Factory Flow Simulation and Ramp-up Optimisation: An Aerospace Case Study

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Abstract. This study explores the application of Discrete Event Simulation (DES) for optimising the factory flow in an aerospace manufacturing setting. GKN Aerospace's manufacturing facilities aim to increase production efficiency through capital investment and automation, aligned with Lean Manufacturing principles of waste reduction and flow improvement. A target has been set for this work of a 25% throughput increase per month by 2027. Through DES modelling, we replicated the different configurations of an aerospace component manufacturing process flow, capturing key operational constraints such as machine availability, resource allocation, and material handling. A baseline model was developed to reflect the standard configuration of new CNC technology and automated loading and unloading operations, which is followed by scenario analysis to compare the deployment of different configurations of the system. The simulation results provide insights into bottlenecks, resource utilisation, and potential improvements, enabling data-driven decision-making for production ramp-up while supporting a culture of continuous improvement. The findings highlight the effectiveness of DES in mitigating operational uncertainties and optimising manufacturing strategies before real-world implementation. This research contributes to aerospace manufacturing by demonstrating how simulation-driven approaches can enhance efficiency and support strategic investment decisions within a Lean Manufacturing framework.

Keywords: Discrete Event Simulation, Lean Manufacturing, Aerospace.

1 Introduction

GKN Aerospace continually assesses its processes to enhance efficiency and meet future aircraft delivery targets. This objective can be pursued through investments in new machinery, automating loading and unloading operations, and scaling up production. A key challenge is ensuring that new investments deliver the intended improvements in throughput while maintaining operational stability.

Digital transformation has emerged as a central strategy towards more efficient processes for most of the manufacturing sector [1]. Within this philosophy, Discrete Event Simulation (DES) has been identified as a powerful methodology for evaluating and optimising the deployment of new CNC centres and automated processes. DES models complex systems as a sequence of discrete events occurring at specific points in time, enabling detailed analysis of workflow dynamics, resource utilisation, and potential bottlenecks. This approach has been widely used in aerospace and other high-value manufacturing sectors to support data-driven decision-making, reduce implementation risks, and improve production efficiency.

This study focuses on aerospace component manufacturing, developing a simulation-driven framework to assess various production scenarios. A baseline model is constructed to represent the standard configuration of the new system, followed by scenario-based optimisation to determine the most effective deployment strategy for new CNC centres and automation technologies. The findings offer valuable insights into production bottlenecks, resource allocation, and potential efficiency gains, contributing to a more resilient and future-ready manufacturing system.

2 Literature Review

The nature of Discrete Event Simulation (DES) is particularly well suited to modelling manufacturing systems. Beregi et al. [2], describe how simulation models represent the events occurring in a manufacturing system in its operation by a sequence of steps that are executed in a computer program. This time-ordered sequence is generated with respect to a set of rules modelling the behaviour of the system. Accordingly, the characteristics and relationships between the elements in a production system can be described in detail.

Case studies in manufacturing have focused on improving efficiency, enhancing decision-making, and optimising operations through simulation-based tools. These include both commercial off-the-shelf (COTS) software—such as AnyLogic [3], Siemens Plant Simulation [4], and Witness [5] —and in-house developed solutions using open-source platforms like SimPy [6]. While COTS tools offer extensive built-in capabilities, open-source alternatives often provide greater flexibility and enable seamless integration with communication protocols, optimisation algorithms, and other external systems. In all cases, detailed documentation on how the software was implemented and integrated with real-world data sources was essential to achieving meaningful improvements in manufacturing performance.

Numerous studies have employed DES to offer practical insights into application of lean principles. Notably, Detty et al. [5] present a case study in which DES is used to model and evaluate the transformation of an existing assembly system in a complex manufacturing environment into a lean-based system, with particular focus on enhancing operational performance.

3 Methodology

This study focuses on optimising a manufacturing process within the GKN Aerospace Filton facility (South Gloucestershire, England - UK). The methodology follows a structured approach, beginning with process mapping and data collection, followed by the development of a baseline simulation model as well as differential scenarios, their subsequent modelling, simulation and analysis of results, and reporting of key findings. Throughout the model development, different methodologies have been adopted for verification and validation. Verification was carried out by systematically testing the model's logic and internal consistency, including the use of degenerate tests, extreme condition tests, and trace analysis to ensure correct implementation of the process logic. Input data connections were verified by adjusting parameters and observing expected changes in model behaviour. Validation was performed in collaboration with subject matter experts (SMEs) from GKN Aerospace, who reviewed outputs for alignment with real-world performance. Additional validation techniques included the use of model animation, such as part tracking and colour mapping, to confirm correct sequencing, entity states, and process flow behaviour.

3.1 Input data

A comprehensive data collection phase was conducted to capture essential process parameters, including cycle times, resource availability, and production constraints. This was supported by GKN Aerospace, ensuring accuracy in process durations, resource allocation, and forecasted production volumes. The collected data formed the foundation for constructing an accurate simulation model.

The parts considered are manufactured through a sequence of distinct machining cycles, referred to as 'stages'. There are two to five stages per part, of different complexity and therefore different cycle time.

Each stage requires a specific fixture to place the part on the pallet. Therefore, most often when a part has to be machined, operators have to first place the required fixture on the pallet.

The system under study consists of four main components: machines, loading and unloading stations, a pallet rack, and a shuttle.

The machines carry out machining operations on the parts. As mentioned, each part is secured to a fixture, which varies depending on the part and its machining stage. To enter the machine, the fixture is mounted on a pallet, which serves as the system's reference. Pallets are loaded into the machines vertically, allowing the cutters to operate on the part.

The loading and unloading stations facilitate the placement and removal of parts and fixtures. H&S recommends the involvement of three people to load parts. At these stations, pallets are positioned horizontally to simplify handling.

The pallet rack functions as a storage unit for pallets that are either unloaded, waiting for machining, or awaiting unloading. Finally, the shuttle transports pallets between these locations. Pallets remain and are transported in a vertical orientation.

Based on discussions with GKN Aerospace, the system can accommodate between two and five machines, one or two loading and unloading stations, and between ten and twenty-four pallet locations within the pallet rack.

A layout of the system reflecting the maximum configuration is shown in Fig. 1.

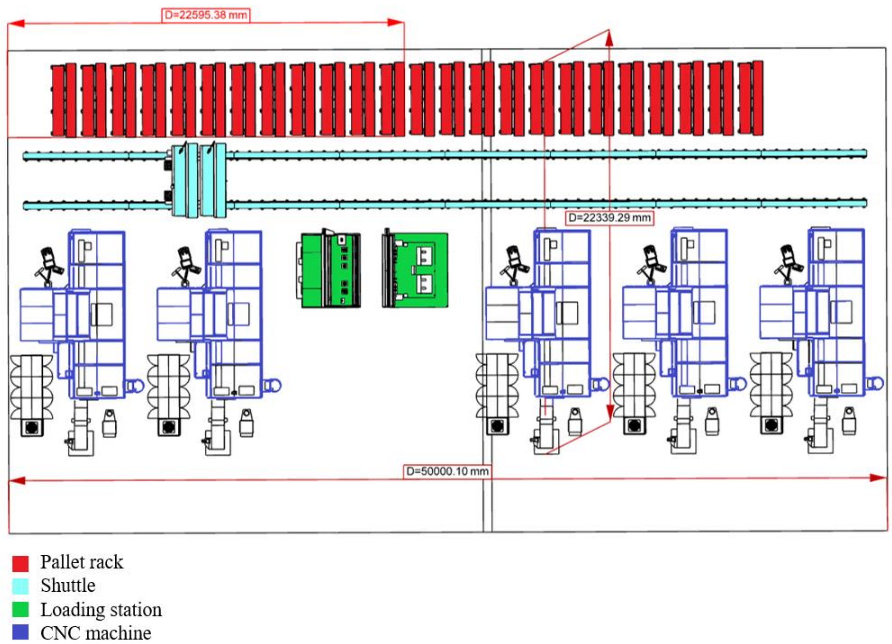

Fig. 1. Layout of the system under analysis showing the main elements: pallet rack, shuttle, loading station and CNC machines. This representation considers the maximum number of elements possible.

A minimum of three operators are required to perform the loading or unloading of either a part or a fixture on or from the pallet. A crane is required when parts must be removed from the pallet.

Operators were modelled based on standard working patterns. These include breaks, shifts, working days per week, and unplanned activities where operators are not at the machines. All of these parameters can be changed in the model.

The availability of the CNC machines was selected as a representative value which can be varied by the user, whereas all the other elements within the system are assumed to have full time availability.

3.2 Modelling aim

The aim of the model is to assess the production capacity of the system and optimise its configuration to fully utilise that capacity. Therefore, the model is required to accommodate a variable number of machines or operators, to facilitate the assessment and interpretation of different scenarios.

Based on this modelling aim, a baseline model has been designed, considering a standard configuration of the system. Starting from this reference, several variables have been considered to test the system's production capacity.

3.3 Scenarios

Baseline scenario. A DES model was developed to replicate the standard configuration of the system that GKN Aerospace is considering. This is based on two CNC machines, twelve pallets and one loading and unloading station.
The aim of this baseline model is to assess whether the new system can absorb the current production level of the existing system. This is currently based on 19 products for an average monthly machining time of *x* hours (with *x* used as a placeholder variable due to data confidentiality agreements with the customer).

Differential scenarios. Two additional scenarios have been considered in the analysis.

The first considers an increase in production capacity to twenty-nine parts for an average monthly machining time of 1.24*x* hours, an approximate 25% increase over the production level considered in the baseline scenario. This scenario introduces three additional pallets, for a total of fourteen.

The second scenario considers the same production target of the other. However, the number of pallets was increased to sixteen, with the aim of assessing if a higher number of pallets can improve the production performance of the system.

Table 1 shows a summary of the presented scenarios.

Table 1. Summary of Analysed Scenarios

Inputs	Baseline	First differential scenario	Second differential scenario
CNC machines	2	2	2
CNC availability	Production representative value	Production representative value	Production representative value
Loading stations	1	1	1
Operators	3	3	3
Shift	24/5	24/5	24/5
Pallets	11	14	16
No. of parts	19	29	29
Avg. hours of machining time per month	x	1.24x	1.24x

3.4 Model development

The model has been developed using ProModel simulation software, version 10.14.350.

The software offers features to import and export data from and to MS Excel sheets, and these have been used extensively to guarantee the possibility of rapidly changing and testing different scenarios.

Specifically, within MS Excel the user can set the number of active machines, loading and unloading stations, number and shift pattern of operators, availability of machines, loading and unloading times per part, and part characteristics such as number of machining stages and related machining times. An example of the parameters that could be set within MS Excel is shown in Fig. 2. Within MS Excel the user also specifies the production target of parts for each month, as well as the assigned fixture and pallet required for each part stage.

The model is therefore built with a certain versatility, as it adapts to the input specified by the user. For instance, routing of pallets is dependent on the number of active machines: if the third machine is not active, a pallet with a part to be machined will not consider that machine among the possible next locations. Whenever a part enters a machine for a machining cycle, the model retrieves the attribute part type and returns the corresponding machining time searching in the MS Excel input file.

Production orders are released at the beginning of each month and they start production as soon as the first pallet required is available. A push-based production strategy was modelled, as the aim is to assess if the input production target can be achieved and the relative performance of the system. A screenshot of one simulation model run is shown in Fig. 3.

At the end of the simulation run, the order log, comprising the scheduled time, production start and end time, is saved as a MS Excel file. There, the user can assess and analyse results thanks to a specifically designed dashboard, shown in Fig. 4.

Certain numerical values used in the scenarios, such as average machining times, have been anonymised using placeholder variables (e.g., *x*) to comply with confidentiality agreements with the industrial partner.

Setting	Explanation	Mode
CNC1	CNC station setting	On
CNC2		On
CNC3		Off
CNC4		Off
CNC5		Off
Load01	Load station setting	On
Load02		Off
Machine Availability	Target machine availability	
Operators	Number of operators in the model	3
Operator days	Operator working days in a week	5
Model Duration	Model duration in years	1
Fixture loading/unloading time	Loading and unloading times	20
Large dimension loading/unloading time		25
Medium dimension loading/unloading time		20
Small dimension loading/unloading time		15

Fig. 2. The input user interface in MS Excel to set parameters of the model.

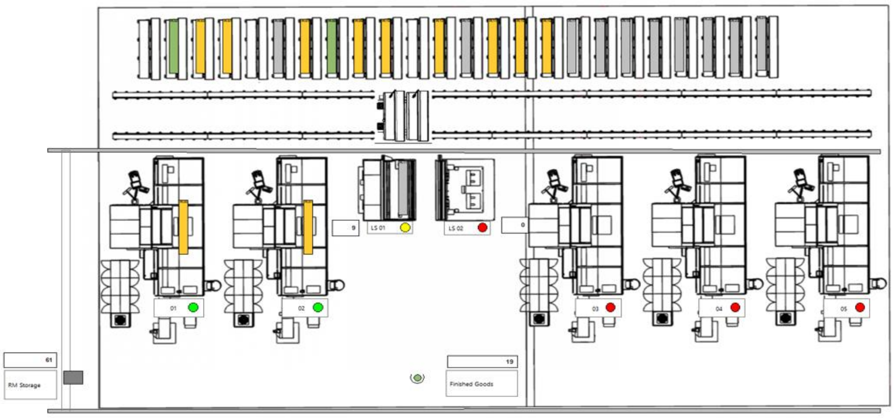

Fig. 3. Simulation Model Running in ProModel.

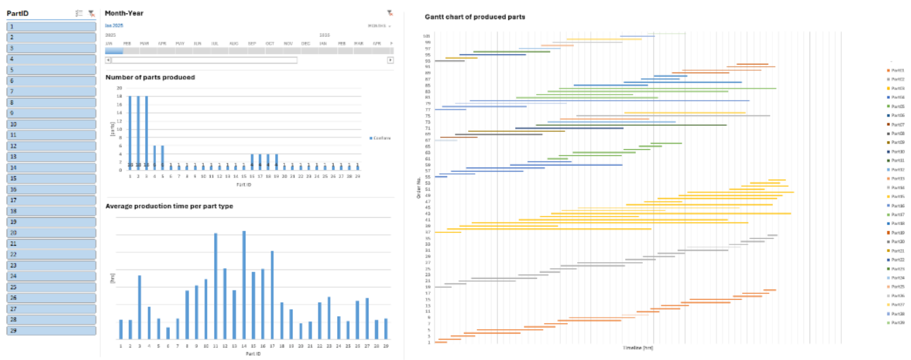

Fig. 4. The MS Excel dashboard showing the simulation results.

4 Findings

Key metrics description. The results have been analysed using three key metrics.

The first metric is the *parts completion rate*, which represents the ratio between the number of produced parts and the scheduled parts. This metric is expected to reach 100% since the system is required to meet the target production level. However, in the first differential scenario, the completion rate falls slightly short at 98.94%, indicating potential inefficiencies or bottlenecks.

The second metric is *CNC machine utilisation*, which measures the extent to which the system is actively used. On average, machines experience downtime for a percentage of their total time, as indicated in the Input data section. Additionally, operator unavailability due to breaks or other constraints can further reduce effective machine availability to an estimated 50-60%. The results show a clear increase in machine utilisation from the baseline to the differential scenarios, suggesting that higher production demand is pushing the system closer to its capacity limits.

The third metric is *hours to complete production*, which tracks the total time required to fulfill the scheduled production. This metric helps assess how changes to system configuration affect the overall efficiency and throughput. A shorter production time indicates better resource utilisation, while an increase may suggest inefficiencies or capacity constraints. However, a short production time might also suggest that the production capacity of the system is not fully exploited.

Results of analysed scenarios. The *baseline scenario* meets the production target (100% completion) in *y* hours (with *y* used as a placeholder variable due to data confidentiality agreements with the customer), with a relatively low CNC machine utilisation of 33.57%.

In the *first differential scenario*, an increase in production demand results in a slight shortfall (98.94% completion) and extends the production time to 1.07*y* hours. Machine utilisation rises to 40.47%, indicating greater system workload.

The *second differential scenario* successfully restores the completion rate to 100% by adjusting pallet assignments, though production time increases marginally to 1.08Y hours. Machine utilisation remains similar to the first differential scenario (40.64%), suggesting that reallocation improves throughput without significantly increasing strain on the system.

Results are summarised in Table 2.

Table 2. Results of analysed scenarios

Inputs	Baseline	First differential scenario	Second differential scenario
Parts completion rate	100%	98.94%	100%
CNC machines utilisation	33.57%	40.47%	40.64%
Hours to complete production	Y	1.07Y	1.08Y

To further evaluate system performance and identify potential capacity improvements, the results have also been visualised as a Gantt chart representing the production sequence over one month. This visualisation helps assess available production capacity and system balance, highlighting possible areas for further optimisation. The visualisations for each scenario are reported in Fig. 5, Fig. 6, and Fig. 7.

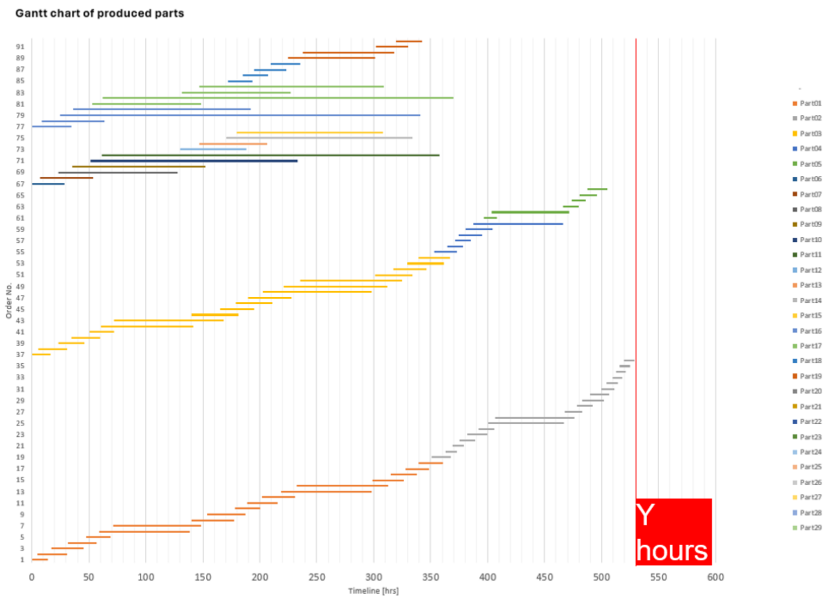

Fig. 5. Production schedule under baseline scenario.

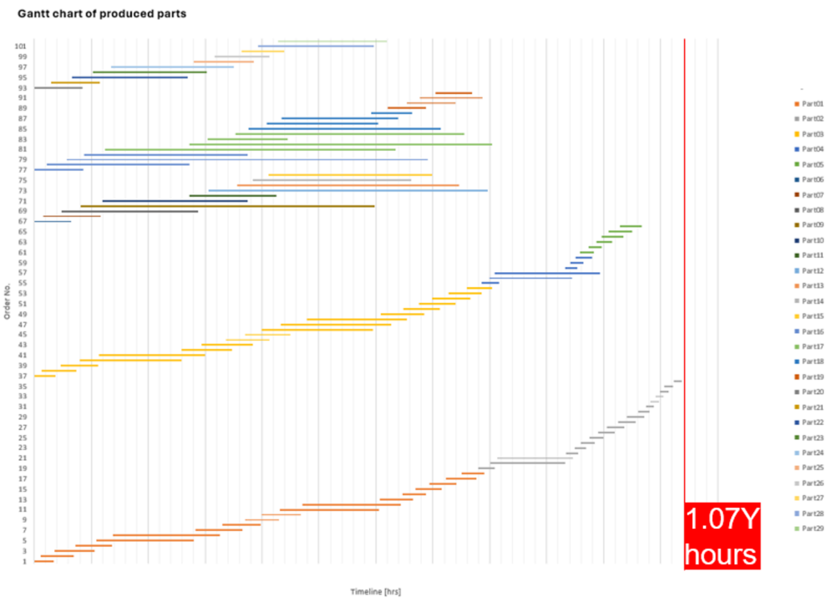

Fig. 6. Production schedule under first differential scenario

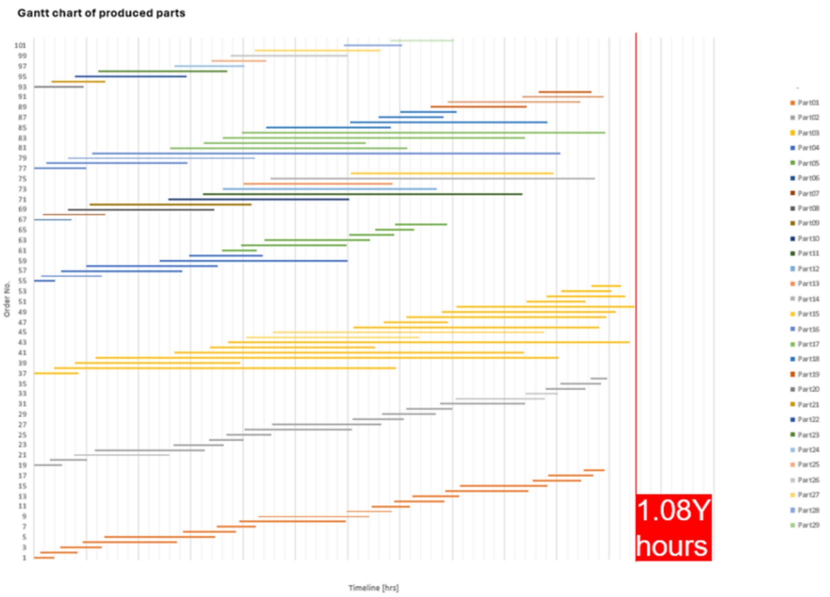

Fig. 7. Production schedule under second differential scenario

5 Conclusions

The development of the Discrete Event Simulation (DES) model provided GKN Aerospace with valuable insights for optimising future investments in a new machining cell. The simulation played a critical role in accurately sizing the system to meet projected demand levels, yielding benefits that extend beyond the individual cell to the broader production system. Specifically, the model helped identify the optimal number of parts to be manufactured on the new system and key resources, such as pallets, ensuring a well-balanced and efficient configuration that aligns with Lean Manufacturing goals of waste minimisation and improved flow.

Beyond its immediate application, the model delivers strategic value through its user-friendly and adaptable design. Implemented with an intuitive MS Excel-based interface, it enables industrial managers and decision-makers to independently run simulations, evaluate scenarios, and support data-driven planning. This supports long-term operational improvements and contributes to both efficiency and resilience of the production process.

The results of the simulation also highlight the importance of resource allocation strategies, such as the assignment of pallets to parts, in achieving production targets and maintaining system efficiency. The model's flexibility enables further studies, particularly in the area of production scheduling. Future research may focus on optimising part sequencing and pallet allocation to enhance throughput, reduce lead times, and further increase the system's overall capacity and responsiveness.

While the current study focused on scenario-based analysis, a more comprehensive sensitivity analysis represents a valuable direction for future work. Assessing how variations in key input parameters, such as machine availability, operator schedules, and part characteristics, impact system performance would strengthen the robustness of the model and deepen understanding of critical operational drivers.

In conclusion, this DES model not only supports informed capital investment decisions but also serves as a scalable and adaptable decision-support tool that can be integrated into broader operational planning strategies, consistent with lean principles of continuous improvement and empowerment of shop-floor decision-making.

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