	34,34	316,0	0,02	0,89	0,39	0,36	295,90	3,1045	1,7744	#NUM!	0,0043	0,0062	0,0041	0,0026	2,4459
LatePct	85,08	NDO	1	2	1	RUDD31G	5	35,43	34,78	320,0	0,67	0,92	0,45	0,22	732,20	3,0940	1,7674	#NUM!	0,0196	0,0268	0,0065	0,0033	8,1613
Total Avg lead	49,51	Welding KRA	1	2	1	RUDD3G	36	3,43	2,63	9,60	1,25	0,14	0,13	0,64	33,00	0,06	0,17	0,47	0,07	0,00	0,00	0,00	#NUM!
CI	2,8993	Welding KRA	1	2	1	RUDD31G_DAS	37	1,83	1,05	43,4	0,81	0,44	0,38	0,64	174,00	0,0773	0,1261	2,8828	0,0376	0,0103	0,0052	0,0037	#NUM!
Prod Lead	6-7 weeks	Welding KRA	1	2	1	RUDD2G_DAS	50	1,61	1,14	158,8	0,44	0,15	0,11	0,64	172,30	0,1003	0,0500	3,0819	0,0193	0,0056	0,0021	0,0037	0,3278
SimTime	1000 days	Lasertrack	1	4	2	RUDD12G_DAS	4	2,05	1,67	174,0	0,47	2,08	0,66	0,33	2235,10	0,0921	0,0447	#NUM!	0,0194	0,0804	0,0078	0,0039	20,2774
WarmUp	380 days	Welding KRA	1	-	1	RUDD1G_DAS	3	3,67	0,42	174,0	2,51	1,42	0,64	0,64	271,50	0,0776	#NUM!	#NUM!	0,0835	0,0300	0,0058	0,0088	0,3877
		Oven	-	-	2	DOvenKillRUDDG	2	1,42	0,00	319,0	0,86	1,64	0,00	0,00	799,00	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!	#NUM!

Table 10:Downstream capacity increase experiment for Gulfstream products

For the Gulfstream programme, increasing the downstream capacity of the skin and beam production stages improves the performance of the system at the beginning of the production chain. In contrast to the demand increase experiment, the first production stages no longer show the huge initial block caused by insufficient component

availability. The backlog propagation observed in the previous scenario is therefore partially mitigated, confirming that the initial congestion was caused by limited capacity in the downstream component manufacturing processes at Edison.

However, the results show that the system is still not fully stabilized under the increased demand scenario. In the standard Gulfstream routing (VALK), the welding stages corresponding to Phase 1 and Phase 2 emerge as bottlenecks. At these stations, utilization reaches 1, indicating that the available welding capacity is saturated. In addition, these stages show extremely high queue times and WIP levels, with average queue times exceeding 40 days and WIP levels around 69 units on average. These values clearly indicate that the welding robot is unable to process the incoming workload at the rate required by the increased demand scenario. As a consequence, large queues accumulate at these stages and propagate delays in terms of backlog times throughout the production steps downstream, leading to total average lead times of approximately 87 weeks for the Gulfstream Rudder and around 133–134 weeks for the elevators.

An additional insight can be drawn when comparing the standard Gulfstream routing with the alternative routing that sends part of the Gulfstream rudder production (2 a week in this case as standard Fokker configuration) through the Dassault welding chain KRA. In this configuration, the total average lead time is significantly lower than in the standard routing. The improved performance suggests that the Dassault welding stations have available capacity that can absorb part of the Gulfstream workload. This means that the amount of Gulfstream rudders sent to the Dassault welding machine (KRA) can be a powerful policy lever.

Overall, the results show that increasing downstream component production capacity successfully removes the initial backlog propagation, but also reveals that the Gulfstream welding robot (machine 20) is the new system bottleneck. These findings suggest that further improvements in performance require either increasing welding capacity at the VALK line or redistributing part of the workload to the alternative welding route at KRA welding route.

4.4 Gulfstream Welding Bottleneck

In order to identify potential solutions to this bottleneck, several capacity configurations were studied in accordance with the company experts. During discussions with the company, three practical alternatives were identified as relevant options for increasing welding capacity at the VALK welding robot line (Phase 1 and Phase 2). These alternatives represent different operational and investment options.

The first option consists of testing additional weekend shifts, allowing the welding robot to operate during Saturdays and Sundays in order to increase the weekly processing capacity. The second option studies the introduction of a third shift during weekdays, enabling continuous operation (24 hours) of the welding station from Monday to Friday. Finally, a third alternative evaluates the installation of an additional welding robot, splitting production at both phases with one welding robot dedicated for each.

All three scenarios were also tested by varying the amount of Gulfstream rudders sent to Dassault welding line (KRA) per week, to assess the most feasible configuration.

4.4.1 Weekend Overtime Configuration

Table 11 shows the effects of varying the number of Gulfstream rudders routed to the Dassault welding machine while enabling weekend overtime. As the number of rudders processed at the KRA welding station increases from two to three to four per week, the utilization of the welding robot KRA increases significantly, reaching values close to full capacity while at the same time utilization at VALK decreases from 1.

Rudders to KRA week	RUDDF (Lead time)	ELEVLHF (Lead time)	ELEVRHF (Lead time)	RUDDFG (Lead time)	ELEVLHFG (Lead time)	ELEVRHFG (Lead time)	RUDDFG KRA (Lead time)	KRA util.	VALK util.	VALK WIP
2	9.72 (±0.13)	10.29 (±0.25)	11.46 (±0.24)	16.37 (±1.76)	32.98 (±3.70)	31.11 (±4.29)	13.05 (±1.23)	0.64	0.93	10.83
3	12.86 (±0.63)	11.81 (±0.42)	14.81 (±0.58)	11.22 (±0.69)	26.77 (±3.90)	26.23 (±1.86)	11.78 (±0.65)	0.83	0.83	4.82
4	24.05 (±1.63)	19.79 (±1.62)	23.80 (±1.69)	15.12 (±0.92)	24.62 (±3.78)	21.32 (±2.43)	20.16 (±1.40)	0.95	0.76	03.09

Table 11: Weekend welding robot overtime configuration experiment

At the same time, the lead times of the Gulfstream products produced through the standard VALK routing decreased as part of the demand being split to the KRA machine. This indicates that the VALK welding station experiences a reduction in congestion when part of the workload is redistributed. However, when four rudders per week are assigned to the KRA routing, the system approaches the capacity limit of that machine, as reflected by the high utilization levels and the increasing lead times.

These results show that in this case the most acceptable results are given by setting number of rudders sent to KRA to 3, as the utilization at both welding robots is more controlled, and not as close to 1 as the other cases, providing some room for mitigating possible stochasticity in the welding robot processing times.

Overall, the results show that while diverting Gulfstream rudders to the KRA welding machine can reduce congestion at the VALK station and improve the lead times of Gulfstream components, excessive quantities lead to saturation at the KRA machine, negatively affecting the performance of the Dassault products.

4.4.4 Three shift configuration

In the case of the three shift configuration, the results for the welding robot performance are presented in Table 12. In this scenario, increasing the number of shifts from two to three does not resolve the congestion at the welding robot. However, increasing the number of Gulfstream rudders sent to the Dassault welding station reduces utilization and WIP at the VALK welding robot while increasing utilization at KRA. This behavior is expected and consistent with the results observed in the previous experiment where additional capacity was introduced through weekend working hours.

Rudders to KRA week	RUDDF (Lead time)	ELEVLHF (Lead time)	ELEVRHF (Lead time)	RUDDFG (Lead time)	ELEVLHFG (Lead time)	ELEVRHFG (Lead time)	RUDDFG KRA (Lead time)	KRA util.	VALK util.	VALK WIP
2	9.54 (±0.16)	10.22 (±0.22)	11.28 (±0.15)	42.85 (±4.76)	65.50 (±5.35)	63.40 (±6.32)	31.16 (±3.11)	0.64	1.00	32.75
3	12.97 (±0.52)	11.81 (±0.29)	14.53 (±0.41)	14.96 (±1.10)	32.17 (±3.96)	33.48 (±3.94)	13.16 (±0.57)	0.83	0.91	9.66
4	24.72 (±2.48)	20.09 (±2.25)	24.20 (±2.41)	16.30 (±2.06)	28.78 (±2.30)	29.20 (±3.71)	21.59 (±2.90)	0.95	0.82	4.91

Table 12: Three shift welding configuration experiment

These results allow for a clear comparison between the two shift configurations. Overall, the configuration with additional weekend hours performs better, even though it adds

fewer total working hours and therefore less theoretical capacity. This difference is explained by the distribution of the working hours. Allowing the welding robot to operate during weekends enables the system to reduce queues when they would otherwise remain static. As a result, the welding robot can continue processing the accumulated queue during weekends. In contrast, the three shift configuration does not include weekends, meaning that queues remain untouched during those periods and congestion is not effectively reduced.

4.4.4 Additional Welding Robot Configuration

Once different shift configurations have been tested, an additional welding robot experiment in the Gulfstream welding station VALK is performed. In this case, the production at Phase 1 and 2, which previously was performed by a unique welding robot, is splitted for 2 robots, namely machine 20 and 52.

Table 13 presents the results obtained after introducing an additional welding robot and varying the number of Gulfstream rudders routed to the KRA welding station. Compared to the previous experiment, where the welding stations operated with lower capacity, an important decrease in the utilization of welding machines 20 and 52 can be observed due to the split of both welding phases. This reduction in utilization indicates that the additional welding capacity successfully decreases congestion at the VALK welding robot step. As a consequence, the production lead times across the system also decrease when compared to the results obtained in the previous increased demand configuration, due to the reduction of backlog times downstream of the welding step and the queue times reduced in the welding robot phases itself.

Rudders to KRA week	RUDDF (Lead time)	ELEVLHF (Lead time)	ELEVRHF (Lead time)	RUDDFG (Lead time)	ELEVLHFG (Lead time)	ELEVRHFG (Lead time)	RUDDFG KRA (Lead time)	KRA util.	M20 util. Phase 1	M20 WIP Phase 1	M52 util. Phase 2	M52 WIP Phase 2
2	9.72 (±0.22)	10.22 (±0.20)	11.74 (±0.28)	8.66 (±0.19)	25.32 (±3.13)	21.82 (±3.49)	9.08 (±0.20)	0.65	0.41	1.19	0.76	02.04
3	13.62 (±0.55)	12.42 (±0.27)	15.47 (±0.43)	9.98 (±0.36)	22.83 (±2.32)	21.82 (±1.90)	11.34 (±0.40)	0.84	0.34	0.87	0.68	1.58
4	25.99 (±3.14)	21.77 (±3.10)	25.73 (±3.27)	18.69 (±2.77)	23.01 (±2.37)	23.46 (±2.61)	22.84 (±3.75)	0.97	0.31	0.70	0.62	1.25

Table 13:Additional welding robot configuration experiment

When increasing the number of Gulfstream rudders routed to the KRA welding robot, the utilization of that machine increases accordingly. At the same time, the production lead times of the Gulfstream products decrease, as part of their workload is processed by the additional welding machine. However, this redistribution of workload negatively affects the Dassault products, which lead times increase as the KRA welding robot becomes more congested due to the increase in the workload, consistent with the previous experiments.

Considering the different configurations, routing two Gulfstream rudders per week to the KRA welding machine provides the most balanced results. In this scenario, the welding stations maintain sufficient utilization while avoiding excessive workload at the KRA robot. Increasing the number of routed rudders beyond this point leads to higher utilization levels and longer lead times for the Dassault products, without providing significant benefits for the Gulfstream ones.

Across all tested scenarios, increasing the capacity at the Gulfstream welding station leads to a noticeable decrease in WIP, utilization, queue times at the welding Gulfstream welding machine and upstream backlog times. These improvements are notable in the decreased production lead times for all products.

However, the average production lead times for the Gulfstream elevators remain significantly higher than those of the Gulfstream rudder across all scenarios. This difference is attributed to Phase 6ABC (machines 23 and 27), where operator utilization reaches a value of 1 while showing large queue times. The presence of this bottleneck also affects downstream processes, which exhibit high average backlog times due to the limited processing capacity in Phase 6. This bottleneck is addressed in the next section.

4.5 Gulfstream Elevator Phase 6 Bottleneck

After identifying the shared workforce limitation in Gulfstream elevators Phase 6 stations (machines 23 and 27), two alternative capacity configurations were initially evaluated. The first configuration assigns two operators on each shift while maintaining the two shift schedule (2–2 configuration). The second configuration tests a different distribution by assigning three operators to morning shift and 1 in evening shift (3–1 configuration). The standard configuration in the current system corresponds to two shifts with two operators assigned in the morning shift and 1 during the evenings (2-1).

2 mornning / 1 evening standard configuration					
Machine	Avg Lead Phase 6	Avg QueueTime	Avg WIP	Jig Util	Op Util
23	37,89	27,08	9,78	0,64	1,00
27	33,94	22,71	8,37	0,63	1,00
2 mornning /2 evening configuration					
Machine	Avg Lead Phase 6	Avg QueueTime	Avg WIP	Jig Util	Op Util
27	25,03	18,94	7,21	0,64	0,99
23	27,19	21,70	8,08	0,65	0,99
3 mornning /1 evening configuration					
Machine	Avg Lead Phase 6	Avg QueueTime	Avg WIP	Jig Util	Op Util
23	7,29	1,57	1,66	0,58	0,67
27	7,77	1,46	1,61	0,58	0,67

Table 14:Performance comparison between workforce configurations

As shown in Table 14, in the 2–2 configuration, Phase 6 remains heavily congested. Both machines 23 and 27 show very high queue times, reaching average values of 21.70 and 18.94 days respectively. This results in large WIP levels, exceeding seven units at both stations, while operator utilization remains close to full capacity (0.99). These indicators confirm that the processing capacity of Phase 6 elevator stations is still not enough under this configuration, and the bottleneck is not effectively relieved.

However, the 3–1 configuration leads to a substantial improvement in the performance of these stations. The average lead time at Phase 6 decreases drastically from approximately 25–27 days to around 7–8 days. Similarly, queue times are reduced to values around 1.5 days, and WIP levels drop to approximately 1.6 units at both stations. Operator utilization also decreases to around 0.67, indicating that the stations are no longer operating at their capacity limit and that the bottleneck has been removed.

These results can be explained by considering the way the workforce is shared between machines 23 and 27. In the 2–2 configuration, two operators are assigned to each shift, which distributes the labor evenly throughout the day. However, because both stations experience similar demand patterns, this configuration does not provide enough

temporary capacity to process the accumulated queues. As a result, operators keep working close to full utilization, and queue time and WIP remains high.

On the other hand, the 3–1 configuration concentrates three operators during the morning shift and only one operator during the evening shift. Since machines 23 and 27 share the same workforce, the additional operators available during the morning shift allow the system to process a larger number of jobs during the period when queues are highest. This temporary increase in capacity enables the stations to reduce the accumulated queued jobs more effectively than the evenly distributed 2–2 configuration.

Once the queues have been reduced, the lower capacity available during the evening shift is still enough to keep up with the incoming workload rate. As a result, the overall congestion at Phase 6 decreases notably, which explains the important reduction observed in queue times, WIP levels, and average lead times.

4.6 Combined System Performance

After identifying the most effective workforce configuration for Phase 6 in the Gulfstream elevator stations (3–1 for machines 23 and 27), additional experiments were conducted to evaluate the combined impact of these improvements together with the welding capacity alternatives presented in the previous sections. Based on the results of the previous experiments, only the most promising routing configurations were selected for further simulations due to the limited computing power.

Three combined scenarios were analyzed:

1. **Scenario 1 –** Weekend welding configuration: weekend overtime at the VALK welding robot, routing three Gulfstream rudders per week to the Dassault welding station (KRA), and applying the 3–1 workforce configuration at the Phase 6 elevator stations.

2. **Scenario 2 –** Three-shift welding configuration: three shifts at the VALK welding robot during weekdays, routing three Gulfstream rudders per week to the KRA welding station, and applying the 3–1 Phase 6 workforce configuration.

3. **Scenario 3 –** Additional welding robot configuration: installation of an additional welding robot at the VALK station (splitting Phase 1 and Phase 2 with dedicated robots) while maintaining the routing of two Gulfstream rudders per week to the KRA welding station, together with the 3–1 workforce configuration at Phase 6.

These scenarios represent the configurations with the best performance identified in the previous experiments for each welding and phase 6 capacity alternatives. The objective of this analysis is to compare their overall system performance once all bottlenecks in the production line have been solved or mitigated.

Figures 10 to 12 present the overall system performance across the three evaluated scenarios in terms of throughput, percentage of late deliveries, and average production lead time. These indicators allow for a direct comparison of the system performance once the Phase 6 bottleneck has been mitigated using the 3–1 workforce configuration.

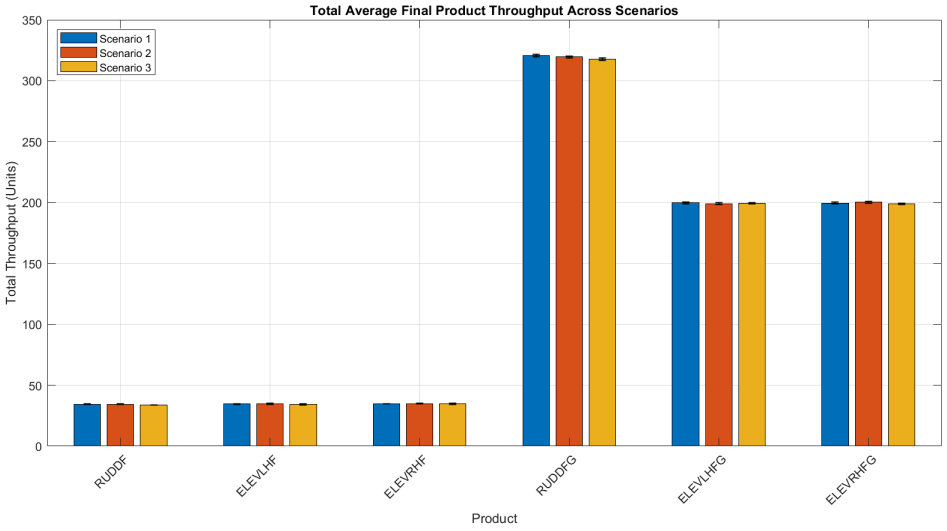


Figure 10: Average total finished product throughput per scenario

Figure 10 compares the throughput obtained under the three scenarios. The results show that throughput remains similar across all configurations for every product. This means that all evaluated scenarios are capable of satisfying the increased production demand and that the system capacity is enough in each case. Therefore, the main differences between scenarios are not related to production capacity but rather to the efficiency of the production flow and the level of congestion within the system.

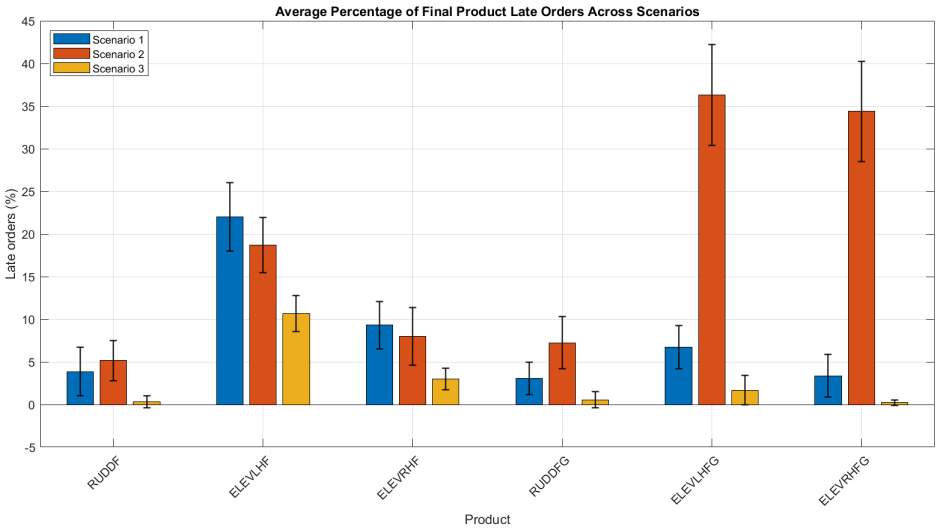


Figure 11: Average percentage of late orders per scenario

The delivery performance of the system is shown in Figure 11, which presents the percentage of late orders across the tested scenarios. Scenario 2 shows the worst performance, particularly for the Gulfstream elevator products, where the percentage of late orders exceeds 34% for both elevator products. Scenario 1 performs better overall but still shows relatively high lateness for the Dassault LH elevator. In contrast, Scenario 3 achieves the best delivery performance, significantly reducing the percentage of late orders for all products and therefore maintaining a service level very close to 1 for all products.

Figure 12 compares the average production lead times obtained under each configuration. Scenario 3 clearly provides the lowest lead times for all products. This improvement is particularly notable for the Gulfstream elevators, which lead times decrease to approximately 7–8 weeks. Scenario 1 also shows relatively low lead times, although slightly higher than those observed in Scenario 3. In contrast, Scenario 2 shows the highest lead times, especially for the Gulfstream elevators, where the average production lead time reaches approximately 20 weeks.

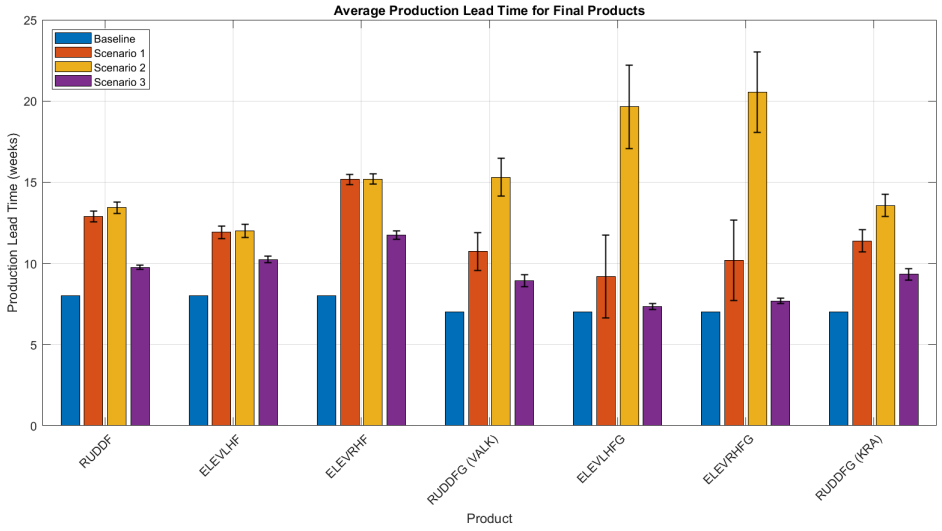


Figure 12: Average total production lead time per scenario

Overall, the results indicate that Scenario 3 provides the best system performance among the evaluated configurations. The introduction of an additional welding robot at the VALK station, combined with the improved workforce allocation at Phase 6, significantly reduces production lead times and minimizes the percentage of late orders while maintaining throughput levels similar to the other scenarios. Scenario 1 also improves system performance but still exhibits higher lateness for some products. In contrast, Scenario 2 performs worst, particularly for the Gulfstream elevator products, due to the higher congestion levels remaining in the system, particularly in the VALK welding robot.

However, improvements in performance are still possible, as the planning parameters throughout the previous experiments were left in their standard configuration, the next section delves into how the planning parameters can be adjusted to further improve performance.

4.7 Planning Parameter Variation

After evaluating the different capacity configurations and identifying the most effective adjustments for the welding stations and the Phase 6 elevator stations, a final set of experiments was conducted to analyze the impact of planning parameters on system performance. The experiments presented in the previous sections focused on mitigating physical bottlenecks in the production system by modifying operational capacity which could not be resolved by planning parameters alone. The parameters driving the planning logic of the implemented MRP were kept at their baseline values throughout the past experiments.

In the real production system, planning parameters such as planned lead times, safety time, safety stock levels, and lot sizes are defined individually for each item and production step. Testing each of these parameters independently would require a very large number of iterations. To maintain a feasible number of simulations while still evaluating the sensitivity of the system to planning decisions, multiplicative factors were applied to the baseline planning parameters.

The factors are the following:

- leadFactorProd: multiplier applied to the planned lead times of produced items.
- leadFactorPurch: multiplier applied to the planned lead times of purchased components.
- ssFactorProd: multiplier applied to the safety stock levels of produced items.
  ssFactorPurch: multiplier applied to the safety stock levels of purchased components.
- lotSizeFactorProd: multiplier applied to the production lot sizes of manufactured items.
- lotSizeFactorPurch: multiplier applied to the lot sizes of purchased components.
- safetyTimeFactorComponent: multiplier applied to the safety time used in produced components.

Furthermore, an earliness KPI is included in this analysis, as the objective is to identify planning parameter values that improve system performance while avoiding excessive early completions that could increase inventory levels and therefore holding costs.

The following experiments evaluate how variations in these planning parameters affect overall system performance in terms of production lead times, delivery performance, and system stability.

4.7.1 Planned Lead Times

For the planned lead time experiment, two scaling factors were initially considered: one for produced items and one for purchased items. However, the delays associated with purchased components in the model are already sufficiently covered by the baseline planned purchase lead times together with the safety times. As a result, varying the planned lead time factor for purchased items was not expected to generate a noticeable effect on system performance. For this reason, the experiment focuses only on the variation of planned lead times for produced items.

For the planned lead time variation experiment, the factor applied to produced items was varied from 1.25 to 2.00 in increments of 0.25. A factor value of 1.25 corresponds to a 25% increase in the baseline planned lead times, while a value of 2.00 corresponds to doubling them.

Scenario 1 – Weekend welding configuration:

In this experiment, the effect of increasing the planned production lead times of produced items is analyzed under Scenario 1, which corresponds to the configuration including weekend overtime at the VALK welding station, routing three Gulfstream rudders per week to the KRA welding machine, and the 3–1 workforce configuration at the Phase 6 elevator stations. The performance of the system is evaluated using the average production lead time, the percentage of late orders, and the average earliness for the final products.

Scenario 1 Average Production Lead Time (weeks)							
LeadFactorProd	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**	**RUDDFG(KRA)**
1	12,88	11,91	15,17	10,73	9,19	10,2	11,39
1,25	8,68	9,14	11,25	8,3	7,74	8,71	8,29
1,5	7,96	8,25	9,65	6,88	7,08	8,16	7,16
1,75	7,24	6,87	7,74	11,07	6,6	7,46	11,34
2	7,48	7,34	7,66	8,11	6,74	7,44	8,22

Table 15: Average production lead times for each Lead time factor for each product in scenario 1

The results show a significant improvement in production lead times when the planned lead time factor increases from 1 to 1.25. For example, the average production lead time of product RUDDF decreases from 12.88 weeks to 8.68 weeks, while ELEVRHF decreases from 15.17 weeks to 11.25 weeks. Similar reductions are observed across all other products. This improvement is due to the reduction in backlog levels within the production system. Increasing the planned lead times results in earlier release of production orders, which adapts the standard planned lead times to the higher production lead times. This makes sure that products in the production chain are available just in time to be processed in the subsequent stations without waiting times related to backlog or material unavailability.

Scenario 1 Average Percentage of Later Orders (%)						
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	3,87	22	9,33	3,08	6,74	3,37
1,25	0	0	0	0	0	0
1,5	0	0	0	0	0	0
1,75	0	0	0	0	0	0
2	0	0	0	0	0	0
Scenario 1 Average Earliness (days)						
LeadFactorProd	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	0	0	0	0	0	0
1,25	0	0	0	0	0	0
1,5	0	0	0	0	0	0
1,75	1,165	0,831	1,035	0,816	0,374	0,721
2	1,154	0,874	1,046	1,032	0,352	0,615

Table 16: Average percentage of late orders and average earliness for each lead time factor in scenario 1

A similar trend is observed in the percentage of late orders. At the initial configuration (lead time factor equal to 1), all products show late deliveries, with ELEVLHF showing the highest value at 22%. However, when the planned lead time factor increases to 1.25, late orders are completely eliminated for all products. This indicates that a relatively small increase in planned lead times is sufficient to mitigate backlog enough so that the products see their lead times reduced and therefore are produced in time.

While increasing the planned lead time factor improves delivery performance, excessively large values introduce early order completion. As shown in Table 16, no earliness is observed for lead time factors up to 1.5. However, when the factor reaches 1.75, earliness begins to appear across all products. For instance, RUDDF shows an average earliness of 1.165 days and ELEVRHF reaches 1.035 days. Increasing the factor further to 2 maintains similar earliness levels without providing significant additional reductions in production lead time.

Overall, these results indicate that increasing planned production lead times helps reduce backlog times and improve delivery reliability. However, excessively large lead times result in early completion of orders which can lead to holding costs. Considering these results, a planned lead time factor around 1.5 appears to provide the best balance between reducing production lead times, eliminating late orders, and avoiding excessive earliness.

Scenario 2 – Three-shift welding configuration:

In Scenario 2, the same planned lead time variation experiment is performed under the configuration where the VALK welding station operates under a three-shift schedule during weekdays.

As in Scenario 1, increasing the planned lead time factor significantly reduces the average production lead times of all products. When the factor increases from 1 to 1.25, a substantial improvement in system performance is observed. For example, the average production lead time of RUDDF decreases from 13.43 weeks to 8.91 weeks, while ELEVRHF decreases from 15.19 weeks to 11.34 weeks. Similar reductions are observed

across the remaining products. This improvement is mainly caused by the earlier release of production orders, which reduces backlog levels.

Scenario 2 Average Production Lead Time (weeks)							
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**	**RUDDFG_KRA**
1	13,43	11,99	15,19	15,31	19,64	20,54	13,57
1,25	8,91	9,31	11,34	11,95	14,98	17,52	9,52
1,5	7,89	8,22	9,51	10,26	13,94	16,53	8,14
1,75	7,23	6,97	7,69	11,6	11,92	13,88	9,31
2	7,56	7,4	7,69	10,39	11,16	12,77	8,62

Table 17: Average production lead times for each Lead time factor for each product in scenario 2

The percentage of late orders also decreases considerably when increasing the planned lead time factor. At the baseline configuration, several products experience a high percentage of late orders, particularly the Gulfstream elevator products, which reach values of 36.29% and 34.38% for ELEVLHFG and ELEVRHFG respectively. When the lead time factor increases to 1.25, late orders are mitigated for most products, although the Gulfstream elevators still experience some delays. These delays are gradually reduced as the lead time factor increases, and completely disappear when the factor reaches 1.75.

Scenario 2 Average Percentage of Later Orders (%)						
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	5,16	18,67	8	7,25	36,29	34,38
1,25	0	0	0	0	10,79	6,85
1,5	0	0	0	0	4,38	2,58
1,75	0	0	0	0	0	0
2	0	0	0	0	0	0
Scenario 2 Average Earliness (days)						
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	0	0	0	0	0	0
1,25	0	0	0	0	0	0
1,5	0	0	0	0	0	0
1,75	1,194	0,846	1,061	1,026	0,354	0,579
2	1,137	0,852	1,105	1,045	0,367	0,613

Table 18: Average percentage of late orders and average earliness for each lead time factor in scenario 2

The earliness results show a similar behavior to Scenario 1. No early order completion is observed for lead time factors up to 1.5. However, when the factor reaches 1.75, earliness begins to appear for all products. For instance, RUDDF shows an average earliness of 1.194 days, while ELEVRHF reaches 1.061 days. Increasing the factor further to 2 results in slightly higher or similar earliness values without providing important additional improvements in production lead times.

These results indicate that increasing planned production lead times significantly improves system performance by reducing backlog levels across production steps. However, excessively large values lead to increasing earliness without providing further benefits. As in Scenario 1, a lead time factor around 1.5 provides a good balance between reducing production lead times, avoiding earliness and mitigating late orders even if they are not completely gone.

Scenario 3 – Additional welding robot configuration:

In Scenario 3, the planned lead time variation experiment is performed under the configuration where an additional welding robot is introduced at the VALK welding station. This configuration already provides increased processing capacity compared to the previous scenarios.

Scenario 3 Average Production Lead Time (weeks)							
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**	**RUDDFG_KRA**
1	9,7477	10,244	11,7488	8,9324	7,3282	7,6813	9,3235
1,25	7,47	8,42	9,77	6,99	6,62	7,33	7,47
1,5	7,39	7,61	8,6	6,21	6,02	7,42	6,46
1,75	6,67	6,65	7,43	10,13	6,28	7,22	10,32
2	6,8	7,09	7,46	7,09	6,38	6,88	7,52

Table 19: Average production lead times for each Lead time factor for each product in scenario 3

The results show that increasing the planned lead time factor still leads to improvements in system performance, although the magnitude of these improvements is smaller compared to the previous scenarios. At the baseline configuration (lead time factor equal to 1), production lead times are already significantly lower due to the additional welding capacity. When the planned lead time factor increases from 1 to 1.25, production lead times decrease further for most products. For example, RUDDF decreases from 9.75 weeks to 7.47 weeks, while ELEVRHF decreases from 11.75 weeks to 9.77 weeks. Similar improvements are observed across the other products. As in the previous scenarios, this behavior can be explained by the earlier release of production orders, which reduces backlog accumulation and lowers backlog times across stations.

Scenario 3 Average Percentage of Later Orders (%)						
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	0,3226	10,6667	3	0,5495	1,6854	0,2247
1,25	0	0	0	0	0	0
1,5	0	0	0	0	0	0
1,75	0	0	0	0	0	0
2	0	0	0	0	0	0
Scenario 3 Average Earliness (days)						
LeadFactor	**RUDDF**	**ELEVLHF**	**ELEVRHF**	**RUDDFG**	**ELEVLHFG**	**ELEVRHFG**
1	0	0	0	0	0	0
1,25	0	0	0	0	0	0
1,5	0	0	0	0	0	0
1,75	1,189	0,843	1,088	0,872	0,346	0,691
2	1,173	0,866	1,09	1,023	0,342	0,598

Table 20: Average percentage of late orders and average earliness for each lead time factor in scenario 3

The percentage of late orders follows a similar trend. At the baseline configuration, a small percentage of late orders is still observed for several products, with ELEVLHF reaching approximately 10.67%. However, increasing the planned lead time factor to 1.25 completely eliminates late orders for all products. Further increases of the factor do not lead to additional improvements in delivery reliability.

The earliness results show the same pattern observed in the previous scenarios. No early order completion occurs for lead time factors up to 1.5. However, when the factor reaches 1.75, earliness begins to appear across all products. Increasing the factor further to 2 produces similar or slightly higher earliness values without providing significant additional improvements in production lead times.

Therefore, the results indicate that increasing planned lead times improves system performance by reducing backlog, even when capacity bottlenecks have already been solved. However, excessively large lead times result in increasing levels of earliness. As in the previous scenarios, a lead time factor around 1.5 provides a good balance between reducing production lead times, eliminating late orders, and maintaining earliness at controlled levels.

Scenario Comparison:

After evaluating the impact of the planned production lead time factor within each scenario, a comparison across scenarios is carried out. Since the sensitivity analysis showed that a lead time factor of 1.5 provides a suitable balance between reducing late orders and controlling earliness, this value is used as a reference point for comparing the three operational configurations.

Figure 13 presents the average production lead times obtained for all products under the three scenarios when the planned lead time factor is fixed at 1.5 (50% increase in each product and semifinished product).

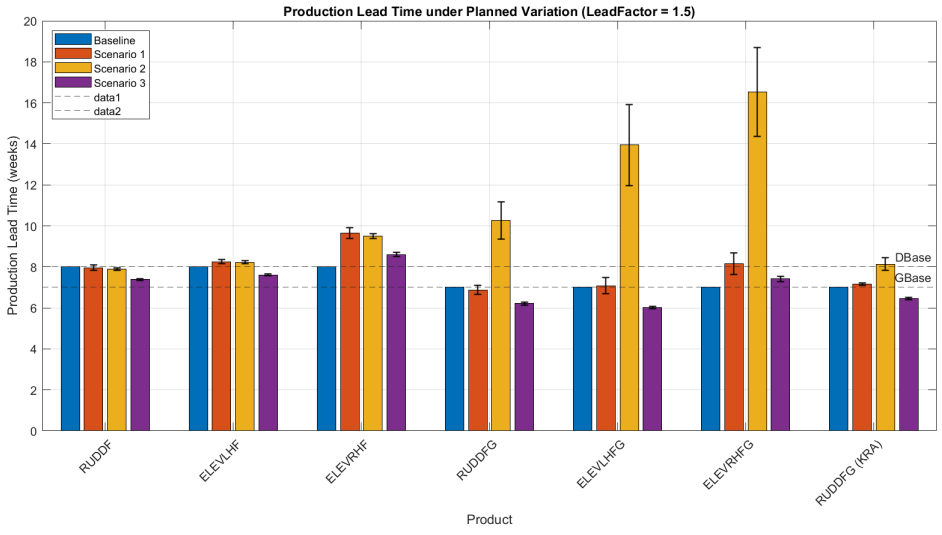


Figure 13: Average total production lead time comparison per scenario per product (LeadTimeFactor=1,5)

The results show that Scenario 3, which introduces an additional welding robot at the VALK welding station, consistently achieves the lowest production lead times across almost all products. For example, the production lead time of RUDDF decreases to 7.39 weeks in Scenario 3, compared to 7.96 weeks in Scenario 1 and 7.89 weeks in Scenario 2.

Similar improvements are observed for the elevators, where production lead times decrease to 7.61 weeks for ELEVLHF and 8.60 weeks for ELEVRHF, representing the lowest values among all scenarios.

Scenario 1, which introduces weekend overtime at the welding station, also achieves relatively good performance, with production lead times only slightly higher than those obtained in Scenario 3. This indicates that the additional weekend capacity is effective in reducing congestion at the welding robot.

In contrast, Scenario 2, where the welding robot operates under a three shift weekday configuration, exhibits significantly worse performance for several products. In particular, the Gulfstream elevator products show much higher production lead times, reaching 13.94 weeks for ELEVLHFG and 16.53 weeks for ELEVRHFG. These results indicate that the three shift configuration does not reduce congestion in the welding robot VALK as effectively as the other alternatives.

Overall, the comparison shows that increasing the welding capacity through the introduction of an additional welding robot provides the most effective improvement in system performance. While the weekend overtime configuration also improves production performance, the additional welding robot leads to lower production lead times and a more balanced workload distribution across the system.

4.7.2 Lot size quantity and safety stock parameters

In addition to planned production lead times, other planning parameters such as lot size quantities and safety stock levels were also considered. These parameters are usually used to mitigate supply uncertainty, reduce ordering frequency, and protect production against variability in demand or supply times.

Lot size policies are closely related to setup times. When setup times are required to switch between products or setup the machine, producing larger batches can improve performance by reducing the frequency of setups. In such cases, larger lot sizes help reduce the time spent on changeovers.

However, in the production system modeled in this study, setup times are not limiting. Each product is processed using dedicated jigs, therefore there is no need for changeovers between different products. As a result, the system is not affected by the setup related times that would benefit by larger production batches.

Under these conditions, increasing the lot size of produced items would mainly result in larger batches going into production, which would increase WIP levels and lead to higher queue times and longer production lead times. Therefore, larger lot sizes would likely degrade system performance instead of improving it.

Similarly, the use of safety stock for finished and semi-finished products is not necessary in the modeled system. Demand in the model is deterministic and known in advance

through the MPS. As a result, there is no demand uncertainty that would justify maintaining additional inventory. Introducing safety stock for these items would therefore only increase inventory levels and generate unnecessary holding costs without improving service level and overall performance.

For purchased items, safety stock and lot size parameters could help mitigate supplier uncertainty. However, in the current model the variability from supplier deliveries is already included through the planned lead time and safety time parameters. As a result, purchased material shortages rarely occur, and additional safety stock or larger lot sizes would not affect performance.

Therefore, sensitivity experiments on these parameters were not studied further, as their variation would not provide meaningful insights within the context of the current model assumptions. Nevertheless, it is important to note that these parameters could become relevant in the model if higher variability and uncertainty was inputted in the supplier delivery time distributions or in the customer demand rate.

5 Managerial Insights

The simulation experiments provide several managerial insights regarding capacity allocation, workforce planning, and production planning policies within the Fokker production system. The results highlight key operational bottlenecks, potential capacity improvements, and planning parameters that significantly influence system performance. The following insights summarize the main implications for production management.

Critical Bottlenecks

The results of the simulation experiments indicate that the VALK welding robot and Phase 6 of the elevator production line in the Marconi facility represent the most critical bottlenecks in the current configuration. Both stations exhibit very high utilization levels and large queue times, which directly affect the overall production lead times.

In particular, the welding robot at VALK shows high sensitivity to increases in demand, leading to congestion and increased WIP when capacity limits are reached. Similarly, Phase 6 of the elevator production line shows operator utilization levels approaching full capacity, generating large queue times and propagating delays to upstream processes.

Additionally, the experiments reveal potential risks in the skin and beam production stages at the Edison facility. Even if Edison is modelled in an aggregated way, magagent should study the idle and available capacity at Edison to assess if it is enough for the coming demand increase.

An important observation across the experiments is that system bottlenecks tend to shift when capacity improvements are implemented. For example, increasing upstream capacity in Edison alleviates backlog propagation but exposes new bottlenecks in the welding stage, while improvements in welding capacity shift the main bottleneck toward the elevator assembly stage (Phase 6). This highlights that production systems should be analyzed holistically, as local improvements may simply move the bottleneck to another part of the system.

From a managerial perspective, these results highlight the importance of continuously monitoring these critical stations and prioritizing them when considering capacity improvements or adjustments.

Capacity and Resource Allocation

The experiments also provide insights into potential capacity improvements that can significantly enhance system performance. The best performing solution identified in the simulation involves introducing an additional welding robot at the VALK facility, effectively splitting Gulfstream welding phases 1 and 2. This configuration reduces the

workload on the existing welding robot and leads to noticeable reductions in queue times and overall production lead times.

As an alternative to physical capacity expansion, increasing weekend working hours also demonstrates strong performance improvements. Interestingly, this configuration performs better than extending capacity during weekdays through additional shifts, even though the total amount of added working hours is lower. This result indicates that the timing and distribution of the working hours plays an important role in reducing queue accumulation, as weekend capacity notably reduces queues at the welding robot during non operation hours for the rest of the stations.

Furthermore, the results indicate that Phase 6 of the elevator production lines requires at least one additional operator during the morning shift to prevent excessive queue formation. Increasing operator availability at this stage significantly improves the flow of production and reduces upstream backlog.

These findings suggest that both equipment capacity and workforce allocation should be considered jointly when addressing system bottlenecks. Moreover, improvements should be implemented sequentially and evaluated from a system wide perspective, as capacity increases at one stage may reveal new bottlenecks elsewhere in the production system.

Production Planning and Policy Decisions

Another important insight concerns production allocation policies between facilities. The number of Gulfstream rudders routed to the KRA facility emerges as a powerful decision variable for balancing system workload specifically at the welding stages.

Increasing the number of rudders processed at KRA improves utilization of the welding robot VALK. However, excessive rerouting can negatively affect the Dassault products, whose lead times may increase when capacity is redistributed. This indicates that cross facility production flexibility can be an effective mechanism for balancing system workload, but it should be applied carefully to avoid transferring congestion from one programme to another.

In addition, the simulation results suggest that the current planning parameters should be updated to better reflect the new production lead times observed in the production system. Adjusting planned lead times within the planning system can improve performance by reducing backlog induced extra time caused by poorly adapted scheduling. However, the experiments also indicate that planning adjustments alone cannot compensate for capacity limitations. While increasing planned lead times improves coordination between planning and execution, physical bottlenecks must still be addressed through capacity adjustments.

Furthermore, the results suggest that planning parameters operate within an effective range rather than improving performance indefinitely. Excessive increases in planned

lead times may lead to unnecessary early releases of orders without providing additional benefits. Therefore, planning parameters should be calibrated to reflect realistic operational conditions while maintaining an appropriate balance between system performance and holding costs associated with early releases.

Performance Measurement and Monitoring

Finally, the experiments highlight the importance of selecting appropriate performance indicators for monitoring system performance. The primary performance metric used in this study is the average production lead time per station, which provides a comprehensive measure of overall performance at the station level.

In addition, queue time and backlog time at individual stations serve as important secondary indicators for identifying local bottlenecks and the decision variables that can be used to mitigate them. Queue times typically indicate capacity shortages at the station level, while backlog times often reflect congestion caused by lack of capacity in upstream processes. According to the simulation results, increases in physical capacity have a significant impact on queue times at the station level and consequently reduce backlog accumulation in downstream processes. At the same time, planning parameters such as planned lead time also influence backlog times by affecting the timing of order releases. By analyzing these key performance indicators together, it becomes possible to identify which decision variables primarily affect specific aspects of system performance.

Together, these performance indicators provide a practical framework for monitoring the operational performance of the production system and evaluating the impact of future planning or capacity decisions. For this reason it is highly recommended for Fokker to implement these KPIs in reality.

6 Future Work

Although the developed simulation model provides valuable insights into the behavior of the Fokker production system under an increased demand scenario, several opportunities exist for extending and improving the model in future research.

Increased System Detail

The current model represents certain parts of the production system at an aggregated level in order to focus on the most relevant decision variables at Marconi. In particular, the Edison facility is modeled as an aggregated downstream process that produces components required for assembly operations at Marconi. While this allows the study to capture the overall system, future research could benefit from modeling the internal processes at Edison in more detail. A more detailed representation of these processes would allow for the identification of specific bottlenecks within the Edison site and provide additional insights into how capacity decisions at that site affect the overall production including Marconi.

Incorporation of Demand and Supply Uncertainty

The current model evaluates system performance under deterministic demand scenarios derived from the available planning data. Future work could extend the model by incorporating stochastic demand patterns, higher supplier lead time variability, and disruptions in material availability. Introducing such uncertainties would allow the model to evaluate the robustness of the production system under more realistic operating conditions.

Workforce and Scheduling Flexibility

The results of the simulation experiments highlight the importance of workforce allocation and shift configurations in mitigating bottlenecks. Future work could extend the model to incorporate more detailed workforce scheduling and skill sets, including operator skill matrices, cross training possibilities, and flexible assignment of operators across multiple stations. This would allow the evaluation of workforce strategies aimed at improving workforce flexibility.

Evaluation of Additional Scenarios

Additionally, future research could expand the scope of the experimental analysis by evaluating additional scenarios. These could include different demand levels, alternative improvements to the baseline configuration, and additional capacity or workforce adjustments across the production system.

Sensitivity Analysis Under Baseline Configuration

Finally, another potential direction for future research is the evaluation of system sensitivity to demand increases under the baseline configuration. In the current study, the experimental analysis focuses primarily on specific demand increase scenarios and capacity improvement alternatives. However, a more systematic sensitivity analysis could be conducted to determine the demand levels at which the production system becomes unstable.

Such an analysis would involve gradually increasing demand levels while maintaining the current system configuration and monitoring key performance indicators. This approach would allow for the identification of critical demand thresholds beyond which the system experiences a significant performance drop.

Identifying these demand limits would provide valuable insights for capacity planning, as it would allow managers to determine when additional resources or shop floor changes become necessary to maintain stability in the production system.

7 Conclusion

This thesis developed a digital twin simulation model to analyze the impact of increased demand on the production system of GKN Aerospace Fokker. The objective of this research was to evaluate how demand increases could affect the production system and the influence of capacity configurations, workforce allocations and production planning parameters in overall system performance. By combining DES simulation with Java coding and Anylogic agents, the model captures both the material flow and the planning logic.

The simulation model was used to evaluate several experimental scenarios focusing on demand increases, capacity improvements, and planning parameter adjustments. The results highlight that system performance is highly influenced by a limited number of critical bottlenecks. In particular, the VALK welding robot and Phase 6 of the elevator production line were identified as the most demand sensitive stages in the production system.

From a managerial perspective, the developed simulation model provides a valuable decision support tool for evaluating different planning and capacity alternatives before implementing them in practice. By enabling the analysis of different production configurations and planning policies, the model supports more informed decision making. These findings align with recent research highlighting the role of simulation digital twins as decision support tools for identifying bottlenecks and improving production control in manufacturing systems (Ragazzini et al., 2024).

Furthermore, the insights generated by the model support decision making across multiple levels at Fokker. Operators and shop floor schedulers benefit from improved visibility of bottlenecks and queue formation at specific stations, allowing for more proactive management of workload and resource allocation. Master schedulers can use the insights regarding planning parameters, such as planned lead times and production allocation between welding robots. In this way, the model contributes to better coordination between planning and execution activities within the organization.

Overall, this research demonstrates the potential of simulations and digital twin approaches for analyzing complex manufacturing systems. The developed model provides both operational insights for improving the performance of the Fokker production system and a methodological contribution by illustrating how planning and material flow can be integrated within a simulation decision support framework.

Annex A: Python script for distribution fitting

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats

# ========= 1) Data =========

x = np.array([

], dtype=float)
# ========= 2) Clean =========
x = x[np.isfinite(x)]
x = x[x > 0]

n = len(x)
xmin = float(np.min(x))
xmax = float(np.max(x))

print("Number of observations:", n)
print("Min / Max:", xmin, xmax)
print("Mean / Std:", float(np.mean(x)), float(np.std(x, ddof=1)))

# ========= 3) helpers =========
def aic_from_loglik(loglik, k):
    return 2 * k - 2 * loglik

def ks_for_dist(name, params, data):
    # KS against a named scipy distribution
```

```
    return stats.kstest(data, name, args=params)

def fit_mle(dist_name, dist_obj, data, force_loc0=False, force_loc=None):
    if force_loc is not None:
        params = dist_obj.fit(data, floc=force_loc)
    elif force_loc0:
        params = dist_obj.fit(data, floc=0)
    else:
        params = dist_obj.fit(data)

    loglik = np.sum(dist_obj.logpdf(data, *params))
    k = len(params)
    AIC = aic_from_loglik(loglik, k)
    ks_stat, ks_p = ks_for_dist(dist_name, params, data)
    return params, AIC, ks_stat, ks_p

# Truncated-at-0 CDF wrapper for KS (for symmetric distributions)
def make_trunc0_cdf(dist_obj, params):
    # Truncate to [0, +inf)
    F0 = dist_obj.cdf(0, *params)
    denom = 1.0 - F0

    def cdf_trunc(t):
        t = np.asarray(t)
        Ft = dist_obj.cdf(t, *params)
        return np.clip((Ft - F0) / denom, 0, 1)

    return cdf_trunc

# ========= 4) candidates =========
```

```
results = []
pdf_plotters = {}  # name -> function(xs)->pdf values (for plotting)

# ---- A) Positive-support MLE (safe for processing times) ----
positive_mle = [
    ("lognorm_loc0", stats.lognorm, dict(force_loc0=True)),     # lognormal(mu,sigma,0)
    ("lognorm_shift", stats.lognorm, dict(force_loc0=False)),   # shifted lognormal
    ("gamma", stats.gamma, dict(force_loc0=True)),
    ("weibull", stats.weibull_min, dict(force_loc0=True)),
    ("expon", stats.expon, dict(force_loc0=True)),
    ("rayleigh", stats.rayleigh, dict(force_loc0=True)),
    ("pareto", stats.pareto, dict(force_loc0=True)),
    ("uniform", stats.uniform, dict(force_loc0=False)),
]

for label, dist, opts in positive_mle:
    try:
        params, AIC, ks_stat, ks_p = fit_mle(
            "weibull_min" if label == "weibull" else ("lognorm" if "lognorm" in label else label),
            dist,
            x,
            force_loc0=opts.get("force_loc0", False)
        )

        results.append({"dist": label, "params": params, "AIC": AIC, "KS_stat": ks_stat, "KS_p":
ks_p})

        # plotting pdf
        def make_pdf(d=dist, p=params):
            return lambda xs: d.pdf(xs, *p)
```

```
        pdf_plotters[label] = make_pdf()

    except Exception as e:
        print(f"Failed fitting {label}: {e}")

# ---- B) Truncated Normal + Truncated Logistic (AnyLogic supports truncation) ----
for label, dist in [("norm_trunc0", stats.norm), ("logistic_trunc0", stats.logistic),
("laplace_trunc0", stats.laplace), ("cauchy_trunc0", stats.cauchy)]:
    try:
        params = dist.fit(x)  # fit untruncated
        loglik = np.sum(np.log(np.maximum(1e-300, dist.pdf(x, *params))))  # approximate
        AIC = aic_from_loglik(loglik, len(params))

        cdf_trunc = make_trunc0_cdf(dist, params)
        ks_stat, ks_p = stats.kstest(x, cdf_trunc)

        results.append({"dist": label, "params": params, "AIC": AIC, "KS_stat": ks_stat, "KS_p":
ks_p})

        # plot truncated pdf: f_trunc(x)=f(x)/(1-F(0)) for x>=0
        F0 = dist.cdf(0, *params)
        denom = 1.0 - F0
        pdf_plotters[label] = lambda xs, d=dist, p=params, den=denom: np.where(xs >= 0,
d.pdf(xs, *p) / den, 0.0)

    except Exception as e:
        print(f"Failed fitting {label}: {e}")

# ---- C) Beta (scaled to [xmin,xmax]) ----
# AnyLogic beta is bounded; best practice is to scale to [0,1] then fit beta.
try:
```

```
    eps = 1e-9
    u = (x - xmin) / (xmax - xmin)
    u = np.clip(u, eps, 1 - eps)
    a_b, b_b, loc_b, scale_b = stats.beta.fit(u, floc=0, fscale=1)
    beta_dist = stats.beta(a_b, b_b, loc=0, scale=1)

    ks_stat, ks_p = stats.kstest(u, "beta", args=(a_b, b_b, 0, 1))
    # AIC for beta on u (comparable only within beta-model; still useful as candidate score)
    loglik = np.sum(beta_dist.logpdf(u))
    AIC = aic_from_loglik(loglik, 2)  # a and b
    results.append({"dist": "beta_scaled", "params": (a_b, b_b, xmin, xmax), "AIC": AIC, "KS_stat": ks_stat, "KS_p": ks_p})

    # pdf back to x: fX(x) = fU(u)/(xmax-xmin)
    pdf_plotters["beta_scaled"] = lambda xs: beta_dist.pdf((xs - xmin) / (xmax - xmin)) / (xmax - xmin)
except Exception as e:
    print("Failed fitting beta_scaled:", e)

# ---- D) Triangular (constructed from min/mode/max) ----
hist, edges = np.histogram(x, bins=25)
mode_bin = int(np.argmax(hist))
mode_est = float((edges[mode_bin] + edges[mode_bin + 1]) / 2)

c_norm = (mode_est - xmin) / (xmax - xmin) if xmax > xmin else 0.5
tri = stats.triang(c=c_norm, loc=xmin, scale=(xmax - xmin))
ks_stat, ks_p = stats.kstest(x, tri.cdf)
results.append({"dist": "triangular_constructed", "params": (xmin, mode_est, xmax), "AIC": np.nan, "KS_stat": ks_stat, "KS_p": ks_p})
pdf_plotters["triangular_constructed"] = lambda xs: tri.pdf(xs)
```

```
# ---- E) PERT (constructed from min/mode/max) ----
# AnyLogic PERT usually uses (min, mode, max)
# We'll build it via Beta with lambda=4 (classic PERT), then map to [min,max].
try:
    lam = 4.0
    a = xmin
    m = mode_est
    b = xmax
    if not (a < m < b):
        raise ValueError("Mode not between min and max; cannot construct PERT.")

    alpha = 1 + lam * (m - a) / (b - a)
    beta = 1 + lam * (b - m) / (b - a)
    pert_beta = stats.beta(alpha, beta, loc=0, scale=1)

    # KS on scaled
    u = (x - a) / (b - a)
    u = np.clip(u, 1e-9, 1 - 1e-9)
    ks_stat, ks_p = stats.kstest(u, "beta", args=(alpha, beta, 0, 1))

    results.append({"dist": "pert_constructed", "params": (a, m, b, lam), "AIC": np.nan,
"KS_stat": ks_stat, "KS_p": ks_p})
    pdf_plotters["pert_constructed"] = lambda xs: pert_beta.pdf((xs - a) / (b - a)) / (b - a)

except Exception as e:
    print("Failed constructing PERT:", e)

# ========= 5) results tables =========
df = pd.DataFrame(results)
```

```
print("\n=== AIC ranking (where comparable; lower is better) ===")
df_aic = df.dropna(subset=["AIC"]).sort_values("AIC").reset_index(drop=True)
print(df_aic[["dist", "AIC", "KS_stat", "KS_p"]].to_string(index=False))

print("\n=== KS ranking (includes constructed models) ===")
df_ks = df.sort_values("KS_stat").reset_index(drop=True)
print(df_ks[["dist", "AIC", "KS_stat", "KS_p"]].to_string(index=False))

# ========= 6) Plot (top 6 AIC + key constructed) =========
xs = np.linspace(xmin, xmax, 400)
plt.hist(x, bins=25, density=True, alpha=0.5, label="Data")

# plot top 6 AIC models
for _, row in df_aic.head(6).iterrows():
    name = row["dist"]
    if name in pdf_plotters:
        plt.plot(xs, pdf_plotters[name](xs), label=f"{name} (AIC={row['AIC']:.1f})")

# plot constructed
for name in ["triangular_constructed", "pert_constructed", "beta_scaled"]:
    if name in pdf_plotters:
        plt.plot(xs, pdf_plotters[name](xs), linestyle="--", linewidth=2, label=name)

plt.xlabel("Processing time")
plt.ylabel("Density")
plt.title("AnyLogic continuous distributions: fit comparison")
plt.legend()
plt.show()
```

```
# ========= 7) AnyLogic parameter prints =========
print("\n--- AnyLogic-ready parameter prints ---")

# ----------------------------
# (A) LOGNORMAL with min=0 (loc forced to 0)
# ----------------------------
s0, loc0, scale0 = stats.lognorm.fit(x, floc=0)  # loc fixed at 0
mu0 = float(np.log(scale0))
sigma0 = float(s0)
print(f"lognormal(mu, sigma, min=0): lognormal({mu0:.6f}, {sigma0:.6f}, 0)")

# ----------------------------
# (B) LOGNORMAL SHIFTED (THIS is your 'lognorm_shift' best-fit)
#     loc is estimated from data (min shift)
# ----------------------------
s_shift, loc_shift, scale_shift = stats.lognorm.fit(x)  # loc free (shifted)
mu_shift = float(np.log(scale_shift))
sigma_shift = float(s_shift)
min_shift = float(loc_shift)

print("\n*** Shifted lognormal (BEST for lognorm_shift) ***")
print(f"mu    = {mu_shift}")
print(f"sigma = {sigma_shift}")
print(f"min   = {min_shift}")
print(f"AnyLogic call: lognormal({mu_shift:.6f}, {sigma_shift:.6f}, {min_shift:.6f})")

# Sanity check: fitted mean/std vs data mean/std
mean_fit = stats.lognorm.mean(s_shift, loc=loc_shift, scale=scale_shift)
std_fit  = stats.lognorm.std(s_shift, loc=loc_shift, scale=scale_shift)
```

```
print("\n--- Shifted lognormal sanity check ---")
print("Data mean:", float(np.mean(x)))
print("Fit  mean:", float(mean_fit))
print("Data std :", float(np.std(x, ddof=1)))
print("Fit  std :", float(std_fit))

# ----------------------------
# (C) gamma(k, theta) with loc=0
# ----------------------------
k, loc_g, theta = stats.gamma.fit(x, floc=0)
print(f"\ngamma(k, theta): gamma({float(k):.6f}, {float(theta):.6f})")

# ----------------------------
# (D) weibull(alpha, beta) with loc=0
# ----------------------------
alpha, loc_w, beta = stats.weibull_min.fit(x, floc=0)
print(f"weibull(alpha, beta): weibull({float(alpha):.6f}, {float(beta):.6f})")

# ----------------------------
# (E) triangular + PERT (constructed)
# ----------------------------
print(f"\ntriangular(min, mode, max): triangular({xmin:.6f}, {mode_est:.6f}, {xmax:.6f})")
print(f"PERT(min, mode, max): pert({xmin:.6f}, {mode_est:.6f}, {xmax:.6f})  # lambda=4 classic")
```

Annex B: Model implementation in Anylogic

1B Model implementation in Anylogic

This chapter describes the implementation of the simulation model based on the conceptual design presented in the previous section. The objective is to explain how the planning logic, material flow, and execution behavior were translated into a DES simulation model using Anylogic and Java programming language.

The implementation focuses on the integration of a rolling horizon MRP planning layer and its interaction with the material flow. Emphasis is placed on model architecture, data handling, and the interaction between planning and execution, rather than on programming details.

1B.1 Data management and master data implementation

The simulation model adopts a data-driven implementation approach, in which all structural, planning, and material flow related parameters are stored in dedicated master datasets. This design ensures consistency between the conceptual model and the executable simulation, while enabling easy scenario analysis and experimentation.

Two primary master datasets are implemented within the model: one representing inhouse produced items (BOM dataset) and one representing purchased items. These datasets follow the structure described in the conceptual design section and define product structures, routing logic, planning parameters, and processing related attributes.

Storage of Master Data

Within the software environment, the BOM and purchased item datasets are stored as structured AnyLogic variables. Each dataset contains all relevant attributes required by both the planning and execution layers, including item relationships, quantities, lead times, safety time and stock parameters, lot sizing rules, and processing time characteristics.

By centralizing this information in master datasets, the model avoids hard coded logic which could cause issues when varying different parameters and ensures that changes to product structure, planning policies, or execution parameters can be made directly at the variables.

Data Loading and Initialization

The master datasets are populated at the beginning of each simulation run using a structure compatible with Java programming language. Furthermore, different functions are available to read the data directly from the dataset content.

This approach allows parameters such as safety stock levels, planned lead times, lot size quantities, processing time distributions, and transport or drying times to be modified easily without altering the simulation logic.

Customer Demand Data Implementation

Customer demand is implemented in the simulation model as an external input dataset. Demand data is stored in an Excel dataset containing all customer orders, including the item identifier, order quantity, and due date.

At the start of each simulation run (simulation time t=0), an initialization event is triggered to read the customer demand dataset. During this event, all demand records are loaded into the model and converted into internal order (customer order agents) representations. This approach ensures that the complete demand for a given simulation is available for the planning layer before the first execution of the MRP logic.

The demand dataset serves as the primary input for generating gross requirements of final products in the planning layer. By separating customer demand from the model logic and storing it in an external dataset, alternative demand scenarios can be evaluated easily by modifying the Excel input without changing the simulation structure.

Support for Experimentation and Scenario Analysis

The separation between model logic and master data enables flexible experimentation. Alternative scenarios can be evaluated by modifying dataset values while keeping the model structure unchanged. This design supports systematic testing of planning policies, capacity configurations, and demand conditions, and facilitates the generation of simulation experiments.

Role in Model Scalability

The implemented data management approach improves model scalability. New products, components, or routing configurations can be added by extending the master datasets, without requiring changes to the material or planning algorithms. As a result, the model can be adapted to future system changes or extended scopes with minimal implementation effort.

1B.2 Agents and populations of agents

The simulation model is implemented using agents to represent both physical and information flows.

Four main agent types are defined in the model: order agents, material token agents, operator agents, and machine population of agents. Together, these agents represent the interaction between planning decisions and material flow behavior.

Order Agents

A single agent type is used to represent customer orders, production orders, and purchase orders. This unified representation allows consistent handling of planning and execution logic, while the specific behavior of an order is determined by its attributes read from the BOM master dataset.

Each order agent contains information such as:

- item identifier
- order quantity
- due date
- planned release time
- order type (production or purchase)
- Processing time distributions in case of purchase orders

For production orders, the order agent represents the output entity of a production step, which becomes available upon completion of processing.

Material Token Agents

Material token agents represent the input materials required for production at each processing step. For every production order released to a machine, a corresponding material token is generated and sent to the same machine. The properties of the material token, including item type, required quantity, transport time, drying time and processing time distributions are derived directly from the BOM master dataset.

In this representation, the BOM defines both:

- the output of a production step (the production order)
- the inputs to that step (the associated material tokens)

This way, the model can also simulate inventory levels.

Material Consumption

Production can only start when both the production order and its corresponding material token are present at the machine. Material tokens are consumed at the start of processing, meaning that all required input materials must be available before processing begins. Partial consumption is not allowed.

This mechanism ensures physical feasibility of production and maintains consistency between inventory levels and material flow.

Operator Agents

Operator agents represent the workforce available for production activities. Each operator is characterized by:

- a defined set of skills corresponding to specific stations or production steps
- a shift schedule determining availability over time

Operators are assigned only to stations that match their standard functions, reflecting Fokker's workforce organization.

Machine population of agents

Machines and production stations are modeled as a population of machine agents, allowing the number of stations to be varied through the agent's own parameters. This design supports scenario analysis involving capacity changes without requiring structural modifications to the model.

Each machine agent is identified by an ID, which is referenced directly in the BOM master dataset. During execution, routing decisions are therefore derived from BOM data, ensuring that production orders and material tokens are directed to the appropriate machines based on master data definitions.

Agent roles

In the execution layer, production orders act as both input and output entities, material tokens act as input entities, machines provide processing capacity, and operators provide labor resources. The interaction of these agents drives processing, waiting, and completion behavior throughout the system.

This agent based logic provides a strong foundation for representing the studied production system.

1B.3 Material Flow

This section describes the implementation of the material flow within the simulation model. Material flow refers to the movement and transformation of physical entities represented by agents through the modeled production system. In this layer, agents interact with machines, operators, and inventories, and where physical constraints such as capacity limitations, waiting times, and material availability happen.

While the planning and information flow layers determine what should be produced and when orders should be released, the material flow drives how and where production actually takes place on the shop floor. This includes the progression of operators, production orders and materials through routing sequences, the consumption of materials and the completion of finished products.

The material flow is implemented using the agent types described in the previous section, and it forms the base on which key performance indicators such as lead time, throughput, WIP, lateness, etc will be measured.

Customer order flow and filtering

Figure 1B illustrates how customer orders are introduced into the model, stored for planning purposes, and subsequently fulfilled based on physical inventory availability.

Customer orders are read from an Excel based dataset through an initialization event at the start of the simulation. Each record contains the ordered item, quantity, and due date. Once the event has read the data set, it sends all customer orders to the material flow layer through an entry block (`enterCustomer`). At this point, all customer orders are stored in a dedicated compilation (list of arrays), which is used by the MRP planning layer to generate gross requirements for final products.

After entering the system, customer orders pass through a delay block (`delayUntilRelease`) that holds each order until its specified due date. This mechanism aligns order fulfillment logic with customer required delivery times and enables measurement of delivery performance.

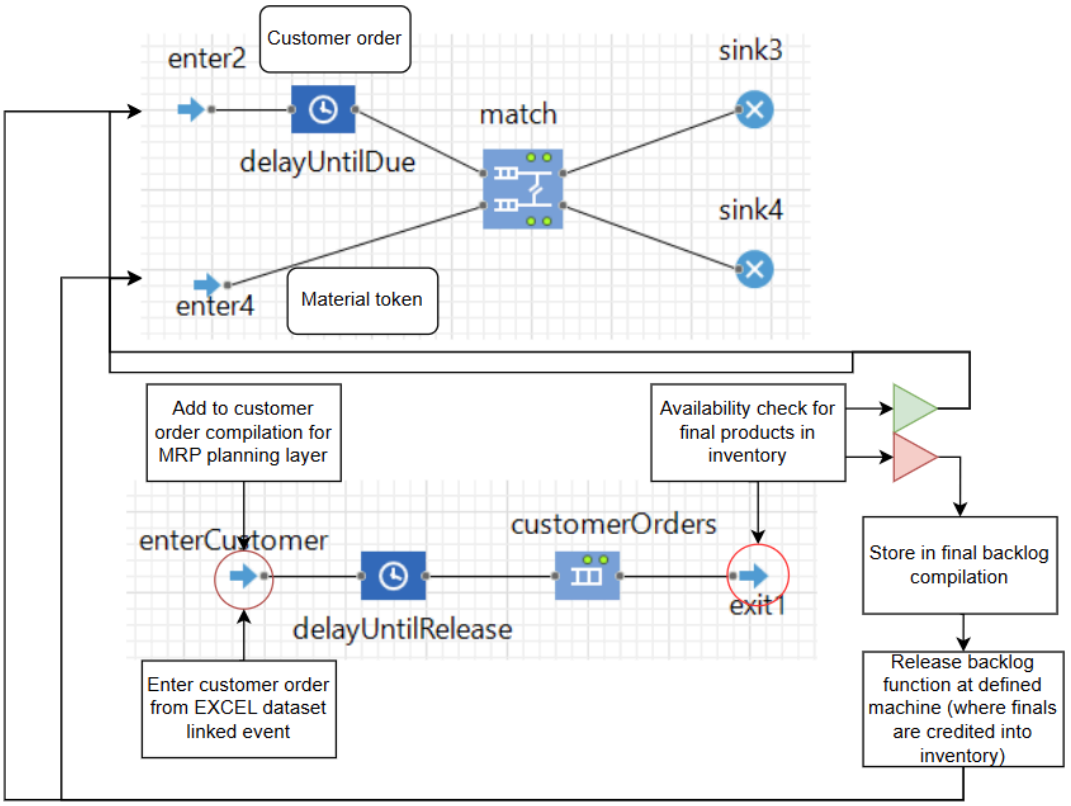


Figure 1B: Customer order flow logic. This diagram represent the modeled blocks in Anylogic along with explanation of which is the function of each block

Once the due date is reached, customer orders proceed to an exit block (`exit1`), where an availability check is performed to verify if enough finished product inventory is available. Two outcomes are possible:

- **If enough finished goods inventory is available**, the customer order is immediately fulfilled. In this case, the customer order and a corresponding material token representing the physical finished product are sent to a different set of flow blocks and consumed form inventory (`enter2` and `enter4`) and inputted into a match block, where it matches customer order quantity and item id with material token quantity and item to be then sent to sink blocks as completed and delivered orders.

- **If enough finished goods inventory is not available**, the customer order is placed into a final backlog compilation. Backlogged orders remain inactive until finished products are credited to inventory. When new finished goods become available, a release backlog function is triggered, re-evaluating inventory availability and releasing feasible customer orders. Released backlogged orders are then sent to the matching block, following the same fulfillment logic as non backlogged orders.

This implementation ensures that customer orders are fulfilled strictly based on physical inventory availability, while capturing waiting times caused by production delays. At the same time, the separation between order storage for planning purposes and material flow level fulfillment allows customer demand to drive planning decisions without directly consuming execution resources.

The described customer order flow supports the measurement of delivery related performance indicators, including order lateness, percentage of late deliveries, and number of late orders.

Production order filtering

Figure 2B shows the implementation of production order filtering and backlog logic within the material flow layer of the simulation model. This logic drives how planned production orders generated by the MRP planning layer are released to execution, sorted by material availability, and either dispatched for processing or sent to backlog.

Production orders are generated by the MRP event and sent to the material flow layer at their planned release times. When the release time computed by the MRP is reached, production orders enter the material flow through an enter block (`enter`). This mechanism ensures that the material flow follows the planning decisions produced by the MRP in terms of time.

Once released, production orders proceed to an exit block (`exit`), where a material availability check is performed. This check verifies whether all required input materials,

as defined in the bill of materials (BOM), are available in sufficient quantities in physical inventory.

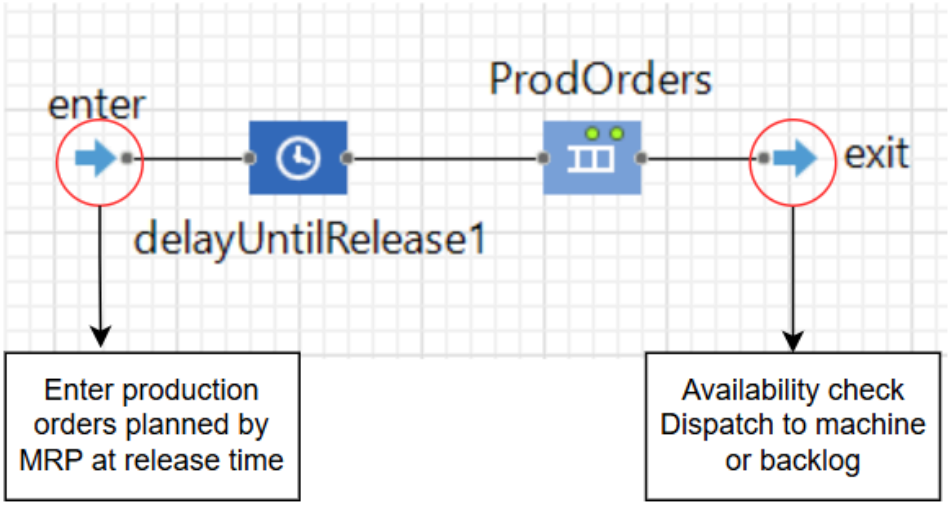


Figure 2B : Production order inputting in the material flow and filtering logic

Two outcomes are possible:

- **If required input materials are not available**, the production order cannot start production and is stored in a backlog compilation. Backlogged production orders remain inactive until the missing input materials become available. When inventory is updated due to inbound material or downstream production completion, a release backlog function re-evaluates the backlog and releases eligible production orders.

- **If all required input materials are available**, the production order is immediately dispatched for production. In this case, a corresponding material token is generated, containing the item types and quantities of all required inputs as defined in the BOM. The production order agent represents the output of the production step, while the material token represents the inputs to that step.

Both the production order and its associated material token are then sent to the machine number specified in the BOM master dataset. Whenever a production order and its respective material token are sent to a machine, the quantities of the items stored in that material token are immediately deducted from the physical inventory. This logic is the same for orders directly dispatched to machines or for orders which have been released from the backlog.

This filtering mechanism ensures that production strictly respects material availability, while enabling the modeling of production backlog caused by material shortages. As a

result, production lead times measured in the simulation include both processing time, queue time and waiting time due to input material being unavailable.

Purchase order material logic

Figure 3B shows the implementation of purchase order material logic within the material flow layer of the simulation model. This logic represents the inbound flow of externally sourced materials and its interaction with production backlog.

Purchase orders are generated by the MRP planning layer and released into the material flow layer at their planned release times. When the release time computed by the MRP is reached, purchase orders enter the material flow through an entry block (`enter1`). At this point, all relevant order attributes such as item identifier, quantity, due date, and processing time distribution and its parameters have already been assigned by the planning logic after reading them from the BOM database.

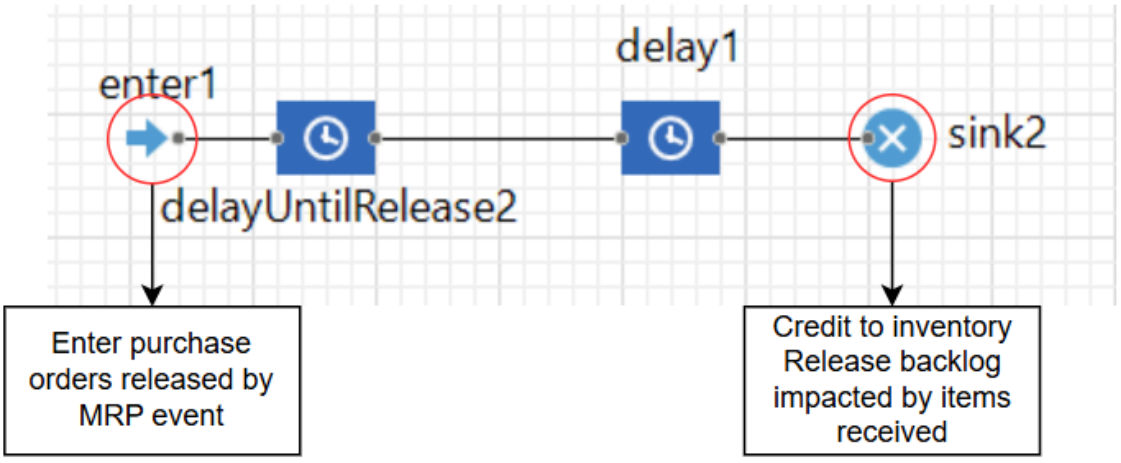


Figure 3B : Purchase order input logic, inventory update and backlog release

After entering the flow, purchase orders pass through a delay block (`delayUntilRelease2` followed by `delay1`) that represents the procurement lead time. The delay duration is drawn from the stochastic processing time distribution specified for the purchased item, allowing stochasticity in supplier lead times to be modeled.

Once the purchase order agents leave the final delay block, purchase orders reach the sink block (`sink2`), at which point the ordered quantities are credited to the physical inventory. This inventory update represents the arrival of purchased materials into the system.

Immediately after inventory is updated, a backlog release function is triggered. This function checks whether any production orders were previously backlogged due to missing input materials that correspond to the received purchased items. If such backlogged production orders exist and sufficient inventory is now available, these orders are released from backlog and dispatched to stations.

In cases where backlogged production orders are released, the required input quantities defined in their material tokens are deducted from physical inventory at the time of release.

This purchase order material logic enables a relationship between inbound supply and production execution, allowing the model to explicitly represent how supplier lead time variability and procurement delays can affect production backlog, lead times, and overall system performance.

Machine modeling

Figure 4B illustrates the implementation of machine modeling and processing logic within the material flow layer of the simulation model. This logic governs how production orders and material tokens are synchronized, processed, and completed at individual production stations, while respecting capacity, workforce, and batch constraints.

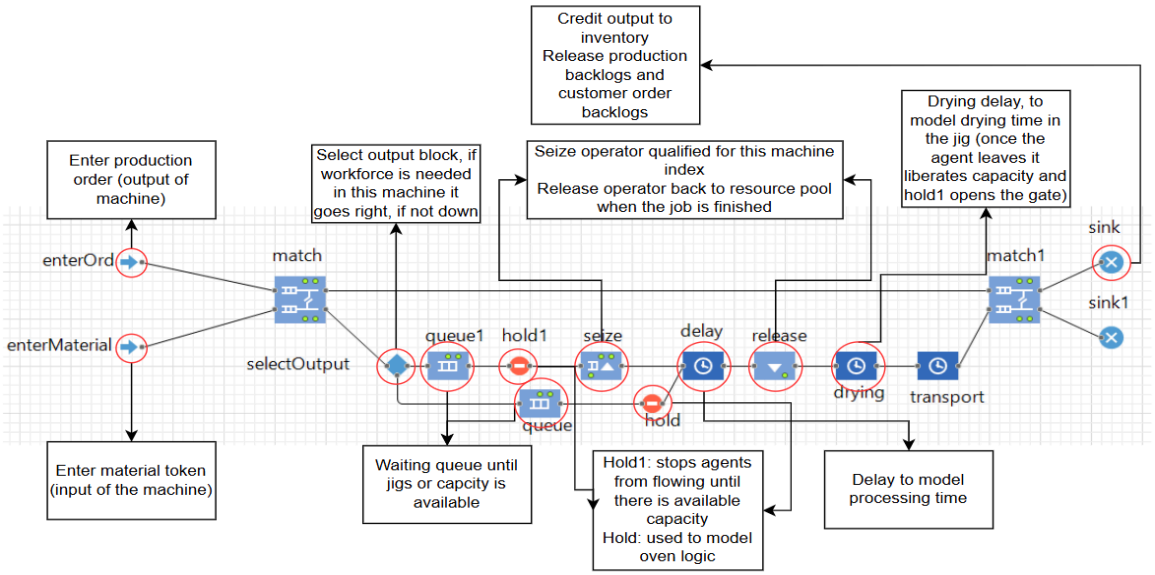


Figure 4B : Machine material flow design and block role

Matching of Production Orders and Material Inputs

For each production step, the production order agent (representing the output of the machine) enters the machine flow through an entry block (`enterOrd`), while the corresponding material token agent (representing the required input materials) enters through a separate entry block (`enterMaterial`). Both agents are matched using a matching block (`match`), which allows processing to proceed only when the material token contains the complete set of inputs required for the production order, as defined in the BOM master dataset.

This synchronization ensures that machines can only start processing when both the production order and all required input materials are present.

Workforce Dependent and Workforce Independent Processing Paths

Once the material token leaves the matching block, a selection block (`selectOutput`) directs the flow depending on whether workforce is required at the given production step.

- **If workforce is not required**, the agent is routed to a processing path that only considers machine capacity.
- **If workforce is required**, the agent is routed to a processing path that additionally considers operator availability and jig capacity.

This design allows different machine types and production steps to be modeled consistently within the same structure.

Capacity Constraints, Queuing and Oven Logic

When agents enter the processing path, they may encounter capacity limitations. A queue block represents waiting for available jigs or machine capacity. A hold (`hold`) block is used to control the release of agents based on available capacity.

For machine index number 2, representing the oven, the hold block (`hold1`) is configured to model batch processing behavior. In this case, the hold block acts as a gate that opens under one of two conditions:

- the number of waiting agents reaches the maximum oven batch capacity
- a predefined waiting time goes by, after which all queued agents are processed simultaneously.

This mechanism models the batch nature of oven processing, ensuring that all items in a batch enter and exit the oven at the same time.

Workforce Assignment and Processing

In production steps that require workforce, a second hold block (`hold1`) controls access to operators and jigs. This block closes when all jigs are occupied and opens only when capacity becomes available. This ensures that operators are only seized when a jig is available.

Once capacity is available, operators qualified for the specific machine index are seized from the resource pool. Processing time is modeled using a delay block, with durations drawn from the stochastic processing time distributions defined in the BOM dataset. Upon completion of processing, operators are released back to their respective resource pools.

Drying and Transport Delays

After processing, a drying delay is applied using a delay block (`drying`). Drying time is modeled as occupying jig capacity, reflecting the fact that drying takes place while the product remains in the jig. Therefore, the hold block (`hold1`) gate will only open when the agent leaves the drying block and therefore liberated capacity.

Transport delays are modeled using a separate delay block (`transport`). Transport time is applied only to aggregated machine indices representing downstream and upstream processes at the Edison site, capturing site transportation effects between Marconi and Edison.

Completion, Inventory Update, and Backlog Release

Once the material token completes processing and arrives at the final matching block (`match1`), it matches with its corresponding production order. At this point, the production order and material token exit the machine flow and is sent to a sink block (`sink/sink1`).

At the time of exiting the matching block, the produced quantity and item are credited to physical inventory. Immediately after inventory is updated, a release backlog function is triggered. This function releases any production orders backlogged due to missing input materials that are now available, as well as customer orders backlogged due to insufficient finished products in inventory in the case of final products.

Machine Populations and Scalability

The machine logic described above is implemented as a population of machine agents. In the current model, the machine population consists of 52 agents, meaning that the same machine logic is replicated for 52 individual stations. Machine indices stored in the BOM

master dataset determine which machine agent is used for each production step. Additionally the capacity of the delay and drying blocks (number of jigs) can be set by code in the Anylogic main section.

This population based implementation allows the number of stations to be varied easily, supporting scenario analysis related to capacity changes without modifying the underlying flow logic.

Workforce modeling

The workforce is modeled in the simulation to capture labor related constraints on production execution. Workforce availability, skill matrices, and shift structure are represented using resource pools and schedules, allowing labor constraints to influence machine utilization, queue formation, and production lead times.

Resource Pools and Skill Based Assignment

The workforce is modeled using twelve distinct resource pools, each representing a group of operators with a specific skill set. This structure reflects the specialization of operators across different production processes and ensures that only qualified operators can perform specific operations.

Each resource pool is associated with a predefined set of machine indices (from the 52 mentioned earlier). During execution, machines can only seize operators from the resource pool corresponding to their assigned machine index. As a result, production steps are constrained not only by station capacity (number of jigs) but also by the availability of station skilled operators.

Workforce Capacity and Shift Scheduling

For each resource pool, workforce capacity is controlled through a dedicated schedule block. In total, twelve schedule blocks are defined, each linked to its respective resource pool. These schedules specify:

- the number of available operators
- the number of shifts
- the working times associated with each shift

By defining workforce availability through schedules, the model captures time dependent labor capacity, including shift boundaries and non working periods. This allows the simulation to represent realistic variations in labor availability over time.

Integration with Machine Execution Logic

Within the machine agent, each machine is assigned an index that determines which resource pool it can request operators from. When an agent reaches a processing step that

requires workforce, the machine tries to seize an operator from the corresponding resource pool.

This integration ensures that workforce constraints are enforced consistently during execution and that operator availability directly affects queueing behavior, station and machine utilization and overall production performance.

1B.4 Information Flow

The information flow represents the planning layer of the simulation model and drives how demand information is transformed into production and purchase decisions. This layer is implemented through a rolling horizon MRP logic that interacts with the material flow layer.

Structure of the MRP Planning Layer

The MRP planning layer is divided into two main logical blocks.

The first block constructs gross requirements for final products by reading the customer order compilation. This compilation contains all customer orders extracted from the Excel demand dataset, including item identifiers, quantities, and due dates. Customer demand is time phased and aggregated to generate gross requirements for each final product.

This first block computes the following calculations for the final products

- net requirements
- projected on-hand inventory
- planned receipts
- planned releases

These calculations follow the netting, lot sizing, and backward scheduling equations introduced in the conceptual model section.

Multi-Level BOM Explosion

The second block takes planned releases for final products and performs a multi-level BOM explosion. Using the same equations presented in the conceptual design, planned releases of parent items are converted into gross requirements for their immediate child components based on the quantities specified in the BOM master dataset.

This explosion process is applied iteratively across all levels of the BOM, generating gross requirements, net requirements, and planned releases for semi-finished products, in-house produced components, and purchased items. In this way, the complete material structure is translated into time based production and purchase requirements.

Order Generation and Interplay with Material Flow

After the MRP calculations are completed, planned releases are converted into order agents. Production orders and purchase orders are generated with their corresponding attributes, including item, quantity, release time, and processing time parameters.

These orders are then sent to their respective entry blocks in the material flow layer at the planned release times as seen in the material flow figures. At the same time, all released orders are stored in an inbound order compilation until their completion, which tracks orders that have been released but not yet finalized.

Rolling-Horizon Replanning and Feedback Loop

The MRP planning logic is executed by an event that runs daily. At each daily run, all planning arrays such as gross requirements, net requirements, projected on-hand inventory, planned receipts and planned releases are recomputed from scratch using the updated system state.

The inbound order compilation plays a critical role in linking the material flow and information flow layers. Orders that are in progress or inbound are used to populate the scheduled receipt arrays in subsequent MRP runs. As a result, net requirements and projected on-hand inventory calculations account for quantities that are already in the material flow. Additionally, the starting inventory for all items is read from the physical inventory variable, therefore informing the MRP about the state the production is currently in.

This feedback mechanism creates a closed loop interaction between planning and production, allowing the MRP logic to adapt to shop floor behavior such as delays, backlog, and variability in processing and supplier times.

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