Iisa Peltonen

Investigating Bottlenecks in a Job Shop Production Environment Through Discrete-Event Simulation

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Author: Iisa Peltonen
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ABSTRACT:

Bottlenecks are a central part of today's production systems and the challenges of their development. Especially in complex production environments, bottlenecks reduce efficiency, cause queues, and increase lead times. However, a key challenge is identifying bottlenecks and influencing their formation by modifying production parameters. The aim of this study is to analyze bottlenecks in a job-shop-type production environment and to determine how bottlenecks can be identified and analyzed using discrete-event simulation. In addition, the study examines how changing scheduling rules, adjusting WIP level, and modifying process variability affect the formation of bottlenecks. The analysis is based on key performance indicators, such as utilization, throughput, work in progress, queue lengths, and queue times.

The study was conducted using the simulation software AnyLogic, where a job shop production model consisting of seven workstations and five product types was developed. Several simulation scenarios were compared by modifying scheduling rules, production load levels, and process variability. The scheduling experiments included FIFO, LIFO, SPT, and LPT rules, while additional scenarios focused on reducing work-in-process (WIP) levels and modifying variability distributions.

The results showed that bottlenecks could be effectively identified using performance indicators such as utilization rate, queue lengths, waiting times, throughput, and WIP. In the baseline scenario, Machine 3 was identified as the primary bottleneck, reaching utilization rates of approximately 96–98% and the longest queue waiting times in the system. The SPT scheduling rule improved production flow and balanced workstation utilization more effectively than FIFO and LIFO, whereas LIFO increased congestion and accelerated queue growth. Lowering the production load reduced congestion and queue accumulation, but excessive reductions decreased throughput from approximately 22 products per hour to 12 products per hour due to underutilized capacity. In addition, increased variability caused the bottleneck to shift from Machine 3 to Machine 1, demonstrating the dynamic nature of bottlenecks.

The study demonstrates that discrete-event simulation is an effective tool for analyzing bottlenecks and evaluating production planning decisions without disrupting real manufacturing operations. The findings also highlight that bottlenecks are dynamic phenomena that can be managed through scheduling decisions, load balancing, and variability control.

KEYWORDS: Production bottlenecks, bottleneck analysis, discrete simulation, job shop production

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TIIVISTELMÄ:

Pullonkaulat ovat keskeinen osa nykypäivän tuotantojärjestelmiä ja niiden kehittämisen haasteita. Erityisesti monimutkaisissa tuotantoympäristöissä pullonkaulat heikentävät tehokkuutta, aiheuttavat jonoja ja pidentävät läpimenoaikoja. Keskeisenä haasteena on kuitenkin pullonkaulojen tunnistaminen sekä niiden muodostumiseen vaikuttaminen tuotannon parametreja muuttamalla. Tämän tutkimuksen tavoitteena on analysoida pullonkauloja job shop -tyyppisessä tuotantoympäristössä sekä selvittää, miten pullonkaulat voidaan tunnistaa ja analysoida diskreetin simuloinnin avulla. Lisäksi tutkimuksessa tarkastellaan, miten aikataulutussääntöjen muuttaminen, keskeneräisen tuotannon määrän säätäminen sekä prosessin vaihtelun muokkaaminen vaikuttavat pullonkaulojen muodostumiseen. Analyysi perustuu keskeisiin suorituskykymittareihin, kuten käyttöasteeseen, läpimenoon, keskeneräiseen tuotantoon, jonopituuksiin ja jonotusaikoihin.

Tutkimus toteutettiin AnyLogic-simulointiohjelmistolla, jossa rakennettiin job shop -tuotantomalli, joka koostui seitsemästä työasemasta ja viidestä tuotetyypistä. Simulaatiossa verrattiin useita eri skenaarioita muuttamalla aikataulutussääntöjä, tuotannon kuormitustasoja ja prosessin vaihtelua. Aikataulutuskokeet sisälsivät FIFO-, LIFO-, SPT- ja LPT-säännöt, kun taas muissa skenaarioissa keskityttiin keskeneräisen tuotannon määrän vähentämiseen ja vaihtelujakaumien muuttamiseen.

Tulokset osoittivat, että pullonkaulat voidaan tunnistaa tehokkaasti suorituskykymittareiden, kuten käyttöasteen, jonopituuksien, jonotusaikojen, läpimenon ja keskeneräisen tuotannon avulla. Perusskenaariossa Machine 3 tunnistettiin järjestelmän pääpullonkaulaksi, ja sen käyttöaste nousi noin 96–98 prosenttiin samalla, kun sillä havaittiin järjestelmän pisimmät jonotusajat. SPT-aikataulutussääntö paransi tuotannon virtausta ja tasapainotti työasemien käyttöastetta tehokkaammin kuin FIFO- ja LIFO-säännöt, kun taas LIFO lisäsi ruuhkautumista ja nopeutti jonojen kasvua. Tuotannon kuormituksen vähentäminen pienensi ruuhkia ja jonojen kertymistä, mutta liian suuret vähennykset laskivat läpimenoa noin 22 tuotteesta tunnissa 12 tuotteeseen tunnissa kapasiteetin alikäytön seurauksena. Lisäksi lisääntynyt vaihtelu siirsi pullonkaulan Machine 3:lta Machine 1:lle, mikä osoitti pullonkaulojen dynaamisen luonteen.

Tutkimus osoittaa, että diskreetti simulointi on tehokas työkalu pullonkaulojen analysointiin ja tuotannonsuunnitteluun liittyvien päätösten arviointiin ilman todellisen tuotannon häiritsemistä. Tulokset korostavat myös, että pullonkaulat ovat dynaamisia ilmiöitä, joita voidaan hallita aikataulutuspäätösten, kuormituksen tasapainottamisen ja vaihtelun hallinnan avulla.

AVAINSANAT: Production bottlenecks, bottleneck analysis, discrete simulation, job shop production

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Abbreviations

BNA – Bottleneck analysis
DBR – Drum-Buffer-Rope
DES – Discrete-event simulation
FIFO – First in, first out
LIFO – Last in first out
LPT – Longest processing time
Min – minutes
OEE - Overall equipment effectiveness
SPT – Shortest processing time
TOC – Theory of Constraints
WIP – Work-in-process

1 Introduction

In the modern production environment improving efficiency and continuous development are key requirements for competitiveness. Companies strive to increase productivity, shorten lead times and maintain high quality, while ensuring cost efficiency and smooth operations. Achieving these goals is made difficult by the complexity and variability of production systems, which cause imbalances in production. One of the most significant factors causing this imbalance is the formation of bottlenecks.

Bottlenecks represent one of the most critical challenges in manufacturing systems, as they limit throughput and decrease overall efficiency by increasing queues and waiting times (Lima et al., 2008, p. 1). Goldratt (1984/2024) defines a bottleneck as a production constraint that limits the throughput. Previous studies show that bottlenecks can cause significant throughput losses, up to 30 %, but their identification and management are often challenging, especially in complex and dynamic production environments (Mahmoodi et al., 2022). This is emphasized in job shop production, where high product variation, varying work stages, and changes in load can cause shifting and difficulty to predict bottlenecks (Yang & Jacobs, 1992, p. 1269).

Understanding and managing bottlenecks is essential for production development. Effective bottleneck management improves production flow, increases resource utilization, and supports overall system performance (Goldratt, 1990, p. 4). Simultaneously, it reduces waste, balances production, and promotes more sustainable operations. Therefore, bottleneck analysis is an important research topic both theoretically and from a practical production development perspective.

The purpose of this thesis is to investigate through simulation how bottlenecks are formed in production lines and how they can be reduced. The study is concentrated around two research questions:

> RQ1: How can production system bottlenecks be identified and analyzed using discrete-event simulation?
>
> RQ2: How do changes in production parameters influence bottleneck dynamics?

The empirical part of the study is carried out by building a discrete simulation model that describes a job shop-type production system. The model is used to analyze production performance based on key metrics such as throughput, utilization, queue lengths, and lead times. Several simulation experiments are used to evaluate how different changes affect the formation of bottlenecks and production efficiency.

The key contribution of this work is to provide a systematic approach to analyzing bottlenecks using simulation. The results provide information on how to develop a more efficient and balanced production system, and how bottlenecks can be better managed in practical production environments.

2 Theoretical framework

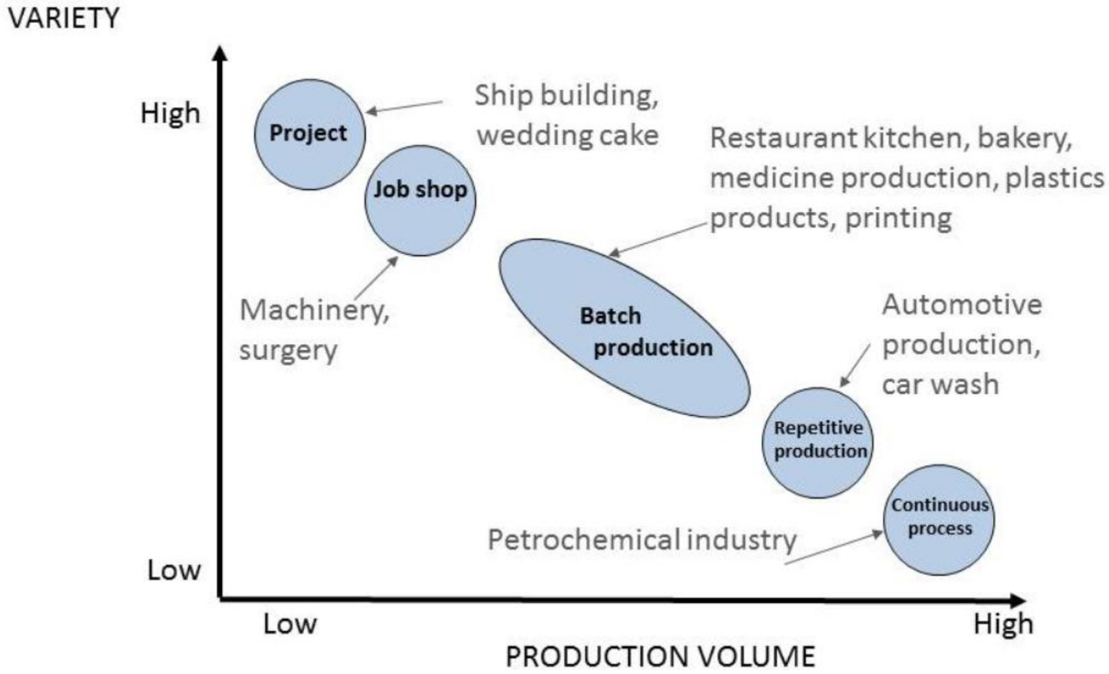
This literature review examines existing research on how bottlenecks are defined, identified, and managed within manufacturing systems. The methodology involves systematically collecting, reviewing, and synthesizing peer-reviewed journal articles, books, conference papers, and industry publications related to bottleneck detection and production flow optimization.

The literature was selected using keywords including bottleneck, bottleneck detection, operations management, capacity constraints, and discrete-event simulation in academic databases. Sources were evaluated based on relevance, publication quality, and the clarity of their methodological contributions. The review focused on identifying common detection methods, such as capacity analysis, queue length monitoring, and throughput evaluation, as well as strategies for bottleneck prevention through planning and control measures.

This chapter first introduces different types of production systems to highlight the need for various production approaches. Particular focus is placed on job shop production, as it serves as the basis for the simulation model used in this research. The chapter then reviews production planning methods and examines bottlenecks and bottleneck analysis in more detail. In addition, methods for preventing bottlenecks are discussed, along with key concepts from continuous improvement, including the theory of constraints and optimized production technology. Finally, the chapter concludes with an overview of discrete-event simulation, which forms the methodological foundation for the analyses conducted in the empirical part of the study.

2.1 Production types

Different types of production exist because products cannot always be manufactured in the same way. Various manufacturing types refer to how goods or services are produced, on what scale, with what methods, and for what purpose (Aswathappa & Shridharabhat, 2008, p. 70). The choice of production method depends on several factors, including product quantity, quality requirements, cost considerations, and customer needs (Goldense, 2015). This choice is further influenced by key process-related decisions in operations management, such as process choice, vertical integration, resource flexibility, customer involvement, and capital intensity (Aswathappa & Shridharabhat, 2008, p. 68). The following picture presents different types of production processes according to product variety and production volume, together with practical examples (Logistiikan maailma, 2025). The model, originally introduced by Hayes and Wheelwright, illustrates how different production types are positioned along the diagonal axis based on the relationship between production volume and the amount of product variants (Logistiikan maailma, 2025).



Picture 1 Production types (Hayes & Wheelwright, 1979).

These decisions define the structure and operation of the production system (Aswathappa & Shridharabhat, 2008, p. 68). Most manufacturing companies fit into five general categories: repetitive, discrete, job shop, batch process, and continuous process

(Goldense, 2015, p. 88). These process types differ in terms of production volume, product variety, flexibility, and resource requirements (Aswathappa & Shridharabhat, 2008, p. 68). Process choice determines how resources are arranged, either around specific products or functional processes, in order to effectively implement the desired production flow strategy (Aswathappa & Shridharabhat, 2008, p. 68).

Job shop processes are used for low-volume, high-variety production, where each product is customized and follows a unique processing route, requiring flexible equipment and skilled labor (Aswathappa & Shridharabhat, 2008, p. 68). Batch processes are suitable for moderate volumes and product variety, where similar products are produced in groups, enabling a balance between flexibility and efficiency (Aswathappa & Shridharabhat, 2008, p. 68). Repetitive processes, also known as assembly line processes, are used for high-volume production of standardized products, where resources are organized around the product and production follows a fixed sequence with limited flexibility (Aswathappa & Shridharabhat, 2008, p. 68). Continuous processes represent highly standardized, high-volume production with minimal variation, typically operating in a constant flow and requiring significant capital investment (Aswathappa & Shridharabhat, 2008, p. 68). Finally, project processes involve highly customized, large-scale, and complex activities that require substantial resources and extended timeframes, such as construction or product development projects (Aswathappa & Shridharabhat, 2008, p. 68). More about these production types and their layouts can be found in the following chapter.

2.1.1 Layout

In production, the layout has an enormous impact on efficiency. Layout refers to arranging and grouping the machines and working stations that produce goods (Aswathappa & Shridharabhat, 2008, p. 140). An inefficient layout in a manufacturing facility can result in increased lead times, decreased overall efficiency, and formation of bottlenecks. A well-planned layout can provide capacity for production, reduce material handling, and improve productivity (Aswathappa & Shridharabhat, 2008, pp. 140-141).

In addition, an effective layout offers several operational and human-resource benefits. It reduces congestion that may hinder the movement of materials and personnel, minimizes hazards and workplace accidents, and promotes employee safety and well-being (Aswathappa & Shridharabhat, 2008, pp. 140-141). Efficient utilization of labor and space is achieved, leading to higher machine and equipment utilization and ease of maintenance (Aswathappa & Shridharabhat, 2008, pp. 140-141). A good layout also improves supervision, facilitates coordination and face-to-face communication where appropriate, and provides flexibility for changes in product volume and variety (Aswathappa & Shridharabhat, 2008, pp. 140-141). Furthermore, by creating a safer and more organized work environment, an effective layout contributes positively to employee morale (Aswathappa & Shridharabhat, 2008, pp. 140-141).

There are multiple ways to design a factory layout. Several factors must be considered when selecting the most suitable layout for production needs. The main factors that influence facility layout are the relationship among the materials, including the storage space and material handling, machinery, and personnel (Aswathappa & Shridharabhat, 2008, p. 141). In addition, product type, workforce characteristics, industry type, and management policies also have an impact when choosing the layout (Aswathappa & Shridharabhat, 2008, p. 141).

The different layout types can be categorized as process layout, functional layout or job shop layout (Aswathappa & Shridharabhat, 2008, p. 144). These refer to a production arrangement in which machines and workstations that perform similar functions are grouped into their own departments (Aswathappa & Shridharabhat, 2008, p. 144). This layout is especially used in batch and single-unit production because it offers flexibility for handling different products and production stages (Aswathappa & Shridharabhat, 2008, pp. 144-146). However, this type of layout requires more floor space and makes material handling and production control more difficult. (Aswathappa & Shridharabhat, 2008, pp. 144-146). In Figure 1, the process layout is shown more closely.

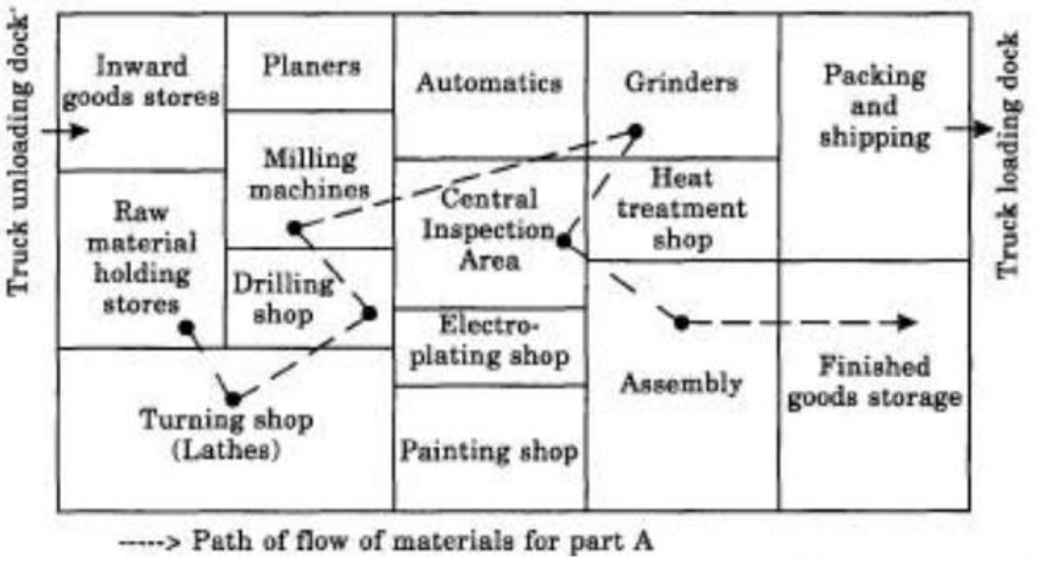


Figure 1 Process -, functional - or job shop layout (Aswathappa & Shridharabhat, 2008, p. 145).

Another option is product layout, line processing layout, or flow-line layout (Aswathappa & Shridharabhat, 2008, p. 144). In this type of production layout, the machines are organized into a line (Aswathappa & Shridharabhat, 2008, p. 146). The materials are fed into the first machine, and finished goods come out from the last machine, as demonstrated in Figure 2 (Aswathappa & Shridharabhat, 2008, pp. 146-147). This type of layout is used when the manufactured goods are standardized and production volume is high (Aswathappa & Shridharabhat, 2008, p. 147). The said layout increases efficiency through smooth material flow, reduced handling costs, shorter production time, and better production control (Aswathappa & Shridharabhat, 2008, p. 147). However, it is inflexible and expensive, and any machine breakdown can disrupt the entire production line (Aswathappa & Shridharabhat, 2008, p. 147).

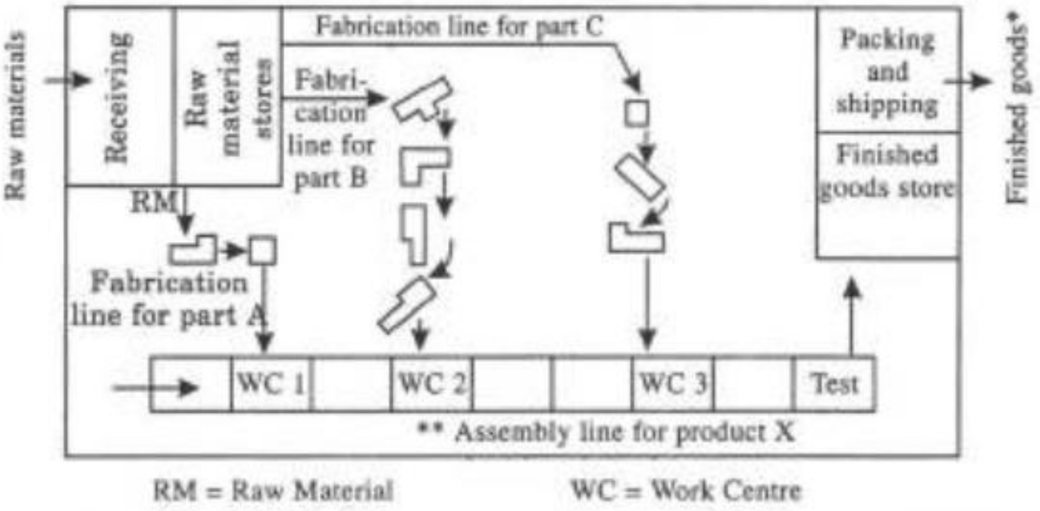


Figure 2 Product layout (Aswathappa & Shridharabhat, 2008, p. 147).

Another type of production layout is a fixed position layout, also known as a static layout (Aswathappa & Shridharabhat, 2008, p. 149). It is designed for the manufacture of bulky and heavy products for which it is impractical or inefficient to move the product from one place to another (Aswathappa & Shridharabhat, 2008, p. 149). Therefore, the product remains in a fixed position, while materials, equipment, and other resources are brought to the product's location (Aswathappa & Shridharabhat, 2008, p. 149). This manufacturing process layout is illustrated in Figure 3.

Figure 3 Fixed position Layout (Aswathappa & Shridharabhat, 2008, p. 149).

In addition, there is a cellular manufacturing layout or group technology layout (Aswathappa & Shridharabhat, 2008, p. 150). Cellular layout refers to a production arrangement in which machines are grouped into cells to manufacture a specific subfamily with similar characteristics and process requirements, as shown in Figure 4 (Aswathappa & Shridharabhat, 2008, p. 150). Its benefits include shorter lead times, lower work-in-progress inventories, less material handling, and improved productivity and delivery reliability (Aswathappa & Shridharabhat, 2008, p. 150).

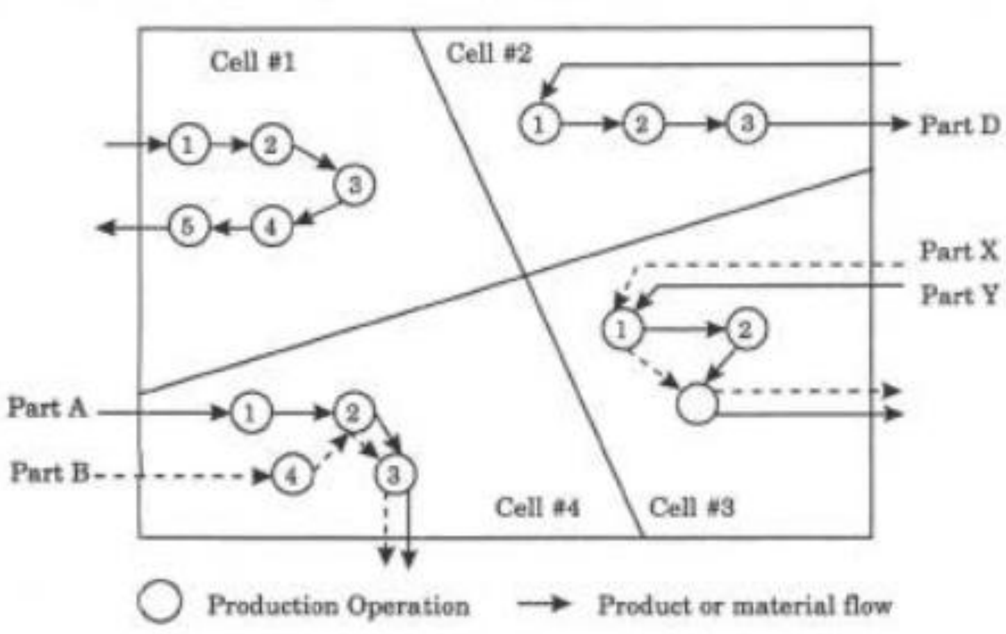


Figure 4 Cellular manufacturing layout (Aswathappa & Shridharabhat, 2008, p. 150).

Lastly, there is a combination or hybrid layout (Aswathappa & Shridharabhat, 2008, p. 150). A combined layout is a production arrangement in which different layout types, such as process and product layouts, are combined in the same factory, as pure layouts rarely occur in practice (Aswathappa & Shridharabhat, 2008). It is used when the products to be manufactured are similar but not completely identical, and the production involves both parts manufacturing and assembly (Aswathappa & Shridharabhat, 2008, p. 150). For example, a process layout is applied in parts manufacturing and a product line layout in assembly (Aswathappa & Shridharabhat, 2008, p. 150). The advantages of this layout are combining the best aspects of different layouts, efficient use of space and resources, flexibility for variable production, and improved overall production efficiency (Aswathappa & Shridharabhat, 2008, p. 150). The disadvantages are more complex planning and management, potentially longer material flows, and the need for careful coordination between different departments (Aswathappa & Shridharabhat, 2008, p. 150). A combination layout is illustrated in Figure 5.

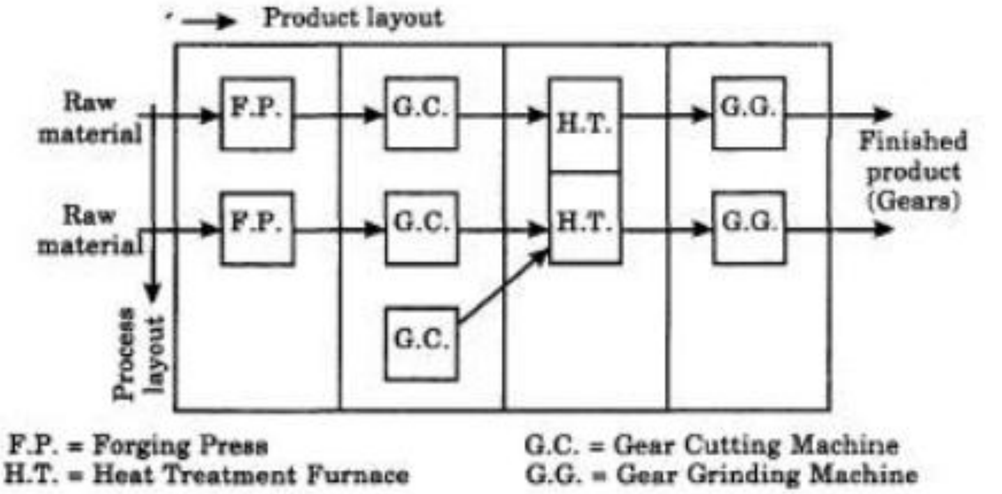


Figure 5 Hybrid layout (Aswathappa & Shridharabhat, 2008, p. 151).

2.2 Job shop production

This section examines the theory of job shop production in greater detail, as the simulation will be conducted in a job shop production environment. Job shop production is a manufacturing system where small batches of customized products are produced using general-purpose machines and skilled labor (Yang & Jacobs, 1992). Each job follows a different processing route through the machines, depending on the specific requirements of the product (Yang & Jacobs, 1992). Job shop process is illustrated in Figure 6.

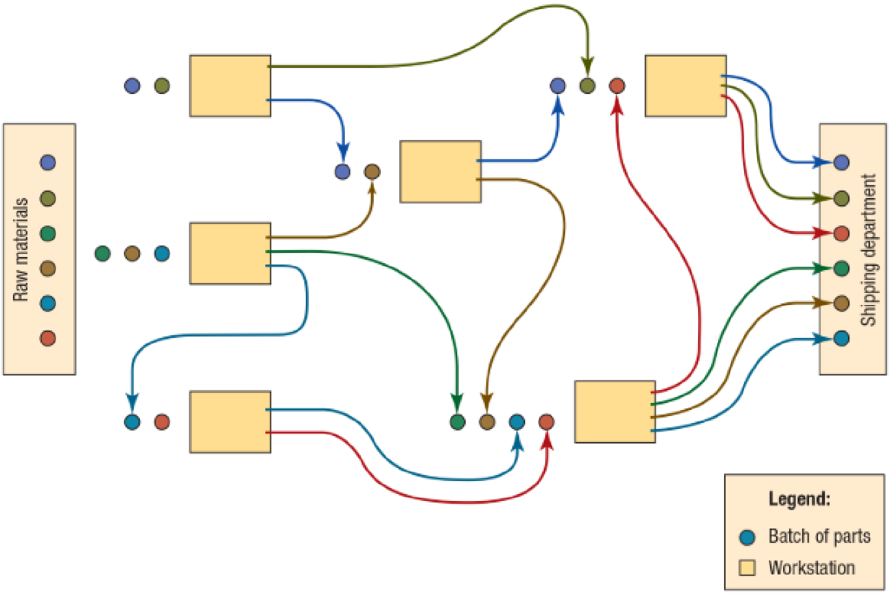


Figure 6 Job shop process (Krajewski & Malhotra, 2025, p. 594).

Job shop production is particularly suitable for batch and single-unit manufacturing due to its flexibility in handling a wide variety of products and varying production requirements (Aswathappa & Shridharabhat, 2008, pp. 144–146). Due to its versatility and low manufacturing volumes, a job shop environment can accommodate a wide variety of tasks and offer customized goods or services (Aswathappa & Shridharabhat, 2008, p. 70).

Job Shop production, however, presents its own challenges. One well-known challenge in the industry is scheduling problems (Yi, Tan, 2020, p. 15). Each factory has a certain number of machines, and each machine has a certain number of jobs to produce (Yi, Tan, 2020, p. 15). In addition each machine has its own processing time per product (Yi, Tan, 2020, p. 15). Every product goes through the machines in a predefined order, and only once throughout the process (Yi, Tan, 2020, p. 15). A scheduling problem occurs when each product is in different stages of production for different amounts of time (Yi, Tan, 2020, p. 16). Another product is ready for the next stage in production, but the machine is occupied by another product that takes longer to finish (Yi, Tan, 2020, p. 16). This causes production imbalances and queues in production (Yi, Tan, 2020, p. 16).

Other challenges are the higher manufacturing costs (Aswathappa & Shridharabhat, 2008, p. 70). Because of the versatility and variability, the cost per unit is high, and the cost estimation is difficult (Aswathappa & Shridharabhat, 2008, p. 70). Also, manufacturing in shops is slow and the work-in-process inventories are high (Aswathappa & Shridharabhat, 2008, p. 70).

2.3 Production planning methods

Production planning plays a central role in determining how effectively a manufacturing system utilizes its resources and meets customer requirements (Jyothi & Dubey, 2023). It is something that companies often invest in (Halonen, 2025). Production scheduling in a job shop environment is typically organized around three main functions: the sales center, the order center, and the production center (Matsui & Nakada, 2003). It involves decisions related to job sequencing, resource allocation, and workload distribution, all of which directly influence key performance measures such as throughput, lead times, work-in-process inventory, and makespan (Jyothi & Dubey, 2023). In addition, it is essential to consider the required tooling, finish, specifications, part count, task time, customer delivery expectations, current part location, and the current and planned workload of each line or station (Halonen, 2025).

In job shop manufacturing environments, where product routes and processing times often vary significantly, production planning becomes particularly challenging (Lang et al., 2020, p. 3057) and has a strong impact on the formation and behavior of production bottlenecks (Krajewski & Malhotra, 2025, p. 594). The variation is often due to non-value-added things that the workers are often asked to do (Halonen, 2025). In this chapter, the most common planning methods for a job shop manufacturing environment are reviewed.

Modern production planning approaches consider dynamic decision-making, where production rates can be adjusted based on system conditions (Uit Het Broek et al., 2020).

Dynamic scheduling methods can be divided into three types: predictive–reactive, robust–proactive, and completely reactive scheduling (Cai et al., 2023, pp. 1373-1374). In predictive–reactive scheduling, an initial schedule is created in advance and then adjusted when disruptions occur (Cai et al., 2023, p. 1374). Robust–proactive scheduling, in contrast, aims to build a stable schedule that can absorb variability with minimal need for changes (Cai et al., 2023, p. 1374). Completely reactive scheduling does not rely on a predefined plan, but instead makes decisions in real time based on the current state of the system (Cai et al., 2023, p. 1374).

Production planning and control are commonly evaluated using a set of key performance measures that describe system flow and efficiency. Overall equipment effectiveness (OEE) is one of the primary performance metrics that evaluates equipment effectiveness by combining availability, performance efficiency, and quality rate (Muthiah & Huang, 2007, p. 4753). More concrete key metrics are throughput time, utilization rate, work-in-process, waiting times, and queues (Goldratt, 1984/2024).

One of the most common metric is the makespan time or throughput time, which means how much total time is required to do all the jobs (Goldratt, 1984/2024). Production is only as efficient as its slowest point, so knowing how much time each step takes is important (Goldratt, 1984/2024). Utilization describes the proportion of available capacity that is actively used in a production system and is commonly expressed as the ratio of actual output rate to maximum achievable capacity (Equation 1) (Krajewski & Malhotra, 2025, pp. 187, 593). Increasing utilization supports cost competitiveness by reducing unused resources (Krajewski & Malhotra, 2025, p. 593).

$$Utilization = \frac{Average\ output\ rate}{Maximum\ capacity}\ x\ 100\% \quad (1)$$

WIP refers to all the unfinished products, components, or assemblies that are needed to produce the final product (Krajewski & Malhotra, 2025, p. 318). Queues and waiting times serve as key indicators of system congestion, reflecting delays in processing and imbalances in resource utilization (Roser et al., 2002, p. 2). Elevated queue lengths and prolonged waiting times are commonly associated with bottlenecks, as they indicate that certain workstations are unable to process incoming jobs at the required rate (Roser et al., 2002, p. 2). These factors need to be considered when doing the production plan.

Production planning is implemented at multiple levels, with scheduling rules representing the operational level that determines job sequencing (Yao et al., 2022). Common rules include first-come, first-served (FCFS), shortest processing time (SPT), earliest due date (EDD), and critical ratio (CR), each influencing system performance and bottleneck behavior differently (Krajewski & Malhotra, 2025, chp 10). These rules can be adapted to varying production conditions and objectives, such as minimizing delays or improving fairness (Kumar & Suresh, 2009, pp. 238 - 253). Discrete-event simulation provides an effective tool for evaluating these rules and identifying bottlenecks and capacity constraints within the system (Krajewski & Malhotra, 2025, pp. 187, 593).

Production planning methods are guided by overarching strategies that define how production is organized and controlled within a manufacturing system (Yao et al., 2022). A fundamental distinction is whether production follows a pull-based approach, driven by actual customer demand, or a push-based approach based on forecasts (Yao et al., 2022). In addition, product strategies, such as make-to-order (MTO) and make-to-stock (MTS), determine whether production is initiated in response to specific orders or based on anticipated demand. Inventory management decisions, such as maintaining buffer stocks or adopting just-in-time (JIT) principles, affect how variability is handled within the system (Kumar & Suresh, 2009, pp. 53-57).

2.4 Bottlenecks

According to Betterton & Silver (2012, p. 4159) there is no single clear definition of a bottleneck; however, they define it as a part of a system or resource that has the greatest impact on overall system performance. For example, a resource that has more demand than capacity, where the work-in-process inventory waiting in the queue is maximum, or has the smallest production rate, usually becomes a bottleneck in production (Betterton & Silver, 2012, p. 4159).

Bottlenecks can be classified into three categories: simple bottleneck, multiple bottlenecks, and shifting bottleneck (Lima et al., 2008, p. 1746). Simple bottlenecks refer to systems where only one resource restricts flow, while multiple bottlenecks occur when two or more resources simultaneously limit production (Lima et al., 2008) . In a shifting bottleneck, the bottleneck is moving between different resources over time due to dynamic changes in workload, batch sizes, or system variability (Lima et al., 2008, p. 1746). The different kinds of bottlenecks are represented in Figure 7.

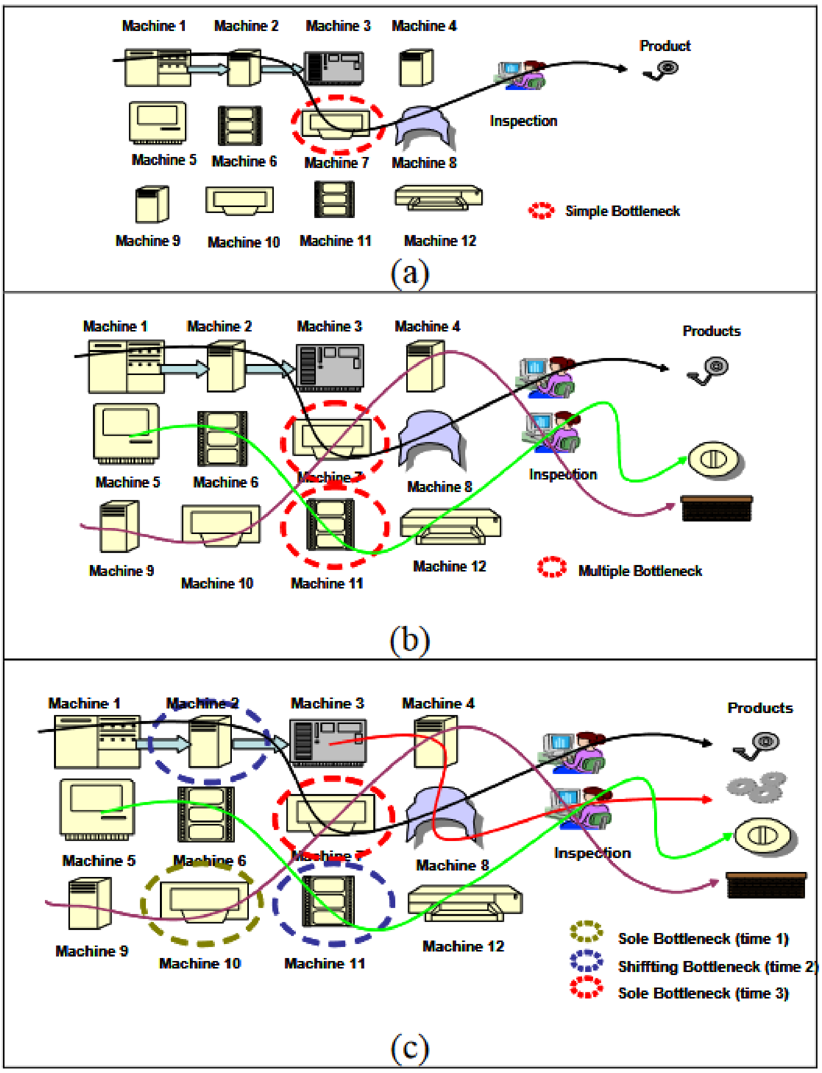


Figure 1: a) Simple Bottleneck, b) Multiple Bottleneck, c) Shifting Bottleneck

Figure 7 Types of bottlenecks (Lima et al., 2008, p. 1746).

For production to be as effective as possible, the bottleneck needs to be detected and eliminated or minimized, as according to Goldratt (1984/2024), production can be as efficient as the constraint is. Bottlenecks can be complex and usually inevitable (Goldratt, 1984/2024). They can hard to detect, thus detection techniques and methods to analyze the production are required (Gundogar et al., 2016). This process is called bottleneck analysis, and it has four critical steps: detection, diagnosis, prediction, and prescription (Mahmoodi et al., 2022, p. 3). In the following parts, the bottleneck analysis phases are defined and explained in more detail.

2.4.1 Bottleneck detection

Bottleneck detection or identification methods are used to locate the bottleneck or bottlenecks in a system (Mahmoodi et al., 2022, p. 3). Bottleneck detection is often based on various data gained from production parameters (Huang et al., 2019, p. 280). These parameters include, for example, buffer level, machine blockage and starvation, machine utilization, machine fault, and processing state (Huang et al., 2019, p. 280).

The most common method is counting the utilization factor of each station (Lima et al., 2008, p. 1747). If the percentage is high, it is likely the bottleneck in production (Lima et al., 2008, p. 1747). Another effective method is through put monitoring, which involves counting the number of units each station outputs per hour (Goldratt, 1984/2024). In addition, one method to detect bottlenecks is cycle time analysis. Comparing cycle time at every workstation and identifying which has the longest cycle time is the bottleneck (Goldratt, 1984/2024).

Queue-based analysis can be used to identify bottlenecks by comparing queue lengths or waiting times at different workstations, where the station with the highest values indicates the constraint (Roser et al., 2002, p. 2). This approach enables both real-time detection of temporary bottlenecks and identification of persistent bottlenecks through average queue or waiting time measures (Roser et al., 2002, p. 2). The bottleneck can be considered a station where either the average waiting time, measured as the average time a job spends in the queue, or the maximum waiting time, measured as the longest time a job spends in the queue, is observed (Betterton & Silver, 2012, p. 4161). The bottleneck is the station that consistently carries the longest queue of waiting jobs over the majority of the production period (Betterton & Silver, 2012, p. 4161). In practice, this involves periodically comparing queue lengths at all machines and tracking which station has the longest queue at each observation point, with the average maximum queue length used as a practical approximation (Betterton & Silver, 2012, p. 4161). These are only some of the detection methods, while several others also exist.

A good starting point for identifying bottlenecks or improving production is to use a quick field method (Goldratt, 1984/2024). This involves walking through the factory and looking for queues, overstock, waiting machines or workers, and other abnormalities (Roser et al., 2002). In contrast to overcapacity, another indication of a bottleneck is when a machine is continuously processing without any idle time (Goldratt, 1984/2024).

2.4.2 Bottleneck diagnosis

Bottleneck diagnosis is performed to find and prioritize the root causes of bottlenecks (Mahmoodi et al., 2022, p. 3). Bottleneck root causes are often due to variability in operations, including unpredictable arrivals, setup durations, processing times, and equipment failures (Mahmoodi et al., 2022, p. 3). These disturbances can be either dominant, which halt production immediately, or recessive, which gradually degrade performance over time (Mahmoodi et al., 2022, p. 3). While recessive disturbances are less visible, they can still lead to substantial long-term throughput losses (Mahmoodi et al., 2022, p. 3).

2.4.3 Bottleneck prediction

Bottleneck prediction methods help decision-makers become aware of future bottlenecks based on historical data (Mahmoodi et al., 2022, p. 3). However, due to the nature of dynamic shops, the detected bottleneck based on historical data is not always the same and can change (Ma et al., 2023, p. 4437). This is highlighted especially in shops that have frequent demand changes and various stochastic disturbances (Ma et al., 2023, p. 4438). In addition to variability on demand, sudden anomalies like machine failures or changes in manufacturing techniques or times make predictions challenging (Huang et al., 2019 p. 278).

Bottleneck management is focused on two different approaches: proactive bottleneck prediction and reactive mitigation strategies (Tang et al., 2024, p. 9). Dynamic bottleneck prediction enables the detection of future bottlenecks in a production system in advance, which helps improve efficiency and resource utilization (Tang et al., 2024, p. 9). Traditional static models are inflexible, whereas dynamic methods based on real-time data offer a more accurate and faster way to predict bottlenecks in changing production environments (Tang et al., 2024, p. 9).

By recognizing these potential bottlenecks early, companies can implement targeted improvements that increase overall efficiency and optimize resource utilization (Tang et al., 2024, p. 9). Bottleneck prediction methods typically rely on shop-floor data and machine logs and are developed using simulation with predictive analytics, network-based analysis, or neural-network-driven approaches (Mahmoodi et al., 2022, p. 3).

2.4.4 Bottleneck prescription

Bottleneck prescription is performed to prescribe a set of recommendations, based on results generated during descriptive and prescriptive analytics, for future improvement (Mahmoodi et al., 2022, p. 3). In practice, this reactive bottleneck management method focuses first on identifying the root cause of the bottleneck and then optimizing resources, such as improving machines, workflows, and schedules. (Tang et al., 2024, p. 9–10). Continuous monitoring and real-time control systems are essential for enabling the production system to adapt to rapidly changing bottlenecks and minimize their impact on production (Tang et al., 2024, pp. 9–10).

2.5 Methods for preventing bottlenecks

One effective approach to managing bottlenecks is load leveling, which balances tasks and distributes work more evenly across resources to avoid overload (Akhtar et al., 2019,

p. 1). Batch size reduction also plays a key role, as smaller batches decrease waiting times and reduce variability in the system (Akhtar et al., 2019). By varying the batch sizes, it is possible to move the bottleneck into a different phase of the production. In a job shop environment with diverse product types, it is important to use the correct batch sizes to keep production running as smoothly as possible (Krajewski & Malhotra, 2025, p. 225).

Scheduling optimization and prioritization are also important, as efficient job sequencing helps prevent temporary congestion at critical stages of the production process (Akhtar et al., 2019). Finally, lead time management, including reducing setup times and improving material flow, is shown to increase system flexibility and minimize bottleneck formation significantly (Akhtar et al., 2019). Maximizing the number of units handled per setup means fewer setups are needed per year (Krajewski & Malhotra, 2025, p. 225). This reduces the overall time spent on setups and at the same time reduces the variability in manufacturing times (Krajewski & Malhotra, 2025, p. 225).

One method for preventing bottlenecks is to create more capacity (Goldratt, 1984/2024). This usually means new investments in means of process automation, hiring new employees or new workstations, or even outsourcing production (Goldratt, 1984/2024). However, adding capacity is effective only when the bottleneck is stable and does not shift or occur at multiple locations (Goldratt, 1984/2024). Some methods for adding capacity require capital investment and may not be the most suitable solution in all cases. However, the time and costs lost at the bottleneck are often offset by improved overall manufacturing efficiency and increased throughput (Goldratt, 1984/2024).

Capacity can also be added by changing the manufacturing process to be more efficient and eliminating the waste time in the process (Goldratt, 1984/2024). This approach investigates the possibility of improving the manufacturing process. There are three main techniques for defining and analyzing the processes, which are flowcharts, work measurement techniques, and process charts (Krajewski & Malhotra, 2025, pp. 92-99). Methods for defining processes make it easier to spot performance gaps, develop improvement ideas, and clearly describe how a redesigned process works (Krajewski & Malhotra, 2025, pp. 92-99).

One method is to analyze the entire process through simulations (Krajewski & Malhotra, 2025, pp. 531–544). This allows modifications to be tested and their impact on production to be evaluated without disrupting the actual manufacturing system (Krajewski & Malhotra, 2025, pp. 531–544). After different scenarios have been tested in the simulation environment, the most suitable changes can then be implemented in real-life production (Krajewski & Malhotra, 2025, pp. 531–544).

2.6 Theory of constraints

When discussing production and improvement methods, the theory of constraints (TOC) is central in the field. TOC aims to answer the questions of what should be changed and how to accomplish that (Freeman, 2006). The constraints are anything physical or non-physical that prevents the company from achieving its goals (Freeman, 2006). Constraints can also be considered things that limit a system from achieving higher performance (Goldratt, 1990, p. 4). The core belief in TOC is that every system has at least one constraint (bottleneck) that limits the performance of the entire system (Goldratt, 1990, p. 4). However, in production, the constraints are bottlenecks that restrain the throughput (Freeman, 2006).

In TOC, the central framework is based on five focusing steps to identify or exploit the system's constraints (Gupta & Boyd, 2008, p.999). The five focusing steps are (1) identify the constraints of a system, (2) decide how to exploit the system's constraints, (3) subordinate everything to the decision in step 2, (4) elevate the system's constraints, and (5) once a constraint is broken, go back to step 1 (Freeman, 2006). In the first step, in addition to identifying the constraints, they have to be prioritized according to their impact on the goal (Goldratt, 1990, p. 5). In step 2, the plan is made for how to manage the relevant constraints, and in step 3, the changes are made because, whatever the constraints are, there is a way to limit their impact (Goldratt, 1990, p. 5). When the capacity of the constraints has reached its maximum level, the next step is to extend and elevate the constraint (Goldratt, 1990, p. 6). When or if the constraint has been broken, then go back to step 1, and this is the last step, and the process will start again (Goldratt, 1990, p. 6). This will create an effective ongoing cycle of improvement (Goldratt, 1990, p. 7).

One of the key practical applications of TOC is the Drum-Buffer-Rope method (DBR) (Thürer & Stevenson, 2018). DBR is a production control method in which the rhythm of the entire system (drum) is determined by the bottleneck, buffers (buffer) protect it from disturbances, and a “rope” (rope) controls the release of material into production so that the bottleneck is not overloaded (Thürer & Stevenson, 2018, p. 3295). Figure 8 visualizes the central idea of the DBR method.

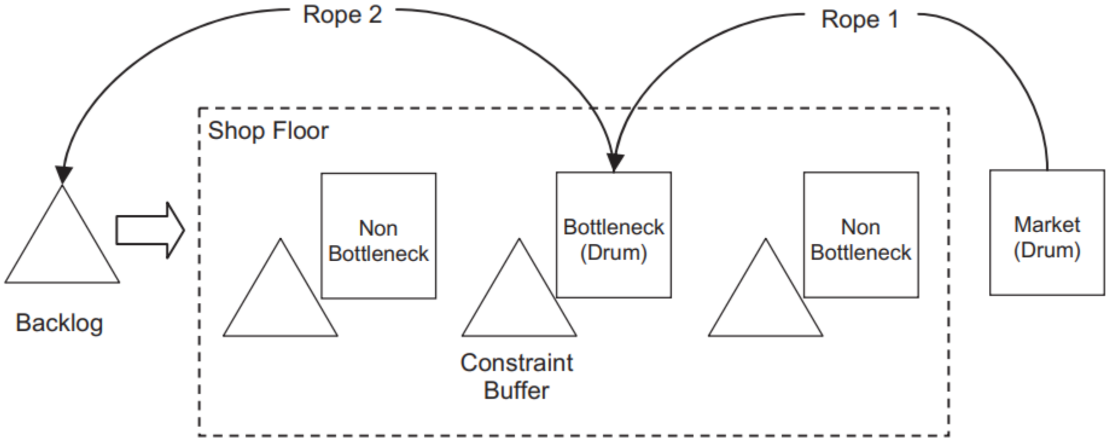


Figure 8 Drum-Buffer-Rope (Thürer & Stevenson, 2018, p. 3295).

The main objective of DBR is to control the release of jobs to the system in accordance with the output rate of the bottleneck, thereby ensuring a smooth and synchronized production flow (Thürer & Stevenson, 2018, P. 3294). Jobs are not released directly to the shop floor but are instead held in a backlog and released based on the bottleneck schedule (Thürer & Stevenson, 2018, p. 3294). In practice, DBR has been shown to improve lead times and due date performance, thereby stabilizing production flow (Thürer & Stevenson, 2018, p. 3294).

Theory of Constraints (TOC) is a heuristic method that is well-suited to simulation environments because of its simplicity, and its iterative principles can be easily modeled and tested in different scenarios (Gundogar et al., 2016, p.2). The main steps that should be taken into account are material, machine, and man (workforce) (Gundogar et al., 2016). These problems can be effectively solved in a simulation-based manner by focusing on identifying and removing bottlenecks and evaluating their impact on the performance of the entire system (Gundogar et al., 2016, p.2).

2.7 Optimized production technology

Optimized production technology (OPT) is a scheduling ideology and software developed by Eliyah Goldratt in the early 1980s (Goldratt, 1984/2024). The main idea of OPT is that production is controlled according to bottlenecks, not by optimizing each work step separately. The goal is a steady flow, where scheduling, inventories, and work in progress are kept to a minimum within the constraints (Şimşit et al., 2014).

When optimizing production, the main focus should be the bottlenecks, as there is no need to optimize the non-bottleneck steps in the production (Goldratt, 1984/2024). This ideology is based on the idea that an hour wasted in the bottleneck is an hour wasted in the whole production (Goldratt, 1984/2024). This is why the goal is to create an optimized and balanced production flow where the scheduling is defined by the constraints (Goldratt, 1984/2024). The way to create a balanced flow is not by optimizing the capacity, but by optimizing the flow so the company meets its goals (Goldratt, 1984/2024). OPT later evolved into the modern TOC approach to production control (Şimşit et al., 2014, p. 931).

2.8 Discrete-event simulation

According to Choi & Kang (2013, p. 17), simulation is defined as “ *the technique of imitating the behavior of some situation by means of an analogous situation or apparatus to gain information more conveniently or to train (or entertain) personnel.”* The simulations are divided into two categories based on the goal (Choi & Kang, 2013, p. 17). The first one, called analytic simulation, is to gain information, and the second one is a virtual environment simulation, where the aim is to train or entertain personnel (Choi & Kang, 2013, p. 17).

The dynamic systems can be divided into 3 types of systems: discrete-event systems, continuous systems, and quantum systems (Choi & Kang, 2013, p. 18). A system is defined according to Zhang and Tsinghua University (2017, p. 67) as *“a set of some elements that are mutually independent and relate to each other and can achieve some specific functions together.”* A continuous system is one in which time and/or state variables change continuously over time, with state variables defined at all points in time and typically described using differential equations (Zhang and Tsinghua University, 2017, pp. 25-26).

Like systems, the simulations can also be divided into different types. The different types of simulation models are discrete-event simulation, agent-based simulation, Monte Carlo simulation, and continuous simulation (Choi & Kang, 2013). Regarding this research, the main interest is in discrete-event simulation.

Discrete simulation refers to a model or method in which discrete event systems are described step by step in time (Choi & Kang, 2013, p. 25). A discrete event system includes, for example, manufacturing systems, transportation systems, service systems, and communication systems (Choi & Kang, 2013, p. 25). *“A discrete-event simulation aims to learn about the behavior and performance potential of the system, and it is accomplished by the activities in which the resources and entities in the DES engage”* (Choi

& Kang, 2013, p. 26). DES helps predict and improve processes such as support, queuing, or warehousing without requiring manual acquisition.

One part of simulation research is verification and validation (Sargent, 2010, p. 166). Verification is defined according to Sargent (2010, p. 166) as ensuring that the simulation model and its implementation are accurate and function as intended. Validation focuses on whether the model accurately represents the real system for its intended purpose (Sargent, 2010, p. 166). A credible simulation requires that it is verified and validated, and the simulation serves its purpose for which it was created (Sargent, 2010, p. 166).

2.8.1 How to build a discrete-event simulation model

When conducting a simulation study, there is a seven-step approach making sure that the simulation is going to be successful (Law, 2009, p. 25). This approach is shown more closely in Figure 9. The first step, like in any other research, is formulating the problem and defining the objectives, scope, and time framing (Law, 2009, p. 25). The next step is data collection and forming the hypothesis and assumptions (Law, 2009, p. 25). Information about the system structure, operating procedures, model parameters, input probability distributions, performance data, and model assumptions must be collected and documented, while the level of model detail should be determined based on project objectives, performance measures, and data availability (Law, 2009, p. 25).

The third step, according to Law (2009, p. 26), is checking the validity of the previous step. If all requirements are met, then the next tasks are to program the model and check if it is valid (Law, 2009, p. 27). The simulation model should be validated by comparing its outputs with real system data when available, reviewing the results with experts for reasonableness, and conducting sensitivity analyses to identify factors that significantly affect system performance (Law, 2009, p. 27; Robinson, 1997).

The fifth step is designing, conducting, and analyzing the experiments (Law, 2009, p. 27). For each system configuration, the run length, warm-up period, and number of replications should be determined, and then the results should be analyzed to decide whether additional experiments are needed (Law, 2009, p. 27). In the last step, the study should be documented by describing the model assumptions, program details, and results, and the findings should be presented often with animation and an explanation of the model development and validation process to support credibility (Law, 2009, p. 27).

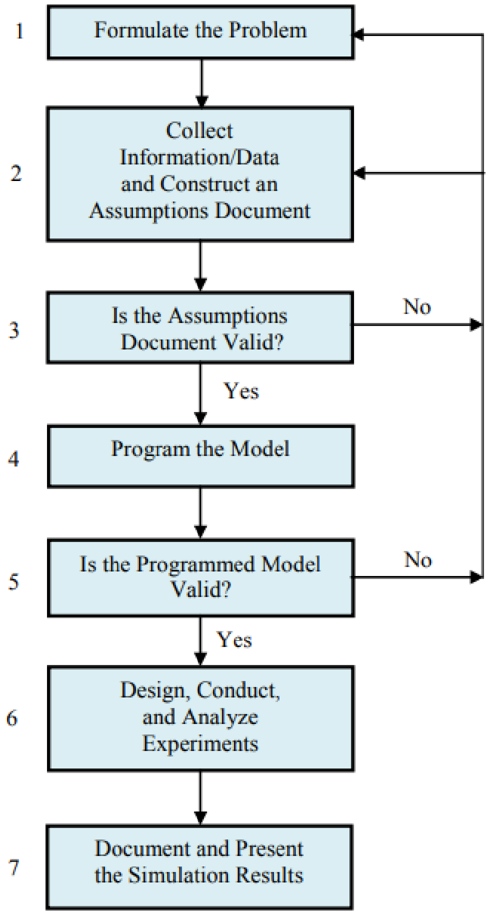


Figure 9 Seven-step model for conducting a simulation (Law, 2009, p. 26).

2.8.2 Variability

In addition to modelling the progress of time, the next challenge is to create variability in the system (Robinson, 2004, p. 26). Modelling variability is a central aspect of simulation because it is unrealistic to expect that everything happens in a clockwise manner on time without any changes or variability in production (Robinson, 2004, p. 26). Variability is needed to simulate for example humans different working phase, irregularities, different processing times and small malfunctions of equipment (Robinson, 2004, p.4)

In this research, the chosen variability to be used is triangular distribution. Triangular distribution is a continuous probability distribution which is bound on both sides (AnyLogic help, N.d). The triangular distribution is counted in the software using formula 1 (AnyLogic help, N.d). The distribution is defined by three parameters: the minimum value, the most likely value (mode), and the maximum value (AnyLogic help, N.d). It is commonly used in simulation models when exact statistical data is unavailable but reasonable estimates for the minimum, most probable, and maximum values of a variable can be determined (AnyLogic help, N.d). The triangular distribution is simple to add for this research and does not require exact data.

$$f(x) = \begin{cases} \dfrac{2(x - min)}{(max - min)(mode - min)}, & min < x \leq mode \\ \dfrac{2(max - x)}{(max - min)(mode - min)}, & mode < x \leq max \end{cases} \qquad (2)$$

2.9 Summary

This chapter provides the theoretical foundation for the study by reviewing production systems, production planning methods, bottlenecks, and discrete-event simulation. Based on the literature reviewed in this chapter, bottlenecks are strongly influenced by production planning decisions, system load, and process variability. The studies show that scheduling rules, WIP levels, and variability can significantly affect production flow, queue formation, and workstation utilization. In addition, bottlenecks are described as dynamic phenomena that may shift within the system over time depending on changing production conditions.

The Theory of Constraints and optimized production technology further demonstrated the importance of managing bottleneck resources effectively to improve overall system performance. Bottlenecks can be identified by monitoring performance indicators such as utilization rates, queue lengths, waiting times, throughput, and WIP levels, as bottleneck workstations typically exhibit high utilization together with growing queues and increased waiting times.

Discrete-event simulation provides an effective method for analyzing these phenomena, as different production scenarios can be tested without disrupting actual production. Therefore, the empirical part of this study focuses on evaluating how changes in scheduling rules, production load levels, and variability affect bottleneck behavior and overall system performance. These factors formed the basis for the simulation scenarios presented in Table 1.

3 Methodology

This study uses a quantitative research approach when investigating the characteristics of bottlenecks. The research combines a literature review with simulation-based analysis, enabling both theoretical understanding and empirical evaluation of bottleneck behavior. This approach allows system performance to be examined objectively using measurable indicators such as utilization, throughput, and waiting times.

Quantitative research is a systematic and empirical approach that focuses on investigating phenomena through the use of statistical, mathematical, and computational techniques (Ghanad, 2023). It emphasizes the collection and analysis of numerical data to identify patterns, relationships, and trends within the research subject (Golafshani, 2015). Quantitative study aims to answer questions how much, how often or why certain phenomena occur (Vilkka, 2021, part 1). To ensure objectivity and consistency in data collection, quantitative research commonly relies on structured tools such as surveys, tests, questionnaires, and statistical measurements or simulations (Ghanad, 2023, p. 3803).

For the empirical study part, the method chosen was simulation, and more specifically discrete-event simulation. The simulation was chosen to complement the literature review by adding a more realistic research setting. Simulation enables the analysis of complex and dynamic systems. Discrete Event Simulation (DES) is particularly well suited for manufacturing systems where events, such as job arrival, machine processing, queue formation, and resource allocation occur at different points in time. DES enables experimentation with different system configurations, making it possible to evaluate bottleneck behavior and improvement strategies under controlled conditions.

The simulations were conducted on AnyLogic simulation software. The model was built in the software to describe a realistic job shop style production company setting. However, the stations were not described too specifically, and all the stations were named as “machines” without specifying the type of work performed at the station. The model represents a production system consisting of workstations, queues, resources, and material flows.

In the simulation, first the stations were created and then decided how many different products this production would be manufacturing. The main entities, resources, and process flows were identified and represented using the AnyLogic Process Modeling Library. System dynamics were modeled through the implementation of queue, seize, delay, and release logic, enabling realistic representation of processing times, resource constraints, and material flow interactions between workstations. Then the figures were created on how the production flow would be, and the manufacturing steps and times for each product were defined. The model is designed to capture bottleneck behavior through key performance indicators, including workstation utilization, queue lengths, waiting times, throughput, and lead times, which provide a detailed basis for identifying capacity constraints and evaluating system performance.

To analyze bottlenecks and evaluate improvement strategies, multiple simulation experiments were conducted. These experiments included variations in resource capacities, scheduling rules, load levels, and changing variability. For each simulation, there were predefined limits set, and the simulations were run until the limits were reached. The limits that caused the error were either the maximum queue capacity or the maximum number of products manufactured. This approach allows assessment of how different planning and operational decisions influence bottleneck formation and system performance.

The analysis focuses on identifying bottlenecks, evaluating their impact on throughput and lead times, and assessing the effectiveness of proposed mitigation strategies. The data is collected from the simulation and exported to Excel, and then the key metrics were compared to find out the bottlenecks and their effects on the production line. The key metrics were WIP, utilization rate, queue, average queue time, and throughput per hour. These metrics were compared in different scenarios, and the analysis was made.

While simulation provides valuable insights, the results depend on model assumptions and input data quality. The model does not capture all real-world uncertainties, such as unexpected human behavior, errors, material shortages, machine breaks, or other extreme disturbances. Therefore, the results should be interpreted as indicative rather than exact predictions of real production performance.

Table 1 Table of experiments.

Case	Description	Description	Purpose
Case 0	Baseline scenario	Original production system parameters	Reference point for comparison
	Changing the processing order		
Case 1.1	LIFO	Processing order based on last-in-first-out	Evaluate the impact of the dispatching rule
Case 1.2	SPT	Processing order based on the shortest processing time	Evaluating scheduling efficiency
Case 1.3	LPT	Processing order based on the longest processing time	Compare scheduling strategies
	Reduced WIP		
Case 2.1	S1 0.15 and S2 0.05	Lowering the sources' feeding rate so that the WIP would not increase that much, and the production	Evaluate the effect of lower WIP
Case 2.2.1	S1 0.2 and 0.15 S2 FIFO	Gradual WIP reduction	Analyze progressive WIP control and compare the scheduling rules
Case 2.2.2	S1 0.2 and 0.15 S2 SPT	Gradual WIP reduction	Analyze progressive WIP control and compare the scheduling rules
	Changing Variability		
Case 3.1	Increasing relative variability	Processing time variation adjusted using a triangular distribution, using percentages	Study the impact of variability
Case 3.2	Absolute variability	Adjusting processing times using fixed time ranges in minutes	Study the impact of variability

In Table 1, all the experiments and their evaluated effect and the purpose of the change are tabulated. The experiment was done under three categories of change. In the first category, the processing order was changed to see how that affected the simulation and how the bottleneck changed. The processing orders that were used were last-in-first-out (LIFO), shortest processing time (SPT), and longest processing time (LPT). The goal was to compare the scheduling strategies and determine whether any performs significantly better or worse than the others, or whether there are any differences between them.

The second strategy was to lower the work-in-process (WIP). This was done in a few different phases. The WIP level was reduced by decreasing the production arrival rates from both sources, which allowed more processing time for machines and prevented the queues from reaching maximum capacity. This was done in 2 steps. First, the arrival rate was lowered to a minimum, and there were no queues forming. In this experiment, only the scheduling rule FIFO was utilized. In the next step, the arrival rate was set somewhere in the middle so that slight queues were forming and the utilization rate on the machines was above 50%. The second one was done on two different perspectives regarding the scheduling rules. The scheduling rules used in comparison were FIFO and SPT.

The third category was investigating the impact of variability in the process. In this scenario, all the original values were used, but the variability was changed. This scenario was done in two different cases. In case 3.1, the relative variability was increased to see if that had any effect on the bottleneck and production. In case 3.2, the variability was changed from relative to absolute variation. This was done because every product has a different delay with each machine, and percentage change does not always give the most realistic variability.

Each simulation scenario was evaluated using a set of performance metrics to assess system performance and identify potential bottlenecks. The selected metrics, presented in Table 2, were used to analyze production flow, resource utilization, and congestion within the system. In particular, these measures enable the identification of bottleneck locations and the evaluation of how the implemented changes affect overall system performance. Together, these metrics provide a comprehensive basis for evaluating system performance and understanding the impact of bottlenecks under different experimental conditions.

Table 2 Performance measures used in evaluation.

Measure	Description	Purpose in evaluation
Throughput	Number of completed jobs/products during the simulation run	Measures overall production output
Queue length	Number of jobs waiting at a workstation	Helps identify bottleneck-related accumulation
Resource utilization	Percentage of time a workstation is busy	Indicates capacity loading
WIP	Number of unfinished jobs in the system at given time	Indicates of system congestion and flow efficiency
Lead time	Average time jobs spend in the system	Measures flow efficiency
Waiting time	Average queue waiting time	Indicates congestion in the system
Makespan	Total time required to complete the production set	Measures overall schedule performance

4 Results: simulation

AnyLogic simulation software is created to be able to understand deeper insights and optimize complex systems and processes across a wide range of industries (AnyLogic, Nd). The software is used in different industries like supply chains, rail logistics, manufacturing, mining & metals, transportation, oil & gas, warehouse operations, and in ports and terminals (AnyLogic. Nd). The software has industry-specific libraries, and it offers multimethod modelling: discrete-event, agent-based, and systems dynamics, and they can be used in any combination with one software (AnyLogic. Nd). It also offers visualization and animation effects, data interoperability options, and many other properties, why the software has gained popularity in the business and manufacturing world.

AnyLogic is used in multiple well-known companies around the world. According to their website, the software is used by variety of car manufacturing companies like Ford, Rolls-Royce, BMW but also delivery companies like FedEx, UPS and DHL (AnyLogic. Nd). Other companies that are also on the list are for example Apple, Coca-Cola, NASA, Paris Aéroport, McDonald's amongst many others (AnyLogic. Nd).

The study primarily relies on AnyLogic’s discrete-event simulation (DES) engine to capture the dynamic behavior of workflows, queues, and resource constraints that give rise to bottlenecks. The Process Modeling Library is used to construct the production flow using blocks such as queue, seize, delay, and release, enabling a detailed representation of workstation operations, setup times, and routing decisions. Additionally, the model leverages resource management tools to analyze machine utilization levels, operator allocations, and capacity limitations. Experimentation features, including parameter variation, scenario comparison, and performance metrics tracking, allows systematic testing of changes in schedules and load levels. The software was chosen for this research for its drag-and-drop functionality, which required relatively little programming skill. Additionally, the software is free of charge, which was a significant factor in the decision-making process. Compared to other software, it was relatively easy to learn and use. A wide range of tutorials and manuals is available online, and AnyLogic also provides an extensive help website with tutorials and instructions. Additionally, AI was used during the learning process to support software usage.

4.1 Initial data

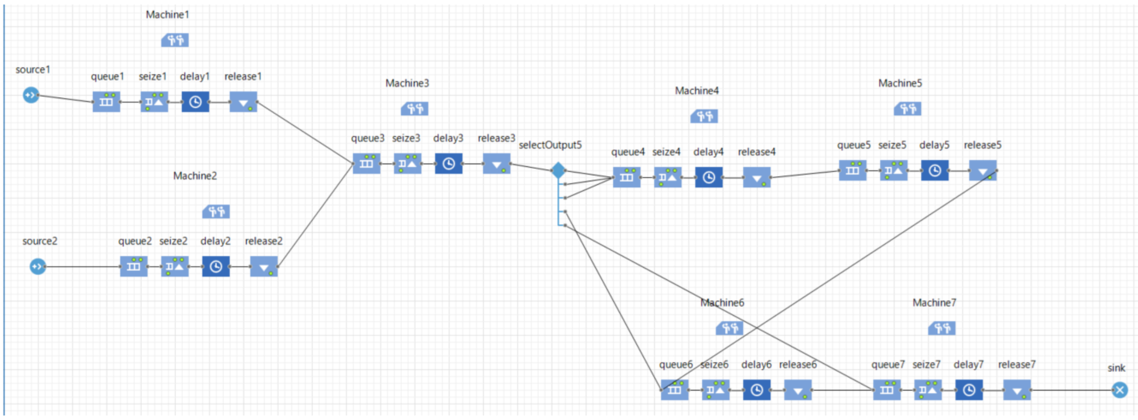
A representative job shop production environment is modeled in AnyLogic, consisting of 7 workstations and five different product types. Each product follows a predefined routing with 3–6 manufacturing steps and distinct processing times, reflecting a realistic industrial production setting. The workstations and processing times remains constant throughout the experiments, while scheduling policies, system load levels, and set production variability is altered.

The simulation experiments are conducted by progressively increasing the production load and comparing key performance indicators such as lead time, workstation utilization, and queue lengths. This approach enabled the identification of bottleneck formation points and allowed analysis of how different parameter settings influence bottleneck behavior. The results are expected to reveal critical factors contributing to bottleneck formation and provide insights into effective strategies for bottleneck management in job shop production systems.

In Picture 2 is the preliminary layout of the factory. The factory produces five different products, each with its own predefined route. The aim, when building the simulation, was to create as realistic manufacturing setting as possible. As this research is only theoretical, the factory setting does not relate to any real-world factory and only simulates a possible setting.

There are seven workstations, and each workstation consists of the phases queue, seize, delay and release. All except machine 3 have one operator, and machine 3 has two, which means that the capacity on that station is two products at the same time. The first station is the queue where goods from the previous machine are put before their turn. Then is the seize which reserves the resources for the job. Delay is the phase that actually does the production step, and then is the release, which releases the resource and sends the goods to the next step.

There are two sources set in this production. Source 1 supplies the station with 0.35 products per minute, and 2 supplies 0.2 products per minute. These values were set to ensure that machines 1 and 2 always have material available, while also preventing the queue before the machines from exceeding the maximum level of 100. Source 1 produces products 3, 4, and 5, and source 2 produces products 1 and 2. Lastly, there is a sink where the finished goods are going.



Picture 2 Simulation model.

Each station has a delay time set. The time has been determined by the products’ fastest possible time, average time, and slowest time. In Table 3, all the delay times are tabulated for each product. If the product does not go through some station, the delay time has been set to zero in the table. The processing times assigned to the products are random, and the aim is to generate different types of products with varying processing times while ensuring that the simulation is initially in a balanced state before bottleneck analysis is conducted. Also, when building the simulation, there is intentionally created bottleneck on machine 3, so this simulation would have a purpose.

Table 3 The delay times for each product.

Machine	**Product 1** (min)	**Product 2** (min)	**Product 3** (min)	**Product 4** (min)	**Product 5** (min)	**Total** (min)
1	0	0	3	2	3	8
2	4	4	0	0	0	8
3	3	1	5	8	7	24
4	3	3	3	0	0	9
5	3	3	3	0	0	9
6	4	1	2	3	0	10
7	2	2	2	2	2	10
Total (min)	19	14	18	15	12	

The times presented in Table 3 are in minutes, and the time that the product needs is defined by a random distribution, whether it is the fastest, slowest, or average time that is needed to produce the product. Most delay times are based on predetermined average values, but some variation occurred, resulting in slightly shorter or longer durations. The fluctuation in production times is very common and realistic in production modeling, and by creating the fluctuation in the simulation, it corresponds to more real-life production. The fastest time is determined by multiplying the determined average time by 0.8, and the slowest time is determined by multiplying the average time by 1.2.

Each product follows a specific production route, as illustrated in Figure 10, which depicts the processing stages for all products. Products 3, 4, and 5 begin their production at Machine 1, whereas products 1 and 2 start at Machine 2. After completing their initial operations, all products proceed to Machine 3. Following this stage, products 1, 2, and 3 are processed at Machine 4, then continue to Machine 5, and subsequently to Machine 6. In contrast, product 4 moves directly from Machine 3 to Machine 6, while product 5 bypasses Machines 4, 5, and 6 and proceeds directly to Machine 7, where all the products are finalized.

For each simulation run, a warm-up period of 60 minutes is applied automatically. Data collection is configured to begin only after the warm-up period to prevent the initially empty production system from biasing the results. This approach improves the realism of the simulation, as real-life production systems rarely start from a completely empty and idle state.

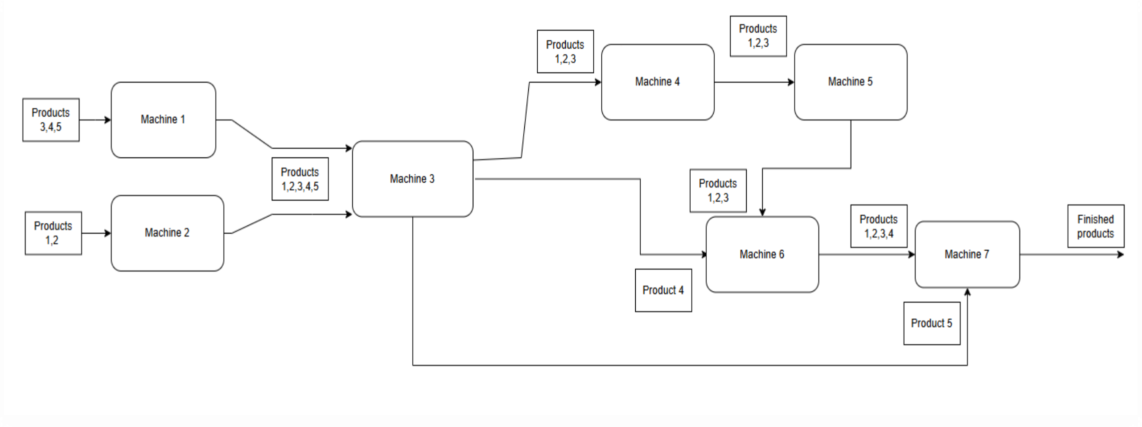
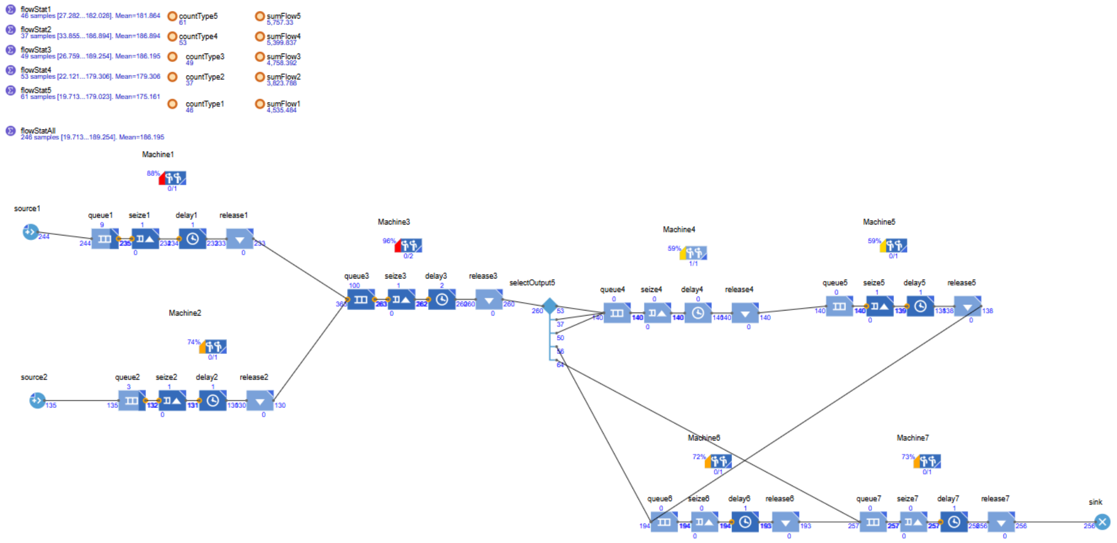


Figure 10 Production flow.

4.2 Simulation

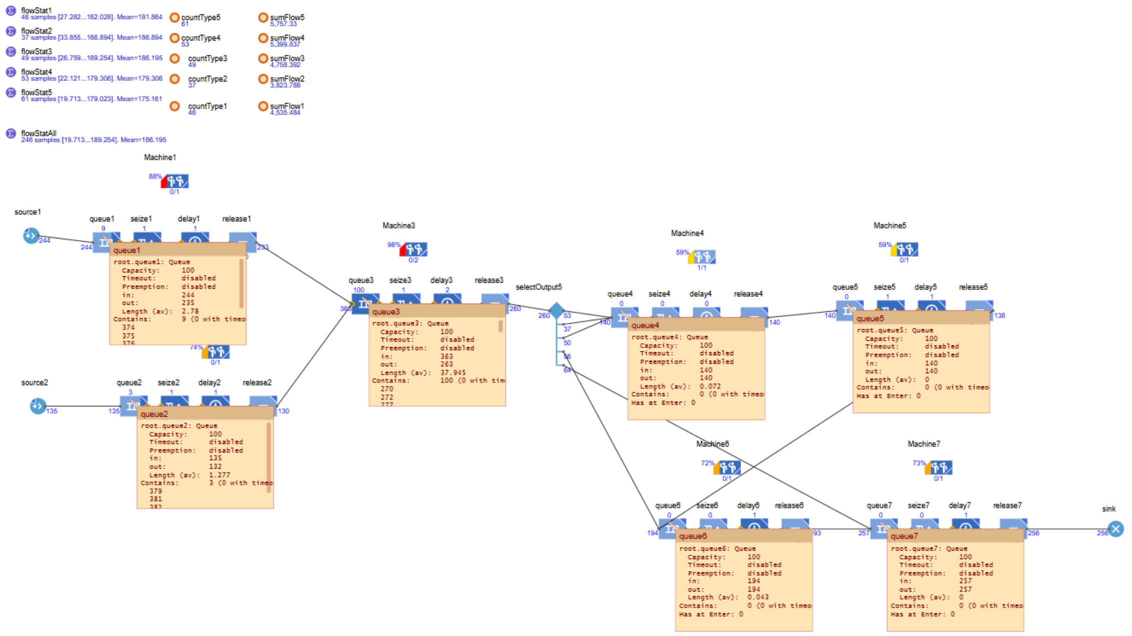
The first simulation is driven with the initial data to determine whether there would be a bottleneck and where it would be. The production flow, and how the load is divided among each machine is illustrated in Picture 3. The simulation is stopped twice. The first stop is at 700.6 minutes, which is halfway through the simulation, and the second stop is until the error. The error is due to overcapacity in the queue, and the time is 1475.65 minutes. Picture 4 is the estate and values of the simulation after the error has occurred. In this simulation the queuing rule that is implemented is first in, first out (FIFO).

In the first stop of the simulation at 700.6 minutes, there are a total of 248 finished products. The finished products are divided accordingly. There are 46 finished type 1 products manufactured, and the mean lead time is 181.886 minutes. There are 37 finished type 2 products manufactured, and the mean lead time is 186.894 minutes. There are 49 finished type 3 products manufactured, and the mean lead time is 186.194 minutes. There are 53 finished type 4 products manufactured, and the mean lead time is 179.306 minutes. And lastly, there are 61 finished type 5 products manufactured, and the mean lead time is 175.161 minutes.



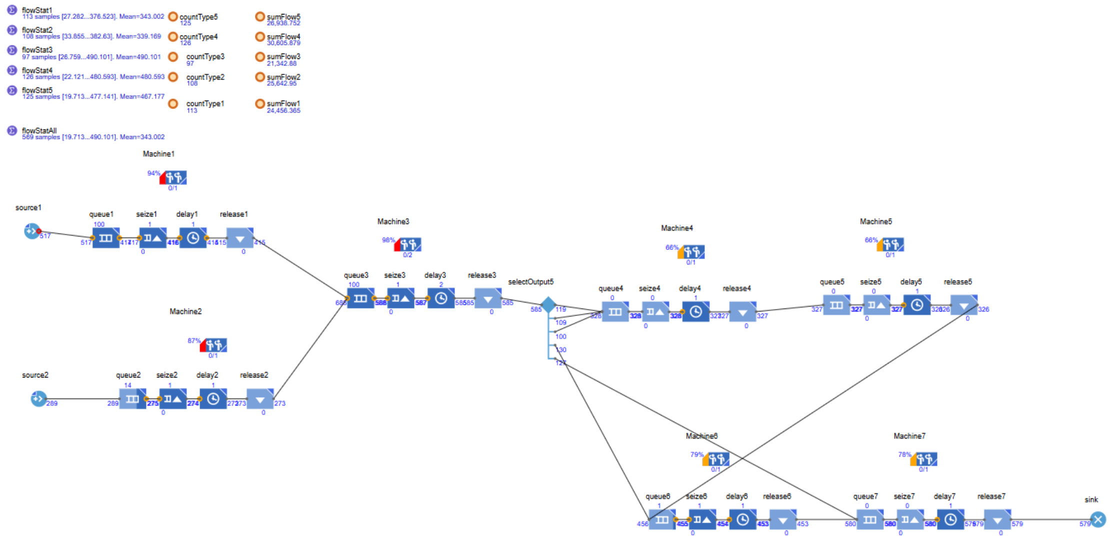
Picture 3 Simulation 1: 700.60 min.

For each machine, there was an average queue time and a utilization rate determined that can be seen in Pictures 3 and 4. In Table 4, it can be seen more closely how the utilization rate evolves during the simulation, but the average queue time for each machine has been taken only at the simulation stops to compare how the average possibly changes. In the first machine the utilization rate is 700.6 minutes at 88% and the average queueing time is 2.78 minutes. In the second machine the utilization rate is 74% and the average queueing time is 1.277 minutes. In the third machine the utilization rate is 96%, and the average queueing time is 37.945 minutes. In the fourth machine the utilization rate is 59% and the average queueing time is 0.072 minutes. In the fifth machine the utilization rate is 59% and the average queueing time is 0.0 minutes. In the sixth machine the utilization rate is 72% and the average queueing time is 0.043 minutes. And in the last machine the utilization rate is 73% and the average queueing time is 0.0 minutes.



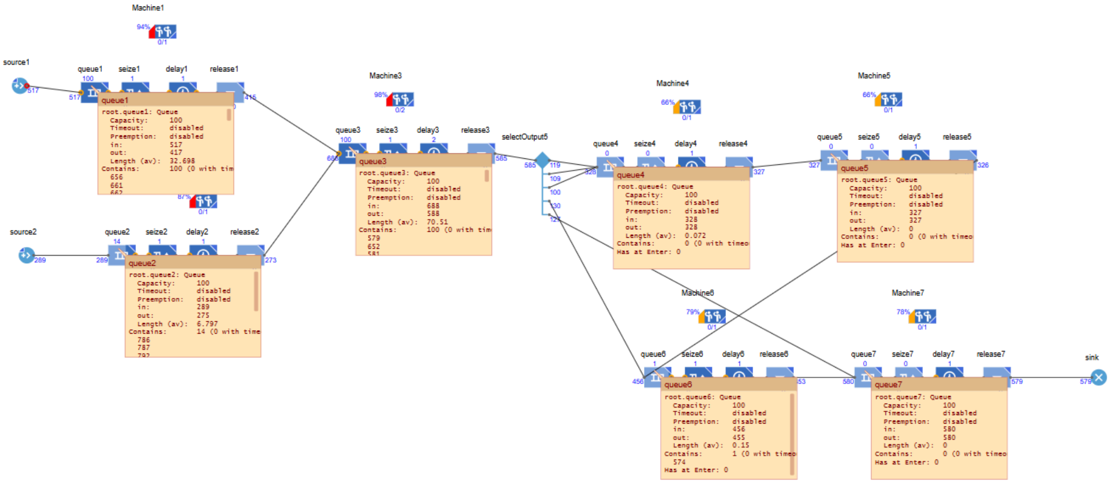
Picture 4 Simulation 1 average queue times: 700.60 min.

The second stop was 1475.65 minutes after the system error, and there is a total of 569 finished products. The finished products are divided accordingly. There are 113 finished type 1 products manufactured, and the mean lead time is 343.002 minutes. There are 108 finished type 2 products manufactured, and the mean lead time is 339.169 minutes. There are 97 finished type 3 products manufactured, and the mean lead time is 490.101 minutes. There are 126 finished type 4 products manufactured, and the mean lead time is 480.593 minutes. And lastly, there are 125 finished type 5 products manufactured, and the mean lead time is 467.117 minutes.



Picture 5 Simulation 1 Values after error at 1475.65min.

In Picture 6, there are the average queueing times of simulation 1 after the error has occurred. The utilization rate can be seen in Picture 5. In the first machine the utilization rate was 1475.65minutes at 94% and the average queueing time is 32.698 minutes. In the second machine the utilization rate is 87% and the average queueing time is 6.797 minutes. In the third machine the utilization rate is 98% and the average queueing time is 70.51 minutes. In the fourth machine the utilization rate is 66% and the average queueing time was 0.072 minutes. In the fifth machine the utilization rate is 66% and the average queueing time is 0.0 minutes. In the sixth machine is 79% and the average queueing time is 0.015 minutes. And in the last machine, the utilization rate is 78% and the average queueing time is 0.0 minutes.



Picture 6 Simulation 1 Average queue times after error at 1475.65min.

Table 4 Simulation 1 statistics.

time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	10	10,00	4	2	0	2	0	0	0	0	52,80 %	43,40 %	61,10 %	28,86 %	23,94 %	49,82 %	33,93 %
120	32	16,00	12	0	0	12	0	0	0	0	68,42 %	64,31 %	80,55 %	44,97 %	41,55 %	60,43 %	53,52 %
180	56	18,67	18	1	0	17	0	0	0	0	78,95 %	60,05 %	87,03 %	52,75 %	50,57 %	66,01 %	63,24 %
240	78	19,50	27	0	0	27	0	0	0	0	81,07 %	64,73 %	90,27 %	51,79 %	49,34 %	67,07 %	64,86 %
300	102	20,40	32	0	4	28	0	0	0	0	83,05 %	62,65 %	92,22 %	58,47 %	58,27 %	69,95 %	68,70 %
360	126	21,00	39	0	0	39	0	0	0	0	82,43 %	68,57 %	93,52 %	58,71 %	58,73 %	69,34 %	70,04 %
420	149	21,29	42	0	0	42	0	0	0	0	81,74 %	67,95 %	94,44 %	60,72 %	60,51 %	69,59 %	71,32 %
480	176	22,00	46	5	0	40	0	0	1	0	83,36 %	63,55 %	95,14 %	65,26 %	64,56 %	72,27 %	73,29 %
540	199	22,11	64	5	2	57	0	0	0	0	85,21 %	66,95 %	95,68 %	62,85 %	63,15 %	74,02 %	74,02 %
600	218	21,80	82	3	3	76	0	0	0	0	86,69 %	70,26 %	96,11 %	60,42 %	60,75 %	71,98 %	72,83 %
660	239	21,73	111	13	4	94	0	0	0	0	87,90 %	72,96 %	96,46 %	58,48 %	58,61 %	72,58 %	72,46 %
720	265	22,08	115	11	4	100	0	0	0	0	88,91 %	75,21 %	96,76 %	59,31 %	59,36 %	72,49 %	73,51 %
780	288	22,15	132	23	9	100	0	0	0	0	89,76 %	77,12 %	97,01 %	60,66 %	60,73 %	73,02 %	74,05 %
840	314	22,43	136	30	6	100	0	0	0	0	90,49 %	78,75 %	97,22 %	61,28 %	61,61 %	74,12 %	74,90 %
900	338	22,53	159	45	14	100	0	0	0	0	91,13 %	80,17 %	97,41 %	61,10 %	61,70 %	74,65 %	75,28 %
960	360	22,50	169	52	17	100	0	0	0	0	91,68 %	81,41 %	97,57 %	61,77 %	62,14 %	74,90 %	75,13 %
1020	387	22,76	170	52	19	99	0	0	0	0	92,17 %	82,50 %	97,71 %	62,14 %	62,34 %	75,77 %	76,00 %
1080	412	22,89	175	60	16	99	0	0	0	0	92,61 %	83,48 %	97,84 %	63,07 %	63,36 %	76,06 %	76,31 %
1140	438	23,05	177	66	11	100	0	0	0	0	92,99 %	84,34 %	97,95 %	63,83 %	64,27 %	76,88 %	76,88 %
1200	463	23,15	189	76	13	100	0	0	0	0	93,35 %	85,13 %	98,05 %	64,82 %	65,27 %	77,66 %	77,18 %
1260	490	23,33	188	81	7	100	0	0	0	0	93,66 %	85,84 %	98,15 %	64,62 %	65,24 %	78,05 %	77,73 %
1320	512	23,27	202	86	14	100	0	0	2	0	93,95 %	86,48 %	98,23 %	64,58 %	65,00 %	78,31 %	77,51 %
1380	539	23,43	200	89	11	100	0	0	0	0	94,21 %	87,07 %	98,31 %	65,67 %	65,93 %	78,78 %	78,15 %
1440	565	23,54	209	97	12	99	0	0	1	0	94,45 %	87,61 %	98,38 %	66,67 %	66,85 %	79,14 %	78,47 %

In Table 4, there is the data from the first simulation. The data has been collected every 60 minutes. The first column indicates how long the simulation has been ongoing. In the next column is how many products have been manufactured in total during that time. In the third column is the throughput per hour, and the fourth column is the work-in-process, as in how many products are still unfinished in the manufacturing process. Then there are the queues for each machine on how many products are waiting, and the last columns are the utilization rate for each machine.

The figures below present the simulation results described above. In Figure 11 are the queues for each machine every 60 minutes. In the horizontal axel is the time passed, and the queue for machine 3 reaches the maximum capacity at 720 minutes, and soon after the queue also increases for machine 1. In the rest of the machine, the queues stay at acceptable levels.

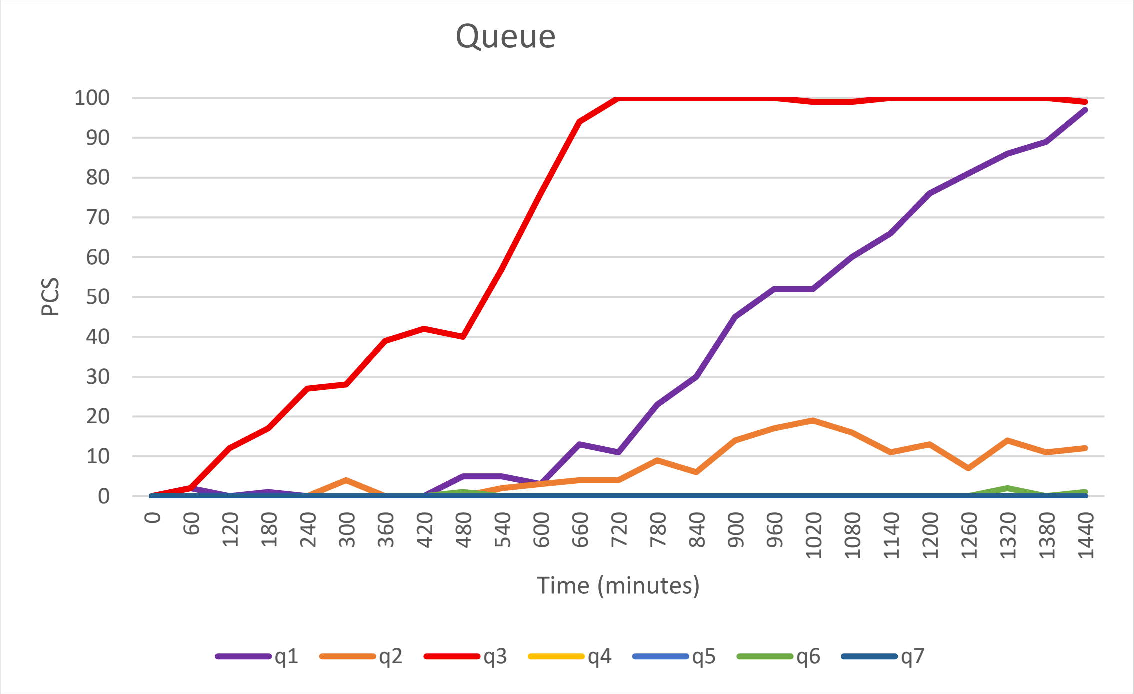


Figure 11 Queue Simulation 1.

The utilization rate is shown in Figure 12. The utilization rate reaches a rapidly high level for machine 3, but also for machine 1 the rate is high, and there is not much excess capacity. Because the capacity levels are high, particularly in machine 3, this leads to the formation of the queues. The Figure 13 shows how the capacity, queues and utilization rates affect the flow, and some key numbers and metrics from the statistics are compared. The figure shows the evolution of how many pieces are finished during each hour and how many are still being processed.

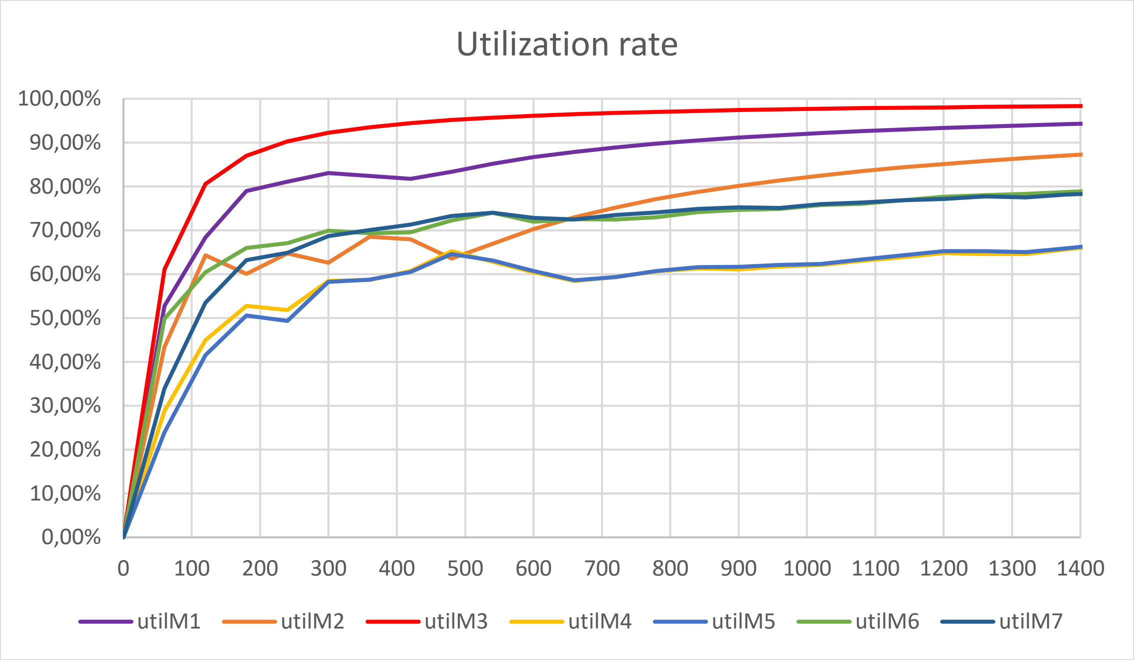


Figure 12 Utilization rate simulation 1.

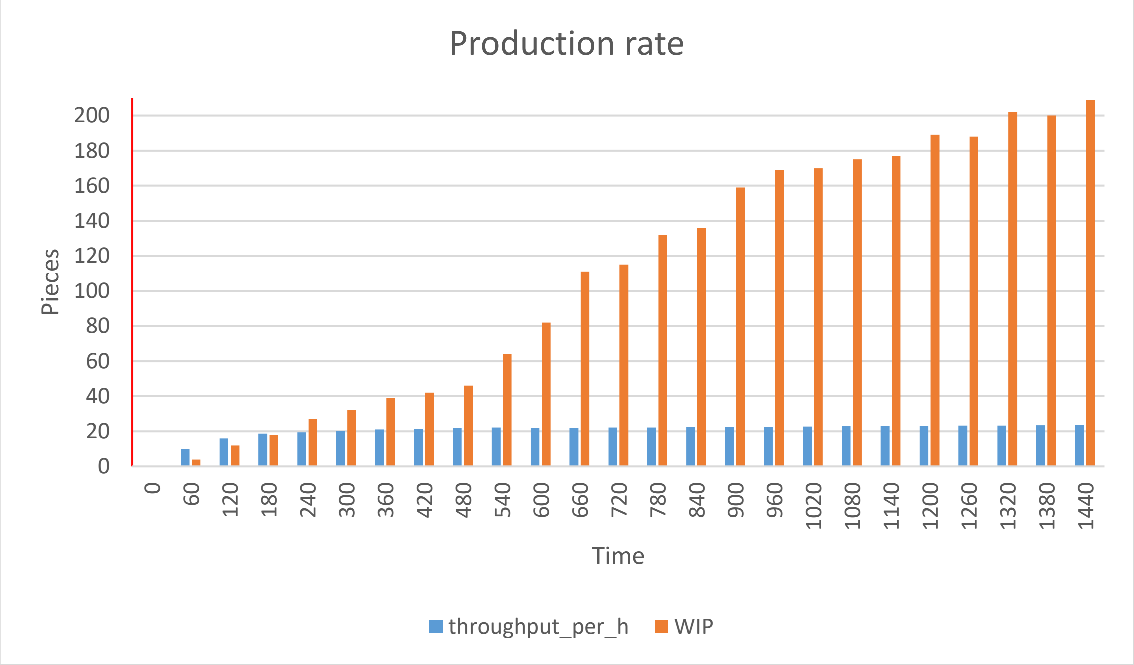


Figure 13 Production rate (pcs).

4.2.1 Case 1: Changing the processing order

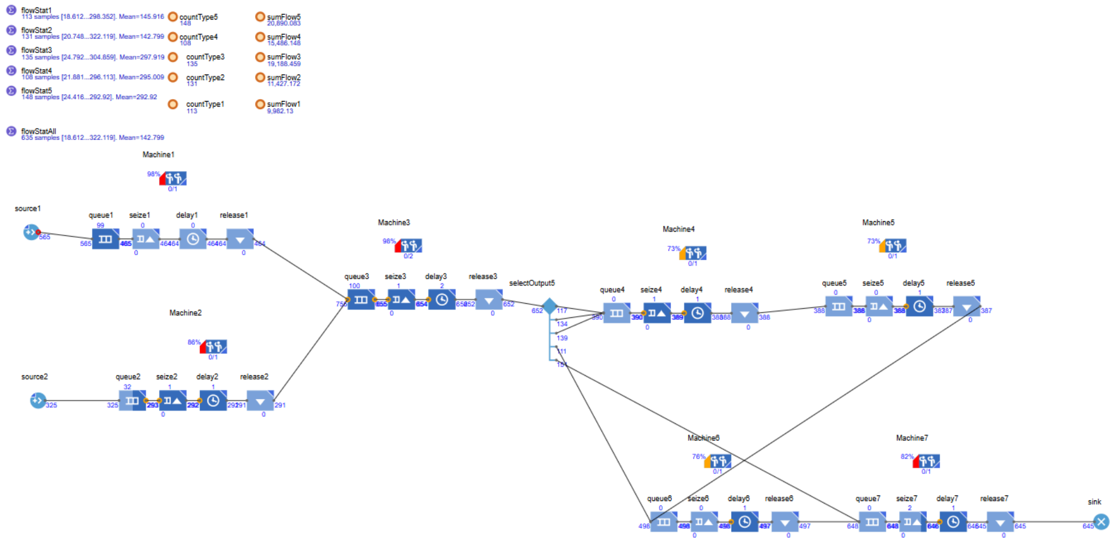
When simulation 1 is done, the next step is to try to improve it and change parameters to see how the production flow and bottlenecks will change. The first case will compare how changing the queueing rules and the order to process the goods will affect production. The production model will stay the same and all the initial data but the processing order will change on Machine 3 where the bottleneck can be assumed to be. First, the queuing rule will be last-in, first-out (LIFO). In the second experiment the processing order will be shortest processing time first and investigate if that has any change on the bottleneck. Third will be the opposite of previous step and do the longest processing time first, and experiment how this will change the output.

There are also other methods for choosing how the production plan is managed. Usually, the due dates are in critical role when doing the schedule. However, because this is not a case study and there are no order log or due dates defined for these products, this study is not able to do these experiments. The product amounts are discussed and taken into consideration in the results section.

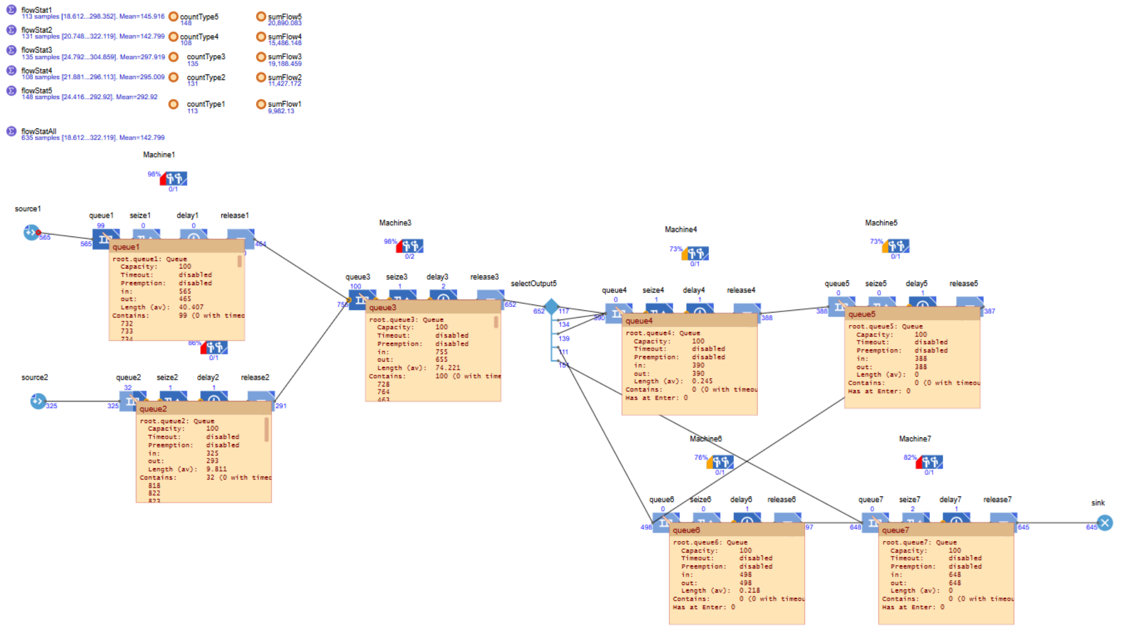
4.2.1.1 Last-in, First-out

The first test to simulation is testing what happens when changing the scheduling rule on machine 3 from FIFO to LIFO and other machines will stay as in the baseline simulation. This is meant to simulate rush orders that often cut the line due to the rush. Normally this rule would be the shortest due date, but because there are no due dates set, LIFO will be acting as this. Another prospect is to find out how the flow will change when the rule is changed to processing the last-come product first.

This simulation was also run until the error occurred (the maximum capacity of the queue was overfilled). The time that the error occurred was 1582.94 minutes. In Pictures 7 and 8, the simulation output is seen. In this case, in total 645 products were finished, and 1140 were unfinished. In the first table on blue (flowstat) are the mean lead times for each product, the number of units produced per product type, and the total production time per product, consistent with the baseline scenario.



Picture 7 LIFO.



```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            565
  out:           465
  Length (av):   40.407
Contains:        99 (0 with timeo
  732
  733
  734
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            325
  out:           293
  Length (av):   9.811
Contains:        32 (0 with timeo
  818
  822
  823
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            755
  out:           655
  Length (av):   74.221
Contains:        100 (0 with time
  728
  764
  463
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            390
  out:           390
  Length (av):   0.245
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            388
  out:           388
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            498
  out:           498
  Length (av):   0.218
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            648
  out:           648
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

Picture 8 LIFO waiting times.

In Figure 14, the utilization rate is shown on each machine. As in the baseline simulation, machine 3 reaches a high utilization rate quickly. However, machines 1 and 2 reach high capacity demands quicker than in the baseline simulation. When adding the queues on machine 3, where in the previous simulation it took 720 minutes to reach the maximum capacity, here it was already 100 after 420 minutes, as shown in Figure 15. Queue 1 also starts to increase fast, while in the other machines it stays at acceptable levels, as in the previous simulation.

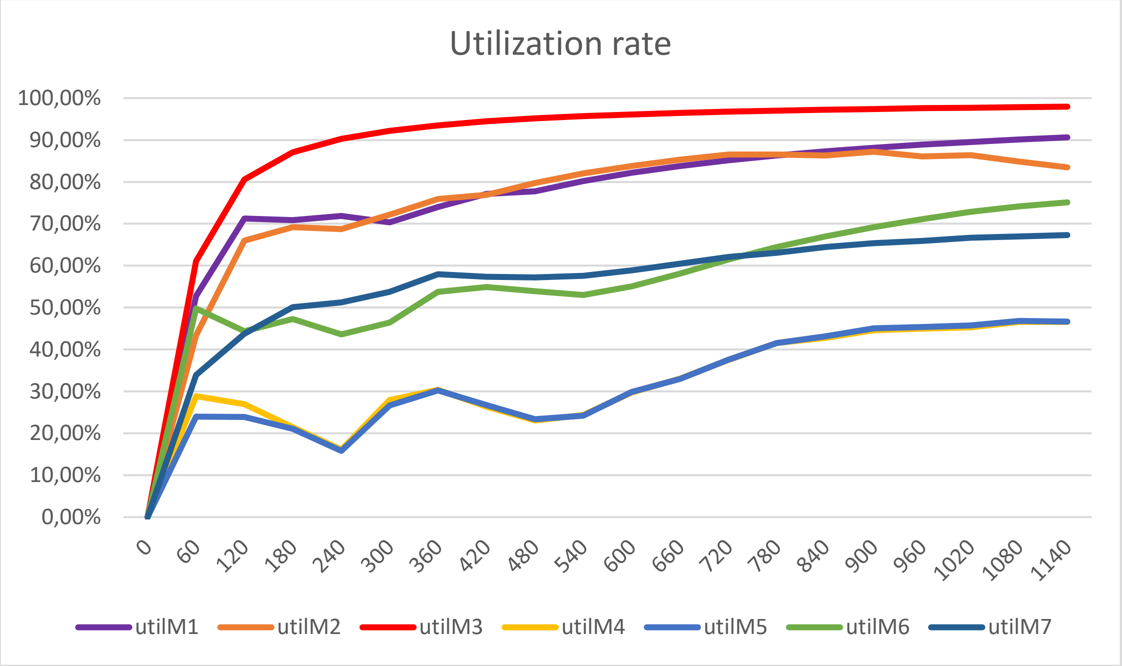


Figure 14 LIFO utilization rates.

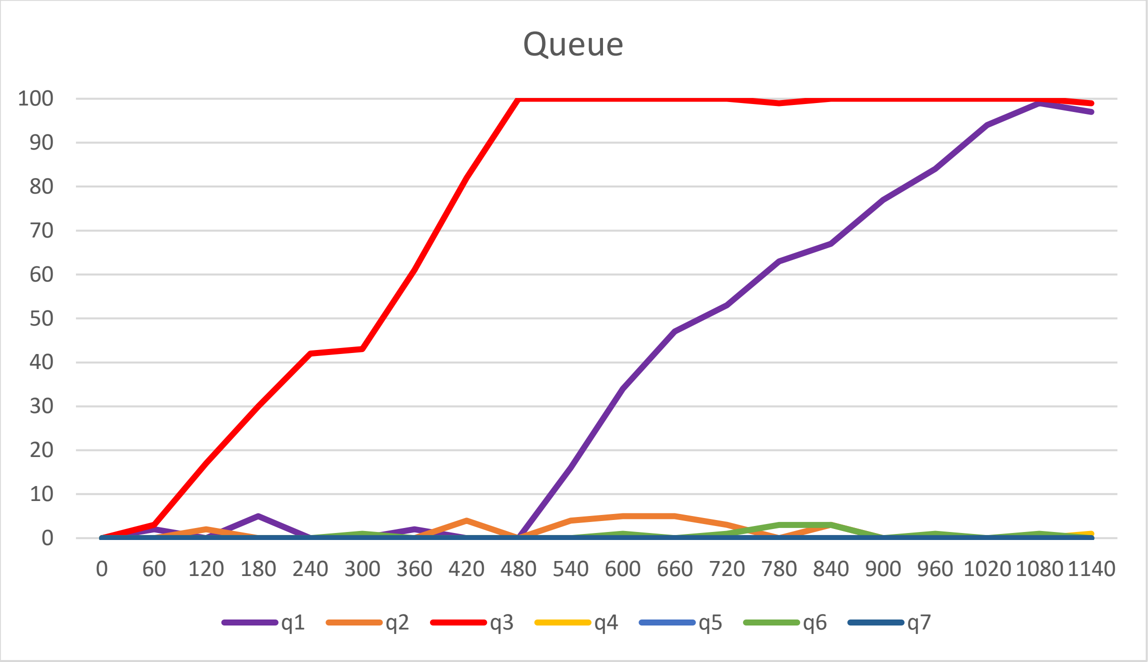


Figure 15 LIFO queues.

In Figure 16 is the production rate showing the throughput and work-in-process to illustrate the efficiency when the rule is changed on machine 3. The throughput per hour stays quite average throughout the simulation, and averagely the throughput is 21.03 finished products per hour. The maximum throughput was 24.42 products per hour, simulation time 1440-1500, and the minimum 10 products that was in the second hour of operation. The standard deviation is 5.13 for the throughput. The WIP's trend is increasing at a constant pace, and initially, there are more unfinished products in production than the throughput. All this can be found in Table 5, where the simulation statistics are collected.

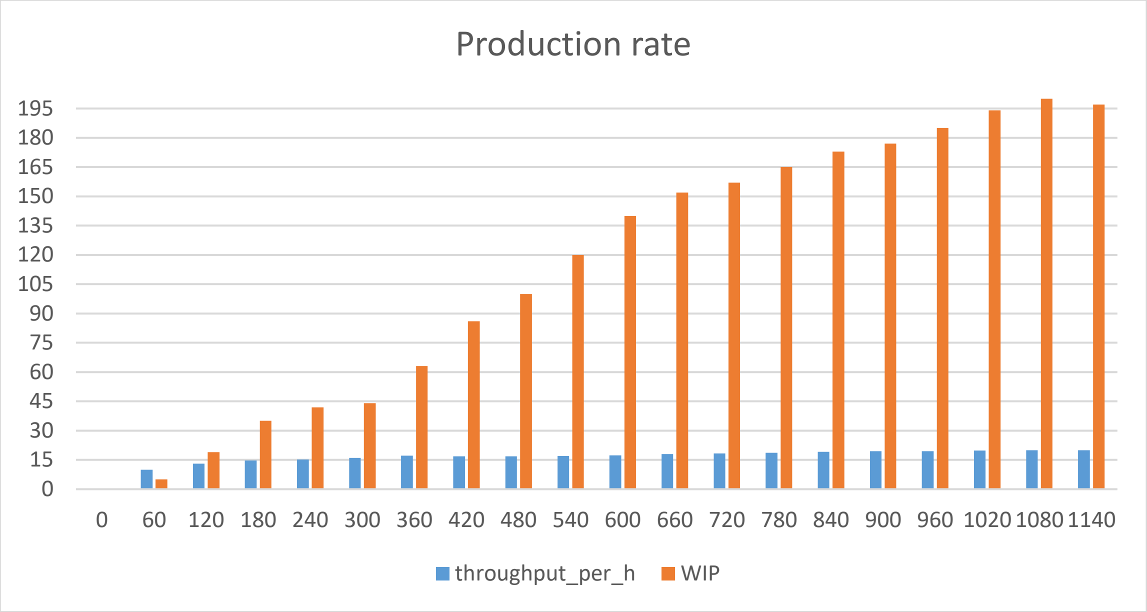
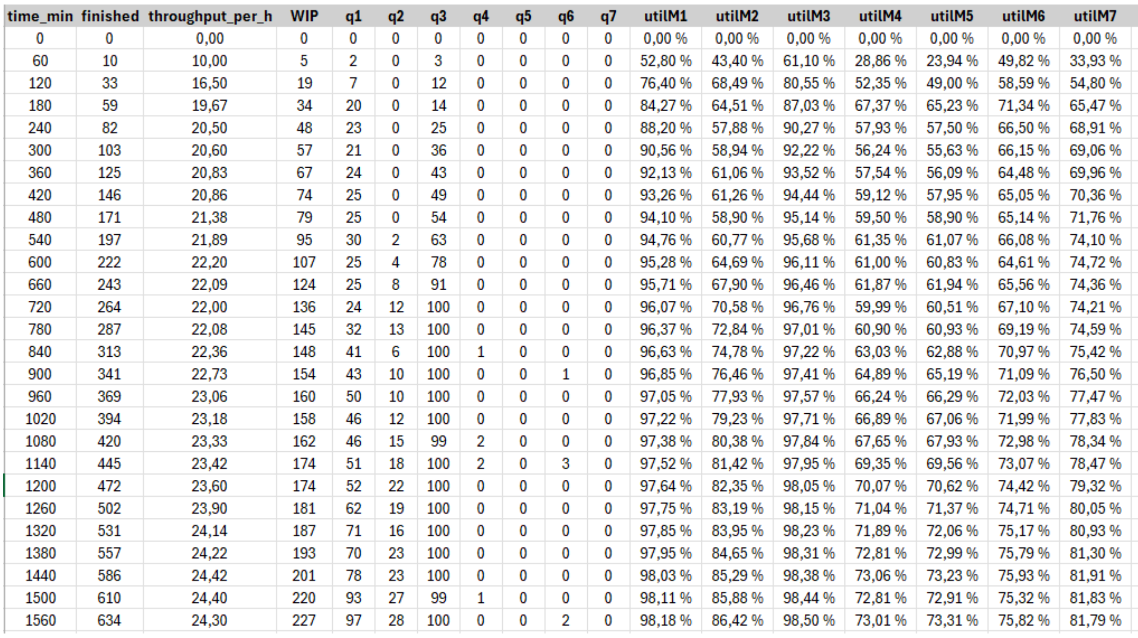


Figure 16 LIFO production rate.

Table 5 LIFO statistics.

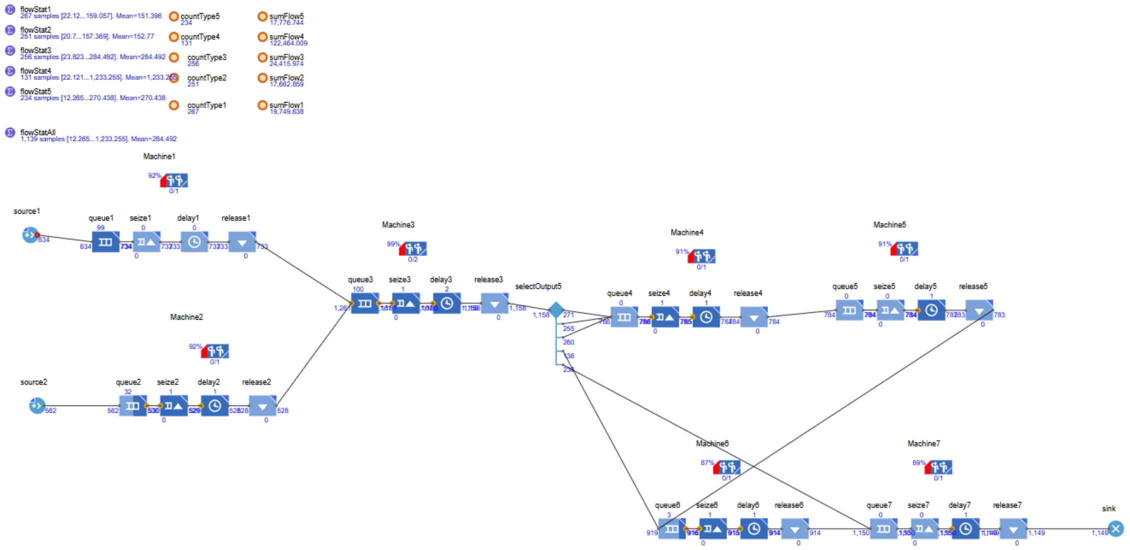


time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	10	10,00	5	2	0	3	0	0	0	0	52,80 %	43,40 %	61,10 %	28,86 %	23,94 %	49,82 %	33,93 %
120	33	16,50	19	7	0	12	0	0	0	0	76,40 %	68,49 %	80,55 %	52,35 %	49,00 %	58,59 %	54,80 %
180	59	19,67	34	20	0	14	0	0	0	0	84,27 %	64,51 %	87,03 %	67,37 %	65,23 %	71,34 %	65,47 %
240	82	20,50	48	23	0	25	0	0	0	0	88,20 %	57,88 %	90,27 %	57,93 %	57,50 %	66,50 %	68,91 %
300	103	20,60	57	21	0	36	0	0	0	0	90,56 %	58,94 %	92,22 %	56,24 %	55,63 %	66,15 %	69,06 %
360	125	20,83	67	24	0	43	0	0	0	0	92,13 %	61,06 %	93,52 %	57,54 %	56,09 %	64,48 %	69,96 %
420	146	20,86	74	25	0	49	0	0	0	0	93,26 %	61,26 %	94,44 %	59,12 %	57,95 %	65,05 %	70,36 %
480	171	21,38	79	25	0	54	0	0	0	0	94,10 %	58,90 %	95,14 %	59,50 %	58,90 %	65,14 %	71,76 %
540	197	21,89	95	30	2	63	0	0	0	0	94,76 %	60,77 %	95,68 %	61,35 %	61,07 %	66,08 %	74,10 %
600	222	22,20	107	25	4	78	0	0	0	0	95,28 %	64,69 %	96,11 %	61,00 %	60,83 %	64,61 %	74,72 %
660	243	22,09	124	25	8	91	0	0	0	0	95,71 %	67,90 %	96,46 %	61,87 %	61,94 %	65,56 %	74,36 %
720	264	22,00	136	24	12	100	0	0	0	0	96,07 %	70,58 %	96,76 %	59,99 %	60,51 %	67,10 %	74,21 %
780	287	22,08	145	32	13	100	0	0	0	0	96,37 %	72,84 %	97,01 %	60,90 %	60,93 %	69,19 %	74,59 %
840	313	22,36	148	41	6	100	1	0	0	0	96,63 %	74,78 %	97,22 %	63,03 %	62,88 %	70,97 %	75,42 %
900	341	22,73	154	43	10	100	0	0	1	0	96,85 %	76,46 %	97,41 %	64,89 %	65,19 %	71,09 %	76,50 %
960	369	23,06	160	50	10	100	0	0	0	0	97,05 %	77,93 %	97,57 %	66,24 %	66,29 %	72,03 %	77,47 %
1020	394	23,18	158	46	12	100	0	0	0	0	97,22 %	79,23 %	97,71 %	66,89 %	67,06 %	71,99 %	77,83 %
1080	420	23,33	162	46	15	99	2	0	0	0	97,38 %	80,38 %	97,84 %	67,65 %	67,93 %	72,98 %	78,34 %
1140	445	23,42	174	51	18	100	2	0	3	0	97,52 %	81,42 %	97,95 %	69,35 %	69,56 %	73,07 %	78,47 %
1200	472	23,60	174	52	22	100	0	0	0	0	97,64 %	82,35 %	98,05 %	70,07 %	70,62 %	74,42 %	79,32 %
1260	502	23,90	181	62	19	100	0	0	0	0	97,75 %	83,19 %	98,15 %	71,04 %	71,37 %	74,71 %	80,05 %
1320	531	24,14	187	71	16	100	0	0	0	0	97,85 %	83,95 %	98,23 %	71,89 %	72,06 %	75,17 %	80,93 %
1380	557	24,22	193	70	23	100	0	0	0	0	97,95 %	84,65 %	98,31 %	72,81 %	72,99 %	75,79 %	81,30 %
1440	586	24,42	201	78	23	100	0	0	0	0	98,03 %	85,29 %	98,38 %	73,06 %	73,23 %	75,93 %	81,91 %
1500	610	24,40	220	93	27	99	1	0	0	0	98,11 %	85,88 %	98,44 %	72,81 %	72,91 %	75,32 %	81,83 %
1560	634	24,30	227	97	28	100	0	0	2	0	98,18 %	86,42 %	98,50 %	73,01 %	73,31 %	75,82 %	81,79 %

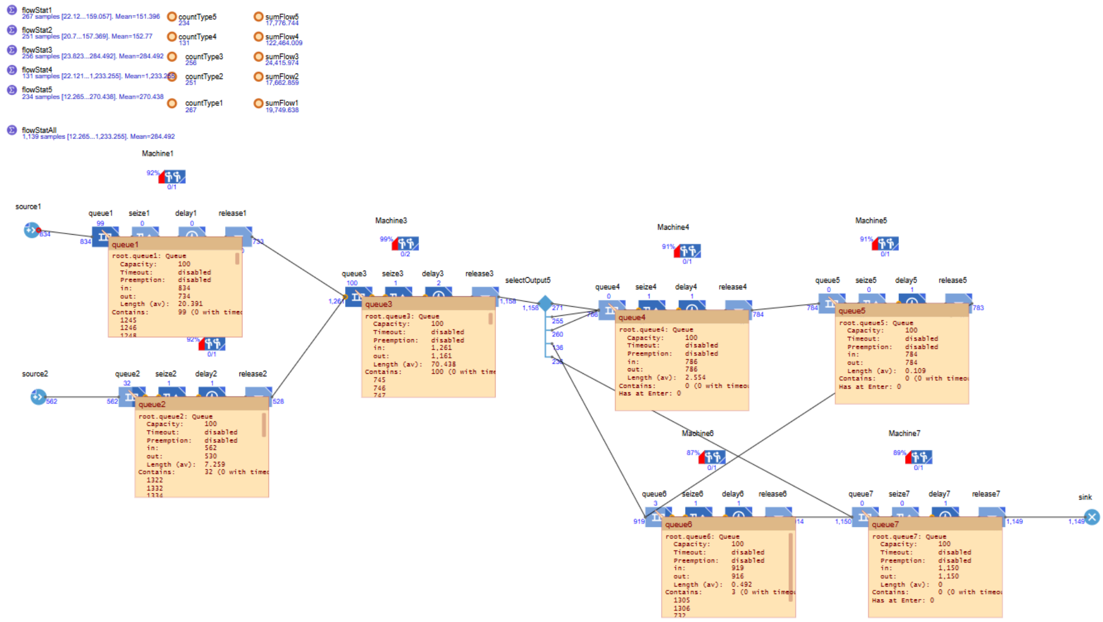
4.2.1.2 Shortest processing time

In this case, the simulation is driven with prioritized processing rule of shortest processing time first. Other stations work with FIFO principal but Machine 3 has the shortest processing time. This is used to get the queue smaller and to see how this will affect the whole process. As in the previous simulations, the data is collected there every 60 minutes to see how the process evolves as the simulation goes forward.

The simulation is run through until the error occurs due to passing the maximum capacity in the queues. The stopping time is 2581.13 minutes. Pictures 9 and 10 show the state of the simulation at this point, and Table 6 is the data from the simulation. In total, during the simulation, there were 1149 products finished and 234 unfinished ones. The number of finished products is almost doubled compared to the previous simulation, and the running time is also increased. However, the lead times for each product vary quite a lot, and for example, product 4 has a significantly higher lead time and a lower number of finished products than the four other product types. This already has some good improvement but still leaves a lot of room for getting better results.



Picture 9 SPT.



```
flowStat1
267 samples [22.12...159.057]. Mean=151.396
flowStat2
251 samples [20.7...157.369]. Mean=152.77
flowStat3
256 samples [23.823...284.492]. Mean=284.492
flowStat4
131 samples [22.121...1,233.255]. Mean=1,233.255
flowStat5
234 samples [12.265...270.438]. Mean=270.438

flowStatAll
1,139 samples [12.265...1,233.255]. Mean=284.492
```

```
countType5   sumFlow5
234          17,776.744
countType4   sumFlow4
131          122,464.009
countType3   sumFlow3
256          24,415.974
countType2   sumFlow2
251          17,662.859
countType1   sumFlow1
267          19,749.638
```

```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            834
  out:           734
  Length (av):   20.391
Contains:        99 (0 with timeo
  1245
  1246
  1248
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            562
  out:           530
  Length (av):   7.259
Contains:        32 (0 with timeo
  1322
  1332
  1334
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            1,261
  out:           1,161
  Length (av):   70.438
Contains:        100 (0 with time
  745
  746
  747
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            786
  out:           786
  Length (av):   2.554
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            784
  out:           784
  Length (av):   0.109
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            919
  out:           916
  Length (av):   0.492
Contains:        3 (0 with timeou
  1305
  1306
  732
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            1,150
  out:           1,150
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

Picture 10 SPT average waiting time.

The utilization rate is still highest on machine 3, but the rate overall in all machines is closer and more balanced compared to each other. Almost every machine the utilization rate is above 90 percent (Picture 9 and Figure 17). There is also a slight improvement in average waiting times (Picture 10) when compared to previous waiting times, but still on machine 3 the waiting time is longer than on the other machines. Also, the production is able to work longer time on survival mood when the q3 hits the maximum capacity and before the queue on machine 1 starts to increase fast (Figure 18).

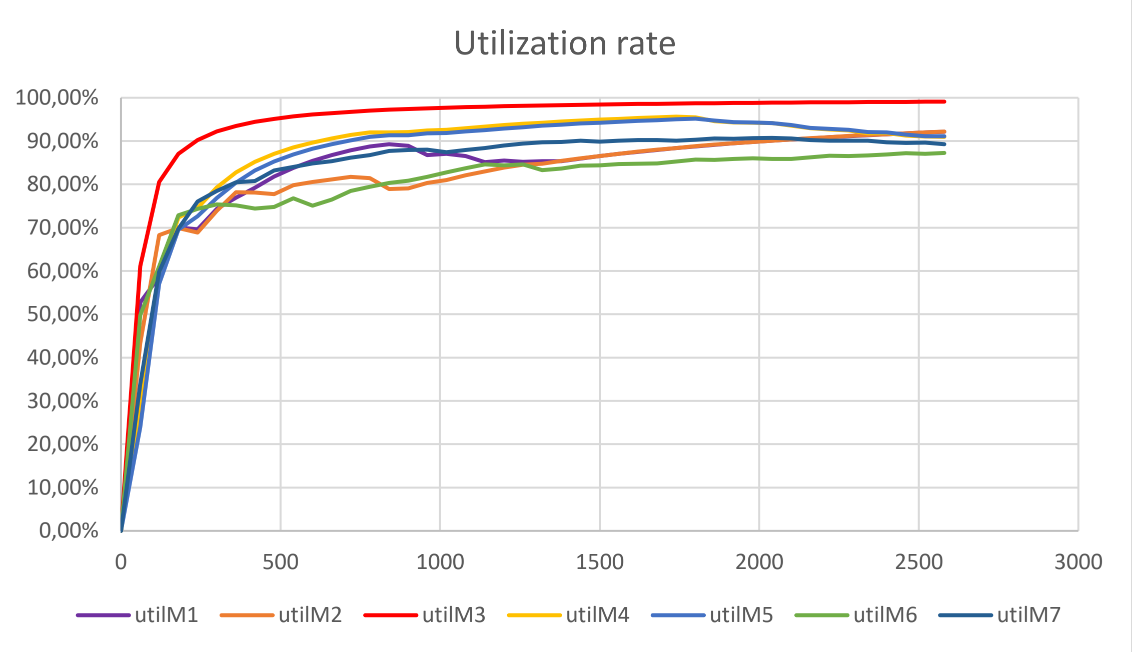


Figure 17 SPT Utilization rate.

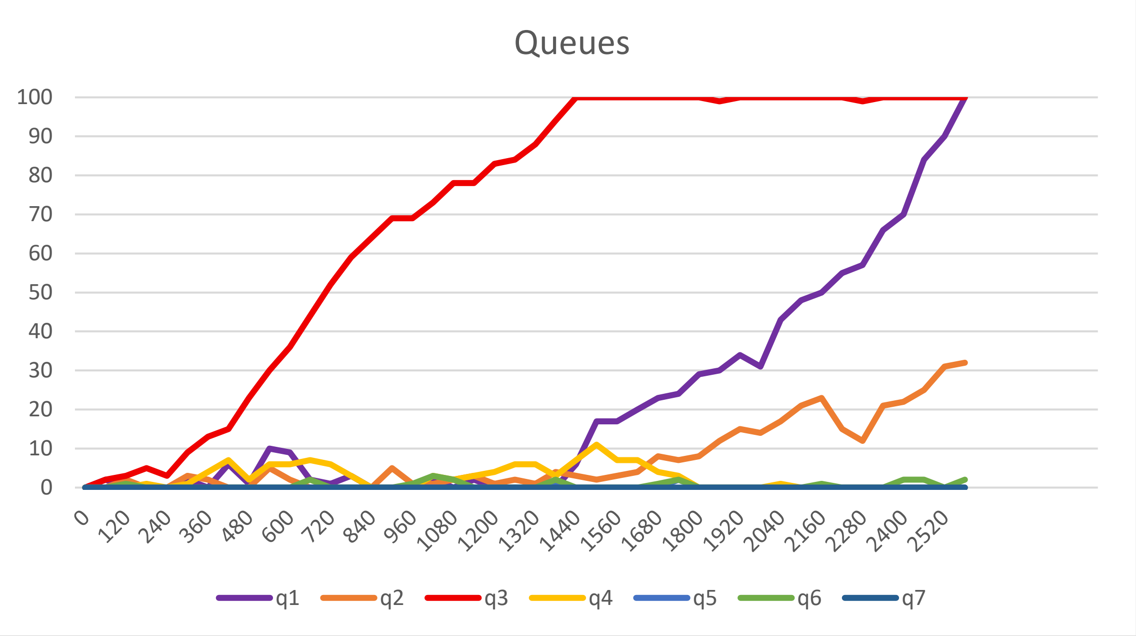


Figure 18 SPT queues.

Also in this case, the throughput per hour is quite steady throughout the simulation, and the increase in WIP is constant (Figure 19). The average throughput per hour is 24.95 products, and the median is 26.92 products, which is higher than the LIFO or FIFO rules.

The standard deviation is slightly lower at 4.91, where in the previous simulation the standard deviation was a bit over 5 products per hour.

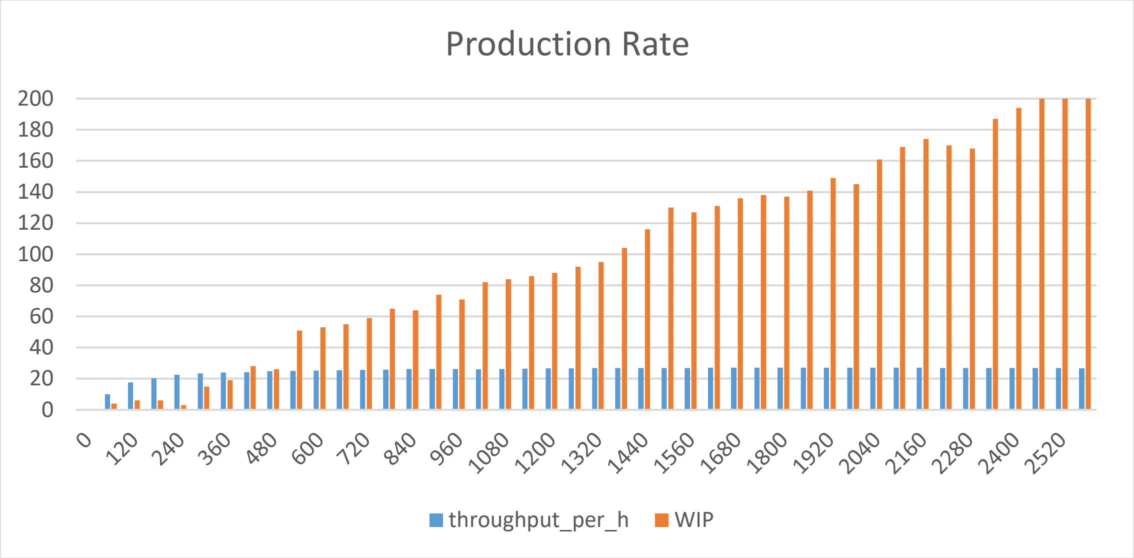
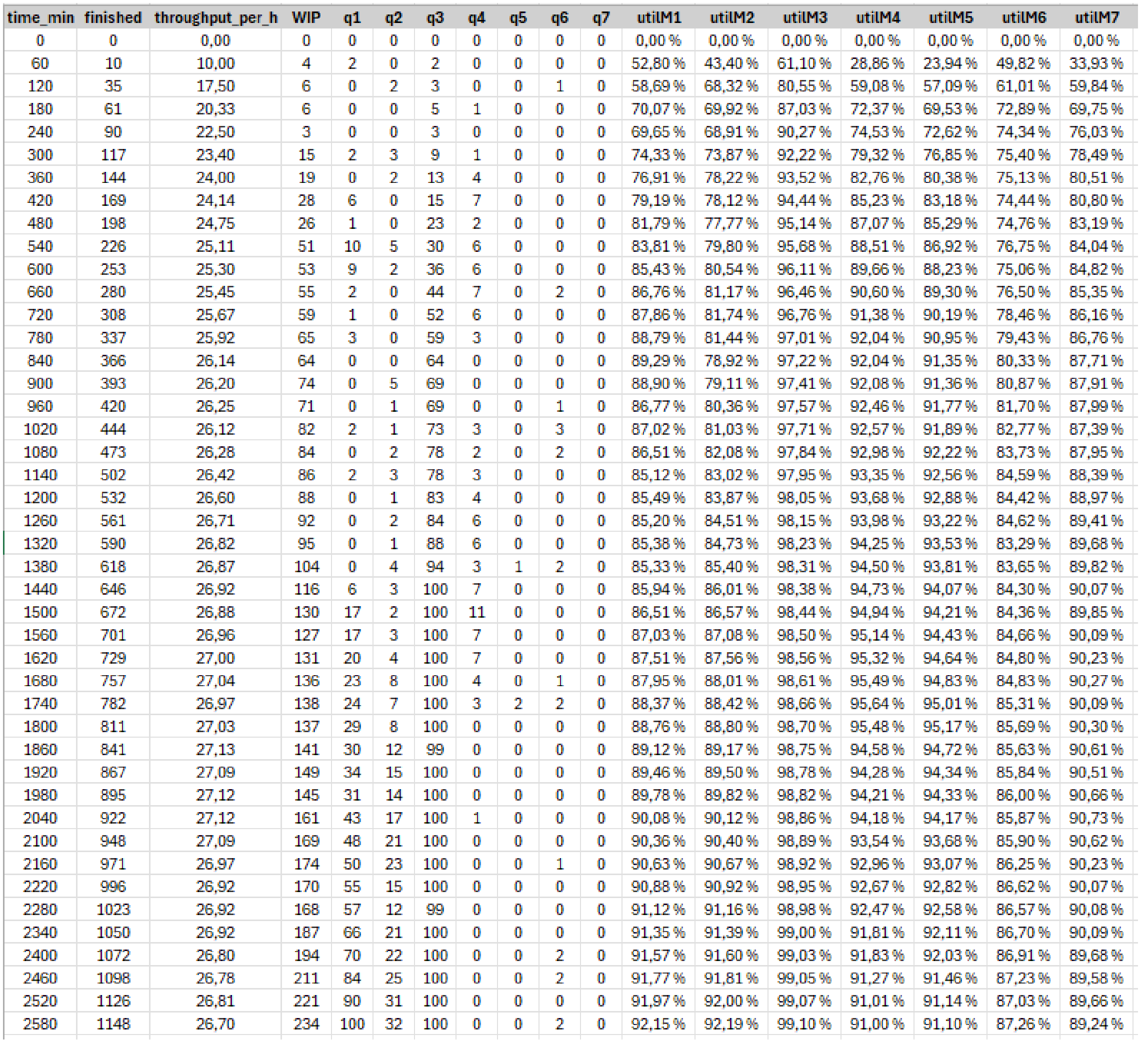


Figure 19 SPT Production rate.

Table 6 SPT statistics.



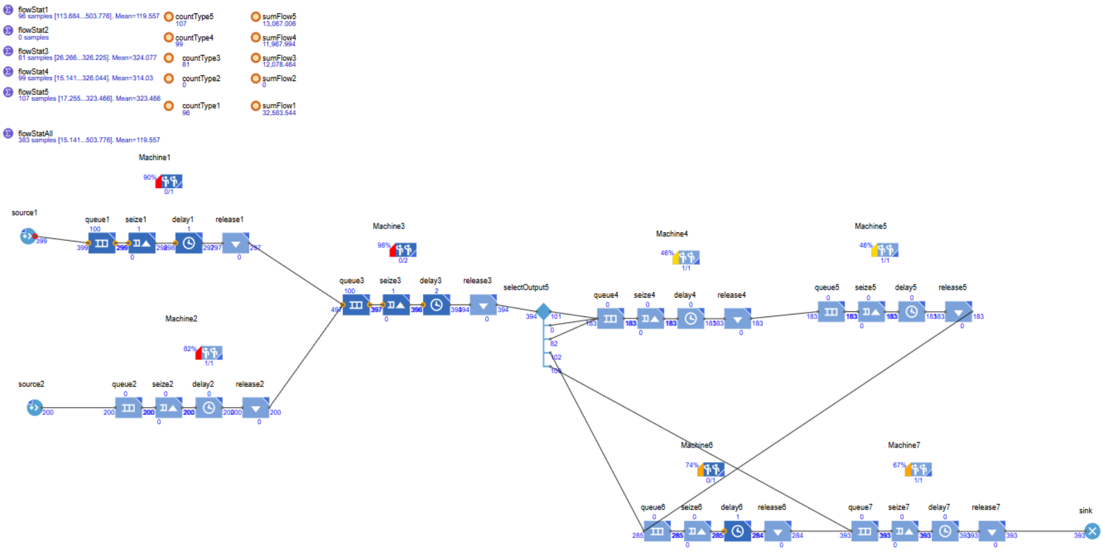
time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	10	10,00	4	2	0	2	0	0	0	0	52,80 %	43,40 %	61,10 %	28,86 %	23,94 %	49,82 %	33,93 %
120	35	17,50	6	0	2	3	0	0	1	0	58,69 %	68,32 %	80,55 %	59,08 %	57,09 %	61,01 %	59,84 %
180	61	20,33	6	0	0	5	1	0	0	0	70,07 %	69,92 %	87,03 %	72,37 %	69,53 %	72,89 %	69,75 %
240	90	22,50	3	0	0	3	0	0	0	0	69,65 %	68,91 %	90,27 %	74,53 %	72,62 %	74,34 %	76,03 %
300	117	23,40	15	2	3	9	1	0	0	0	74,33 %	73,87 %	92,22 %	79,32 %	76,85 %	75,40 %	78,49 %
360	144	24,00	19	0	2	13	4	0	0	0	76,91 %	78,22 %	93,52 %	82,76 %	80,38 %	75,13 %	80,51 %
420	169	24,14	28	6	0	15	7	0	0	0	79,19 %	78,12 %	94,44 %	85,23 %	83,18 %	74,44 %	80,80 %
480	198	24,75	26	1	0	23	2	0	0	0	81,79 %	77,77 %	95,14 %	87,07 %	85,29 %	74,76 %	83,19 %
540	226	25,11	51	10	5	30	6	0	0	0	83,81 %	79,80 %	95,68 %	88,51 %	86,92 %	76,75 %	84,04 %
600	253	25,30	53	9	2	36	6	0	0	0	85,43 %	80,54 %	96,11 %	89,66 %	88,23 %	75,06 %	84,82 %
660	280	25,45	55	2	0	44	7	0	2	0	86,76 %	81,17 %	96,46 %	90,60 %	89,30 %	76,50 %	85,35 %
720	308	25,67	59	1	0	52	6	0	0	0	87,86 %	81,74 %	96,76 %	91,38 %	90,19 %	78,46 %	86,16 %
780	337	25,92	65	3	0	59	3	0	0	0	88,79 %	81,44 %	97,01 %	92,04 %	90,95 %	79,43 %	86,76 %
840	366	26,14	64	0	0	64	0	0	0	0	89,29 %	78,92 %	97,22 %	92,04 %	91,35 %	80,33 %	87,71 %
900	393	26,20	74	0	5	69	0	0	0	0	88,90 %	79,11 %	97,41 %	92,08 %	91,36 %	80,87 %	87,91 %
960	420	26,25	71	0	1	69	0	0	1	0	86,77 %	80,36 %	97,57 %	92,46 %	91,77 %	81,70 %	87,99 %
1020	444	26,12	82	2	1	73	3	0	3	0	87,02 %	81,03 %	97,71 %	92,57 %	91,89 %	82,77 %	87,39 %
1080	473	26,28	84	0	2	78	2	0	2	0	86,51 %	82,08 %	97,84 %	92,98 %	92,22 %	83,73 %	87,95 %
1140	502	26,42	86	2	3	78	3	0	0	0	85,12 %	83,02 %	97,95 %	93,35 %	92,56 %	84,59 %	88,39 %
1200	532	26,60	88	0	1	83	4	0	0	0	85,49 %	83,87 %	98,05 %	93,68 %	92,88 %	84,42 %	88,97 %
1260	561	26,71	92	0	2	84	6	0	0	0	85,20 %	84,51 %	98,15 %	93,98 %	93,22 %	84,62 %	89,41 %
1320	590	26,82	95	0	1	88	6	0	0	0	85,38 %	84,73 %	98,23 %	94,25 %	93,53 %	83,29 %	89,68 %
1380	618	26,87	104	0	4	94	3	1	2	0	85,33 %	85,40 %	98,31 %	94,50 %	93,81 %	83,65 %	89,82 %
1440	646	26,92	116	6	3	100	7	0	0	0	85,94 %	86,01 %	98,38 %	94,73 %	94,07 %	84,30 %	90,07 %
1500	672	26,88	130	17	2	100	11	0	0	0	86,51 %	86,57 %	98,44 %	94,94 %	94,21 %	84,36 %	89,85 %
1560	701	26,96	127	17	3	100	7	0	0	0	87,03 %	87,08 %	98,50 %	95,14 %	94,43 %	84,66 %	90,09 %
1620	729	27,00	131	20	4	100	7	0	0	0	87,51 %	87,56 %	98,56 %	95,32 %	94,64 %	84,80 %	90,23 %
1680	757	27,04	136	23	8	100	4	0	1	0	87,95 %	88,01 %	98,61 %	95,49 %	94,83 %	84,83 %	90,27 %
1740	782	26,97	138	24	7	100	3	2	2	0	88,37 %	88,42 %	98,66 %	95,64 %	95,01 %	85,31 %	90,09 %
1800	811	27,03	137	29	8	100	0	0	0	0	88,76 %	88,80 %	98,70 %	95,48 %	95,17 %	85,69 %	90,30 %
1860	841	27,13	141	30	12	99	0	0	0	0	89,12 %	89,17 %	98,75 %	94,58 %	94,72 %	85,63 %	90,61 %
1920	867	27,09	149	34	15	100	0	0	0	0	89,46 %	89,50 %	98,78 %	94,28 %	94,34 %	85,84 %	90,51 %
1980	895	27,12	145	31	14	100	0	0	0	0	89,78 %	89,82 %	98,82 %	94,21 %	94,33 %	86,00 %	90,66 %
2040	922	27,12	161	43	17	100	1	0	0	0	90,08 %	90,12 %	98,86 %	94,18 %	94,17 %	85,87 %	90,73 %
2100	948	27,09	169	48	21	100	0	0	0	0	90,36 %	90,40 %	98,89 %	93,54 %	93,68 %	85,90 %	90,62 %
2160	971	26,97	174	50	23	100	0	0	1	0	90,63 %	90,67 %	98,92 %	92,96 %	93,07 %	86,25 %	90,23 %
2220	996	26,92	170	55	15	100	0	0	0	0	90,88 %	90,92 %	98,95 %	92,67 %	92,82 %	86,62 %	90,07 %
2280	1023	26,92	168	57	12	99	0	0	0	0	91,12 %	91,16 %	98,98 %	92,47 %	92,58 %	86,57 %	90,08 %
2340	1050	26,92	187	66	21	100	0	0	0	0	91,35 %	91,39 %	99,00 %	91,81 %	92,11 %	86,70 %	90,09 %
2400	1072	26,80	194	70	22	100	0	0	2	0	91,57 %	91,60 %	99,03 %	91,83 %	92,03 %	86,91 %	89,68 %
2460	1098	26,78	211	84	25	100	0	0	2	0	91,77 %	91,81 %	99,05 %	91,27 %	91,46 %	87,23 %	89,58 %
2520	1126	26,81	221	90	31	100	0	0	0	0	91,97 %	92,00 %	99,07 %	91,01 %	91,14 %	87,03 %	89,66 %
2580	1148	26,70	234	100	32	100	0	0	2	0	92,15 %	92,19 %	99,10 %	91,00 %	91,10 %	87,26 %	89,24 %

4.2.1.3 Longest processing time

In this experiment, the processing rule is changed to longest processing first (LPT). This is done to see how it will affect all the bottlenecks if at all. The differences in the delay times are not that significant, so there should not be a substantial from the shortest processing time first, but as seen in the previous simulation, there is an impact. This simulation is done to compare the results and its effects to see if there is a difference in results.

During the run of the simulation, there were 393 products conducted for 1172.77 minutes. The average throughput was 16.33 pieces per hour, and the median was 17.28 products with a standard deviation of 4.594. This method has the weakest result so far in every other aspect except the standard deviation, which was the best. However, even though the throughput counts are on the lower end, the average waiting times are much better than, for example, in the SPT method, where the waiting time for machine 3 was 74 minutes, and for machine 1 is 20 minutes. Here the corresponding waiting times are 10 and 60 minutes when rounded (Picture 11).

Another thing that needs to be looked at is the finished product types in this simulation. In other simulation there have been all 5 different product types of somewhat same amounts finished but in this processing rule there is not a single finished product type 2. Product types 1 and 5 load the production most. Type 1 spending almost triple the time of other types and type 5 has the most finished products amount.

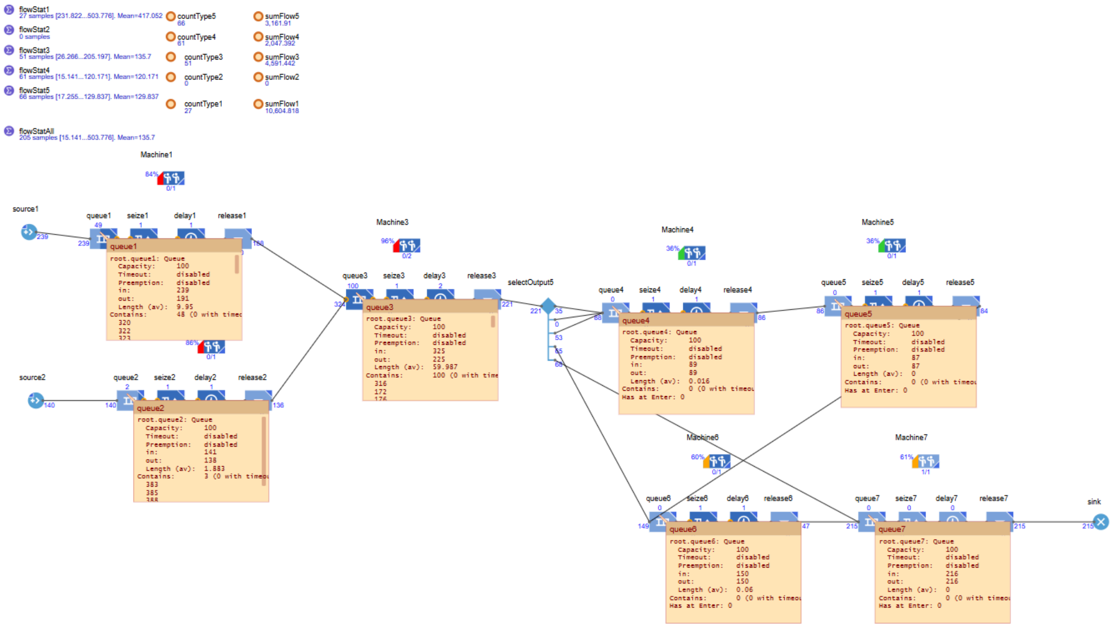


flowStat1
96 samples [113.684...503.776]. Mean=119.557
flowStat2
0 samples
flowStat3
81 samples [26.266...326.225]. Mean=324.077
flowStat4
99 samples [15.141...326.044]. Mean=314.03
flowStat5
107 samples [17.255...323.466]. Mean=323.466
flowStatAll
383 samples [15.141...503.776]. Mean=119.557

countType5
107
countType4
99
countType3
81
countType2
0
countType1
96

sumFlow5
13,067.006
sumFlow4
11,967.994
sumFlow3
12,078.464
sumFlow2
0
sumFlow1
32,583.544

Picture 11 LPT.



```
flowStat1
27 samples [231.822...503.776]. Mean=417.052
flowStat2
0 samples
flowStat3
51 samples [26.266...205.197]. Mean=135.7
flowStat4
61 samples [15.141...120.171]. Mean=120.171
flowStat5
66 samples [17.255...129.837]. Mean=129.837

flowStatAll
205 samples [15.141...503.776]. Mean=135.7

countType5
66
countType4
61
countType3
51
countType2
0
countType1
27

sumFlow5
3,161.91
sumFlow4
2,047.392
sumFlow3
4,591.442
sumFlow2
0
sumFlow1
10,604.818
```

```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            239
  out:           191
  Length (av):   9.95
Contains:        48 (0 with timeo
  320
  322
  323
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            141
  out:           138
  Length (av):   1.883
Contains:        3 (0 with timeo
  383
  385
  388
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            325
  out:           225
  Length (av):   59.987
Contains:        100 (0 with time
  316
  172
  176
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            89
  out:           89
  Length (av):   0.016
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            87
  out:           87
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            150
  out:           150
  Length (av):   0.06
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            216
  out:           216
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

Picture 12 LPT Average queue.

The utilization rate is very front heavy and the production is getting stuck on machine 3. After machine 3 the utilization rates decrease drastically and in machines 4 and 6 it is under 50%, and on machine 6 it is 74% (Picture 11). Otherwise, Figures 21, 22, and 23 look closely the same as previously. Machine 3 is causing the queue, and because of that the queue starts to increase quickly, also in this simulation. The WIP increases rapidly to a maximum, like in the previous cases. Table 7 shows the statistics more closely from this simulation.

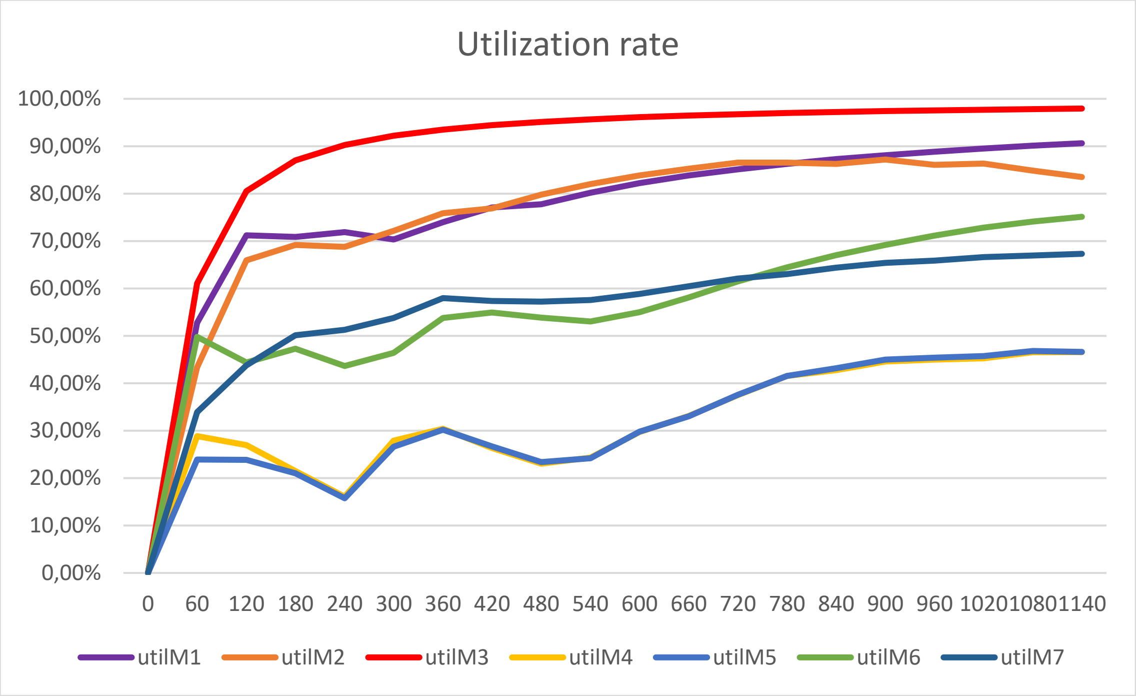


Figure 20 LPT Utilization rate.

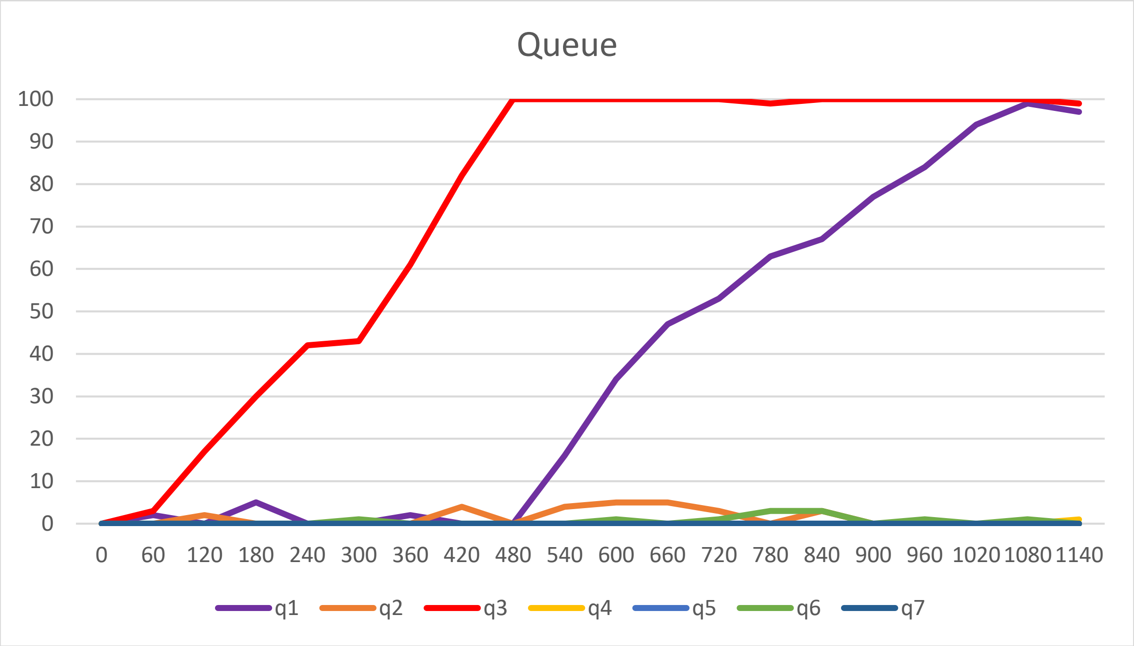


Figure 21 LPT queues.

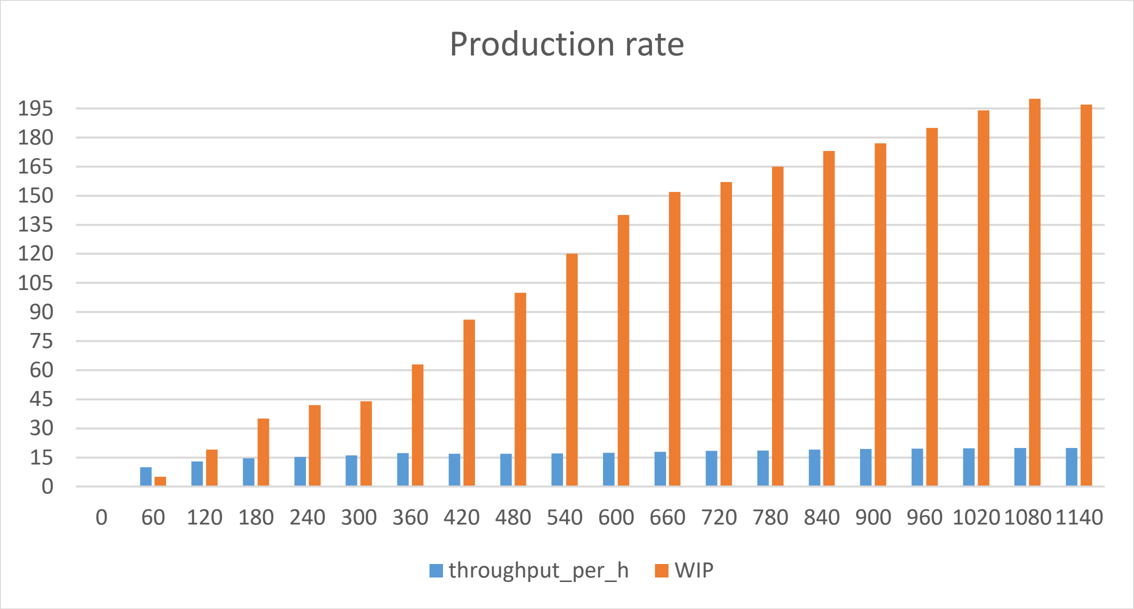


Figure 22 LPT production rate.

Table 7 LPT Statistics.

time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	10	10,00	5	2	0	3	0	0	0	0	52,80 %	43,40 %	61,10 %	28,86 %	23,94 %	49,82 %	33,93 %
120	26	13,00	19	0	2	17	0	0	0	0	71,24 %	65,97 %	80,55 %	26,95 %	23,88 %	44,40 %	43,76 %
180	44	14,67	35	5	0	30	0	0	0	0	70,85 %	69,16 %	87,03 %	21,47 %	21,04 %	47,27 %	50,11 %
240	61	15,25	42	0	0	42	0	0	0	0	71,89 %	68,75 %	90,27 %	16,10 %	15,78 %	43,64 %	51,25 %
300	80	16,00	44	0	0	43	0	0	1	0	70,33 %	72,18 %	92,22 %	27,93 %	26,63 %	46,40 %	53,80 %
360	103	17,17	63	2	0	61	0	0	0	0	74,01 %	75,88 %	93,52 %	30,41 %	30,23 %	53,77 %	57,94 %
420	118	16,86	86	0	4	82	0	0	0	0	77,12 %	76,88 %	94,44 %	26,34 %	26,72 %	54,93 %	57,36 %
480	135	16,88	100	0	0	100	0	0	0	0	77,74 %	79,77 %	95,14 %	23,05 %	23,38 %	53,88 %	57,20 %
540	153	17,00	120	16	4	100	0	0	0	0	80,21 %	82,02 %	95,68 %	24,33 %	24,17 %	53,02 %	57,57 %
600	174	17,40	140	34	5	100	0	0	1	0	82,19 %	83,82 %	96,11 %	29,72 %	29,83 %	55,03 %	58,88 %
660	197	17,91	152	47	5	100	0	0	0	0	83,81 %	85,29 %	96,46 %	33,09 %	33,01 %	58,12 %	60,45 %
720	220	18,33	157	53	3	100	0	0	1	0	85,16 %	86,52 %	96,76 %	37,53 %	37,56 %	61,51 %	62,06 %
780	242	18,62	165	63	0	99	0	0	3	0	86,30 %	86,53 %	97,01 %	41,56 %	41,56 %	64,47 %	63,05 %
840	267	19,07	173	67	3	100	0	0	3	0	87,28 %	86,29 %	97,22 %	42,77 %	43,17 %	67,01 %	64,42 %
900	291	19,40	177	77	0	100	0	0	0	0	88,13 %	87,20 %	97,41 %	44,58 %	45,02 %	69,21 %	65,39 %
960	312	19,50	185	84	0	100	0	0	1	0	88,87 %	86,05 %	97,57 %	44,97 %	45,38 %	71,13 %	65,89 %
1020	336	19,76	194	94	0	100	0	0	0	0	89,52 %	86,36 %	97,71 %	45,26 %	45,71 %	72,83 %	66,65 %
1080	358	19,89	200	99	0	100	0	0	1	0	90,11 %	84,89 %	97,84 %	46,55 %	46,82 %	74,14 %	66,98 %
1140	379	19,95	197	97	0	99	1	0	0	0	90,63 %	83,48 %	97,95 %	46,57 %	46,64 %	75,12 %	67,31 %

4.2.2 Case 2: Lowering WIP

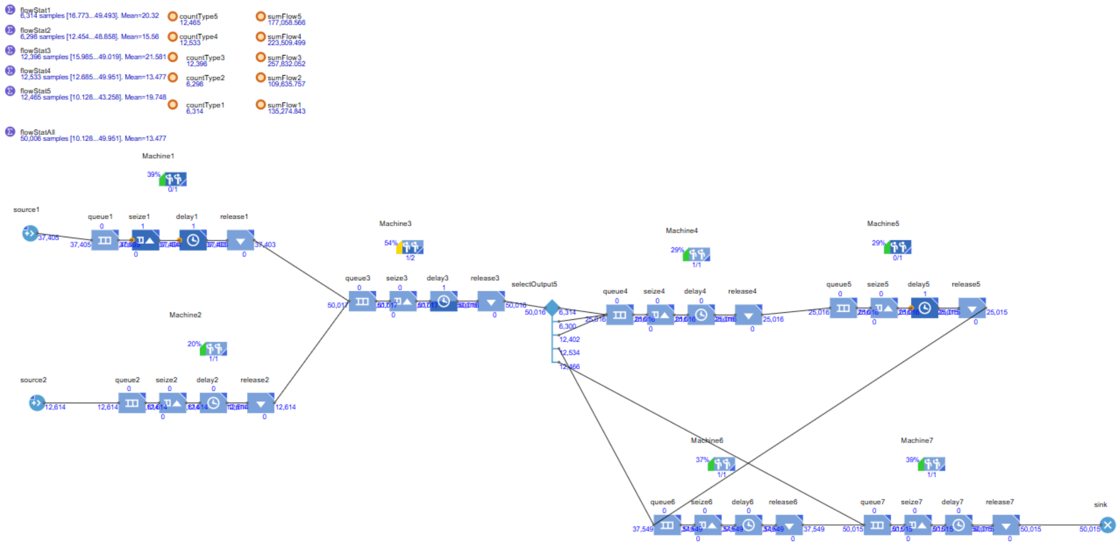
In this case, the method is to use one common lean method and lower the work-in-process value. The experiment will be done by changing the arrival rate on sources. The first experiment is done by using the FIFO rule and lowering the arrival rate to almost 0 products per minute. In the second experiment, the arrival rate was raised a bit, so the arrival rate was somewhere in between, and the effects were compared. The latter simulation was also done using two different scheduling rules to see if that has an impact on the system.

4.2.2.1 FIFO S1 0.15 and S2 0.05

In this case, the arrival rate for both sources decreased drastically to see how that will affect. The simulation continued until the maximum capacity of created agents (50000) was reached. The time of the simulation stopping is 251 236.78 minutes. The arrival rate on Source 1 was 0.15 products per minute and in Source 2 the arrival rate was set at 0.05 products per minute. This means that a new product comes to processing from source 1 every 6.66 minutes and from source 2 every 20 minutes. The aim is to lower the WIP and prevent the formation of the queues.

The simulation result can be seen in Pictures 13 and 14. In this case, there were no errors due to capacity issues in the queues. The simulation was run until the maximum capacity of 50 000 products was achieved. Comparing the results from this simulation to all the previous ones, the problems are widely different. The utilization rates are very low on each machine, and the queues are nonexistent. The lead times are as low as they can get because there are no queues and therefore no waiting times to add time to the lead times. Based on those meters, there is no problem with the bottleneck. However, there is another kind of problem with this solution. This kind of production is not very efficient because of all the overcapacity that is not used.

The time that it takes to reach the limit is 251 236,78 minutes, and there are 50 015 products produced during that time. The average throughput is 11.87 products per hour, and the median is 11.94 products. Standard deviation is 0.26 so the production is very steady each hour. In Table 8 are part of the statistics of this simulation, but because the simulation gave so much data, only the first part of the table is shown; however, the trends continued same throughout the data. The Pictures 13 and 14 show the end state of the simulation.



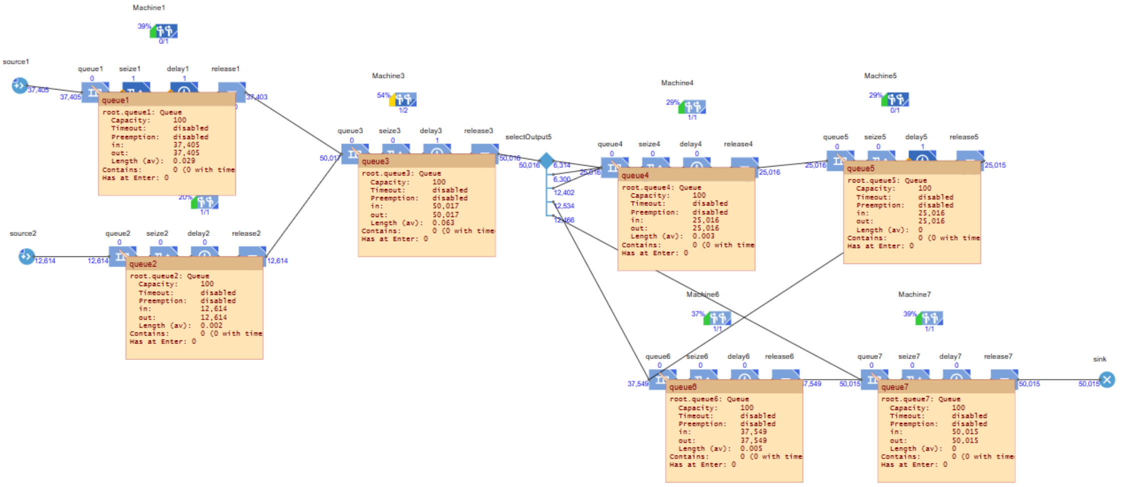
```
flowStat1
6,314 samples [16.773...49.493]. Mean=20.32
flowStat2
6,298 samples [12.454...48.658]. Mean=15.56
flowStat3
12,396 samples [15.985...49.019]. Mean=21.581
flowStat4
12,533 samples [12.685...49.951]. Mean=13.477
flowStat5
12,465 samples [10.128...43.258]. Mean=19.748

flowStatAll
50,006 samples [10.128...49.951]. Mean=13.477

countType5
12,465
countType4
12,533
countType3
12,396
countType2
6,298
countType1
6,314

sumFlow5
177,058.566
sumFlow4
223,509.499
sumFlow3
257,832.052
sumFlow2
109,635.757
sumFlow1
135,274.843
```

Picture 13 FIFO S1 0.15 and S2 0.05.



```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            37,405
  out:           37,405
  Length (av):   0.029
Contains:        0 (0 with time
Has at Enter: 0
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            12,614
  out:           12,614
  Length (av):   0.002
Contains:        0 (0 with time
Has at Enter: 0
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            50,017
  out:           50,017
  Length (av):   0.063
Contains:        0 (0 with time
Has at Enter: 0
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            25,016
  out:           25,016
  Length (av):   0.003
Contains:        0 (0 with time
Has at Enter: 0
```

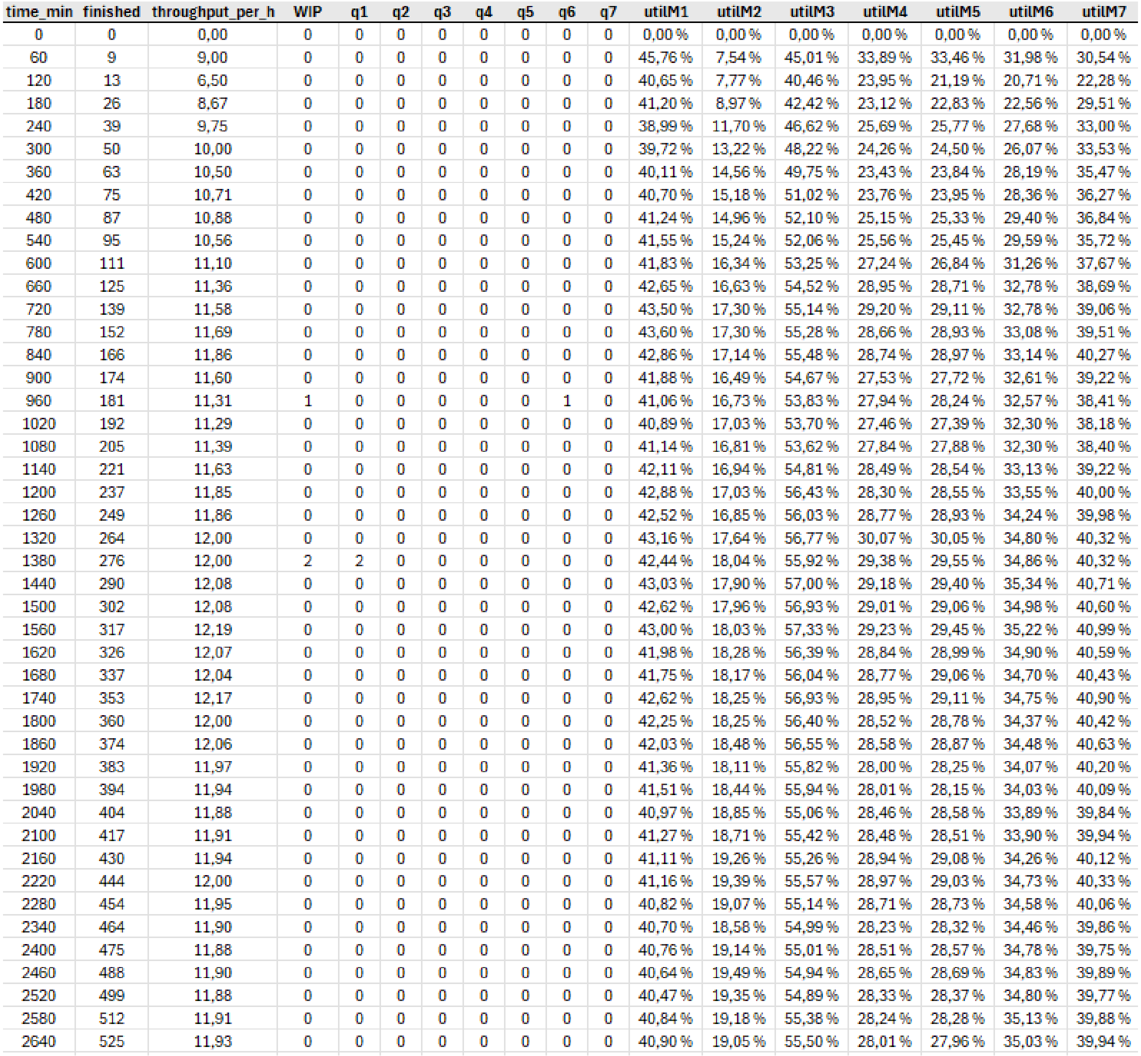
```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            25,016
  out:           25,016
  Length (av):   0
Contains:        0 (0 with time
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            37,549
  out:           37,549
  Length (av):   0.005
Contains:        0 (0 with time
Has at Enter: 0
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            50,015
  out:           50,015
  Length (av):   0
Contains:        0 (0 with time
Has at Enter: 0
```

Picture 14 FIFO S1 0.15 and S2 0.05 waiting times.

Table 8 FIFO S1 0.15 and S2 0.05 Statistics.

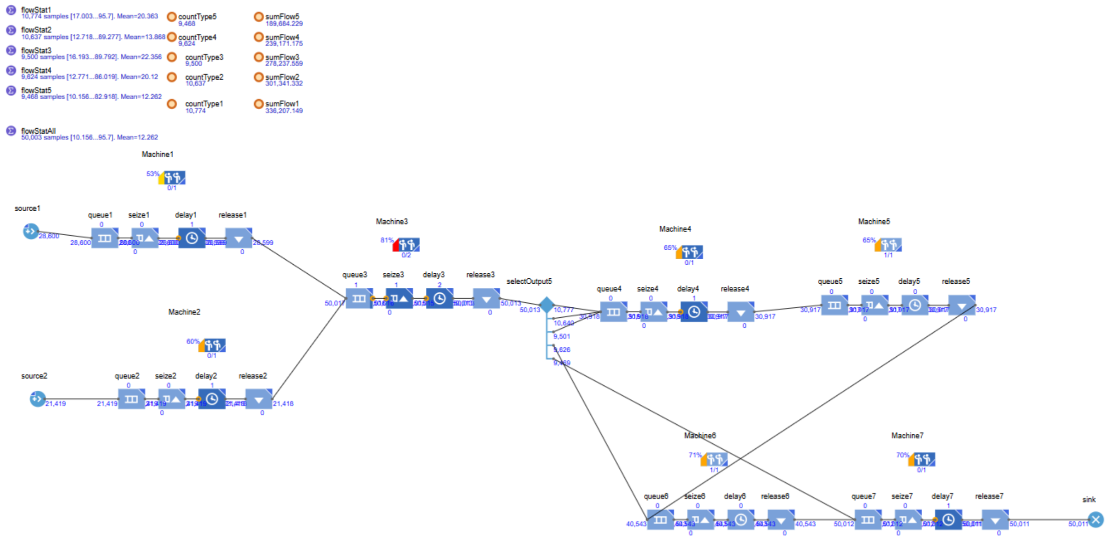


time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	9	9,00	0	0	0	0	0	0	0	0	45,76 %	7,54 %	45,01 %	33,89 %	33,46 %	31,98 %	30,54 %
120	13	6,50	0	0	0	0	0	0	0	0	40,65 %	7,77 %	40,46 %	23,95 %	21,19 %	20,71 %	22,28 %
180	26	8,67	0	0	0	0	0	0	0	0	41,20 %	8,97 %	42,42 %	23,12 %	22,83 %	22,56 %	29,51 %
240	39	9,75	0	0	0	0	0	0	0	0	38,99 %	11,70 %	46,62 %	25,69 %	25,77 %	27,68 %	33,00 %
300	50	10,00	0	0	0	0	0	0	0	0	39,72 %	13,22 %	48,22 %	24,26 %	24,50 %	26,07 %	33,53 %
360	63	10,50	0	0	0	0	0	0	0	0	40,11 %	14,56 %	49,75 %	23,43 %	23,84 %	28,19 %	35,47 %
420	75	10,71	0	0	0	0	0	0	0	0	40,70 %	15,18 %	51,02 %	23,76 %	23,95 %	28,36 %	36,27 %
480	87	10,88	0	0	0	0	0	0	0	0	41,24 %	14,96 %	52,10 %	25,15 %	25,33 %	29,40 %	36,84 %
540	95	10,56	0	0	0	0	0	0	0	0	41,55 %	15,24 %	52,06 %	25,56 %	25,45 %	29,59 %	35,72 %
600	111	11,10	0	0	0	0	0	0	0	0	41,83 %	16,34 %	53,25 %	27,24 %	26,84 %	31,26 %	37,67 %
660	125	11,36	0	0	0	0	0	0	0	0	42,65 %	16,63 %	54,52 %	28,95 %	28,71 %	32,78 %	38,69 %
720	139	11,58	0	0	0	0	0	0	0	0	43,50 %	17,30 %	55,14 %	29,20 %	29,11 %	32,78 %	39,06 %
780	152	11,69	0	0	0	0	0	0	0	0	43,60 %	17,30 %	55,28 %	28,66 %	28,93 %	33,08 %	39,51 %
840	166	11,86	0	0	0	0	0	0	0	0	42,86 %	17,14 %	55,48 %	28,74 %	28,97 %	33,14 %	40,27 %
900	174	11,60	0	0	0	0	0	0	0	0	41,88 %	16,49 %	54,67 %	27,53 %	27,72 %	32,61 %	39,22 %
960	181	11,31	1	0	0	0	0	0	1	0	41,06 %	16,73 %	53,83 %	27,94 %	28,24 %	32,57 %	38,41 %
1020	192	11,29	0	0	0	0	0	0	0	0	40,89 %	17,03 %	53,70 %	27,46 %	27,39 %	32,30 %	38,18 %
1080	205	11,39	0	0	0	0	0	0	0	0	41,14 %	16,81 %	53,62 %	27,84 %	27,88 %	32,30 %	38,40 %
1140	221	11,63	0	0	0	0	0	0	0	0	42,11 %	16,94 %	54,81 %	28,49 %	28,54 %	33,13 %	39,22 %
1200	237	11,85	0	0	0	0	0	0	0	0	42,88 %	17,03 %	56,43 %	28,30 %	28,55 %	33,55 %	40,00 %
1260	249	11,86	0	0	0	0	0	0	0	0	42,52 %	16,85 %	56,03 %	28,77 %	28,93 %	34,24 %	39,98 %
1320	264	12,00	0	0	0	0	0	0	0	0	43,16 %	17,64 %	56,77 %	30,07 %	30,05 %	34,80 %	40,32 %
1380	276	12,00	2	2	0	0	0	0	0	0	42,44 %	18,04 %	55,92 %	29,38 %	29,55 %	34,86 %	40,32 %
1440	290	12,08	0	0	0	0	0	0	0	0	43,03 %	17,90 %	57,00 %	29,18 %	29,40 %	35,34 %	40,71 %
1500	302	12,08	0	0	0	0	0	0	0	0	42,62 %	17,96 %	56,93 %	29,01 %	29,06 %	34,98 %	40,60 %
1560	317	12,19	0	0	0	0	0	0	0	0	43,00 %	18,03 %	57,33 %	29,23 %	29,45 %	35,22 %	40,99 %
1620	326	12,07	0	0	0	0	0	0	0	0	41,98 %	18,28 %	56,39 %	28,84 %	28,99 %	34,90 %	40,59 %
1680	337	12,04	0	0	0	0	0	0	0	0	41,75 %	18,17 %	56,04 %	28,77 %	29,06 %	34,70 %	40,43 %
1740	353	12,17	0	0	0	0	0	0	0	0	42,62 %	18,25 %	56,93 %	28,95 %	29,11 %	34,75 %	40,90 %
1800	360	12,00	0	0	0	0	0	0	0	0	42,25 %	18,25 %	56,40 %	28,52 %	28,78 %	34,37 %	40,42 %
1860	374	12,06	0	0	0	0	0	0	0	0	42,03 %	18,48 %	56,55 %	28,58 %	28,87 %	34,48 %	40,63 %
1920	383	11,97	0	0	0	0	0	0	0	0	41,36 %	18,11 %	55,82 %	28,00 %	28,25 %	34,07 %	40,20 %
1980	394	11,94	0	0	0	0	0	0	0	0	41,51 %	18,44 %	55,94 %	28,01 %	28,15 %	34,03 %	40,09 %
2040	404	11,88	0	0	0	0	0	0	0	0	40,97 %	18,85 %	55,06 %	28,46 %	28,58 %	33,89 %	39,84 %
2100	417	11,91	0	0	0	0	0	0	0	0	41,27 %	18,71 %	55,42 %	28,48 %	28,51 %	33,90 %	39,94 %
2160	430	11,94	0	0	0	0	0	0	0	0	41,11 %	19,26 %	55,26 %	28,94 %	29,08 %	34,26 %	40,12 %
2220	444	12,00	0	0	0	0	0	0	0	0	41,16 %	19,39 %	55,57 %	28,97 %	29,03 %	34,73 %	40,33 %
2280	454	11,95	0	0	0	0	0	0	0	0	40,82 %	19,07 %	55,14 %	28,71 %	28,73 %	34,58 %	40,06 %
2340	464	11,90	0	0	0	0	0	0	0	0	40,70 %	18,58 %	54,99 %	28,23 %	28,32 %	34,46 %	39,86 %
2400	475	11,88	0	0	0	0	0	0	0	0	40,76 %	19,14 %	55,01 %	28,51 %	28,57 %	34,78 %	39,75 %
2460	488	11,90	0	0	0	0	0	0	0	0	40,64 %	19,49 %	54,94 %	28,65 %	28,69 %	34,83 %	39,89 %
2520	499	11,88	0	0	0	0	0	0	0	0	40,47 %	19,35 %	54,89 %	28,33 %	28,37 %	34,80 %	39,77 %
2580	512	11,91	0	0	0	0	0	0	0	0	40,84 %	19,18 %	55,38 %	28,24 %	28,28 %	35,13 %	39,88 %
2640	525	11,93	0	0	0	0	0	0	0	0	40,90 %	19,05 %	55,50 %	28,01 %	27,96 %	35,03 %	39,94 %

4.2.2.2 FIFO 0.2 S1 and 0.15 S2

Because of the overcapacity in the previous simulation, the arrival rate is increased for this next simulation. The arrival rate is chosen somewhat randomly, somewhere between the baseline simulation and the previous simulation. For this simulation, the arrival rates chosen were 0.2 products per minute for source 1 and 0.15 products per minute for source 2. This means 1 product every three minutes from source 1 and from source a new product every 6.66 minutes.

In this case, the simulation was run until the maximum number of products was manufactured. The results from the simulation can be seen in Pictures 15 and 16. The simulation lasted 142 622.14 minutes, and during that time, there were 50 011 products manufactured. The deviation between different product types was not that significant, even though types 1 and 2 were the majority types. The lead times were still sensible as in the previous experiment, but here, a queue formation can be seen before machine 3. In terms of the waiting times, in other machines they are close to 0, but in machine 3 they are a bit above a minute (Picture 16), where in the previous simulation there were no queues or waiting times.



flowStat1
10,774 samples [17.003...95.7]. Mean=20.363

flowStat2
10,637 samples [12.718...89.277]. Mean=13.868

flowStat3
9,500 samples [16.193...89.792]. Mean=22.356

flowStat4
9,624 samples [12.771...86.019]. Mean=20.12

flowStat5
9,468 samples [10.156...82.918]. Mean=12.262

flowStatAll
50,003 samples [10.156...95.7]. Mean=12.262

countType5
9,468

countType4
9,624

countType3
9,500

countType2
10,637

countType1
10,774

sumFlow5
189,684.229

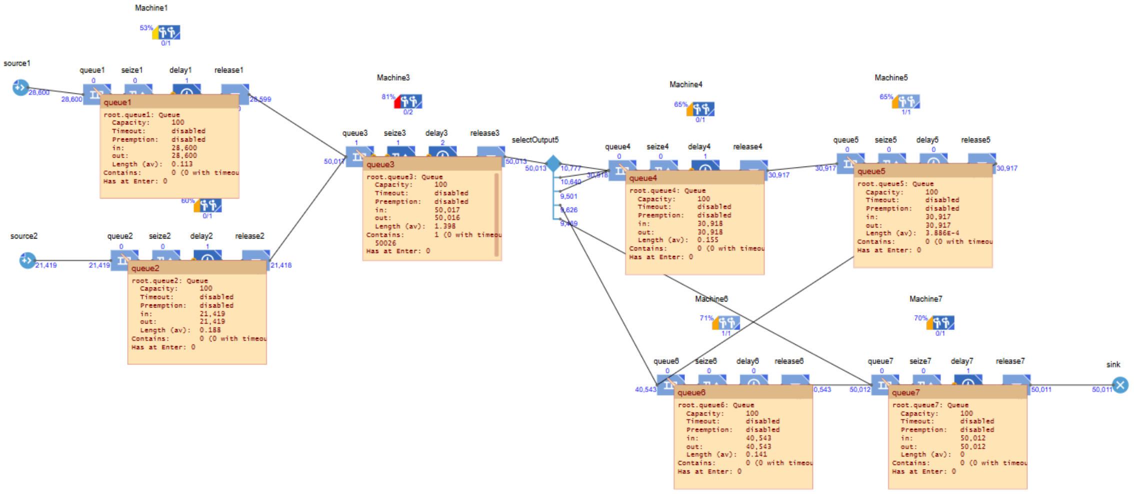
sumFlow4
239,171.175

sumFlow3
278,237.559

sumFlow2
301,341.332

sumFlow1
336,207.149

Picture 15 FIFO 0.2 S1 ja 0.15 S2.



```
root.queue1: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           28,600
  out:          28,600
  Length (av):  0.113
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
root.queue2: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           21,419
  out:          21,419
  Length (av):  0.188
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
root.queue3: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           50,017
  out:          50,016
  Length (av):  1.398
Contains:       1 (0 with timeou
  50026
Has at Enter: 0
```

```
root.queue4: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           30,918
  out:          30,918
  Length (av):  0.155
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
root.queue5: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           30,917
  out:          30,917
  Length (av):  3.886E-4
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
root.queue6: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           40,543
  out:          40,543
  Length (av):  0.141
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
root.queue7: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           50,012
  out:          50,012
  Length (av):  0
Contains:       0 (0 with timeou
Has at Enter: 0
```

Picture 16 FIFO 0.2 S1 ja 0.15 S2 waiting times.

The utilization rates can be seen in Figure 24 and Pictures 15 and 16. All the utilization rates are very steady throughout the simulation, and there is no variation during it. Machine 3 has the highest utilization rate, slightly over 80%, which means there is still capacity available. Another indicator of excess capacity is queue length. Figure 25 illustrates data from the middle of the queue. Note that the scale here is different from the other figures. The figures show that the queues are momentary and mainly only before machine 3, and they start to form much later. In Table 9, it can be seen that at the beginning of the simulation, there are no queues.

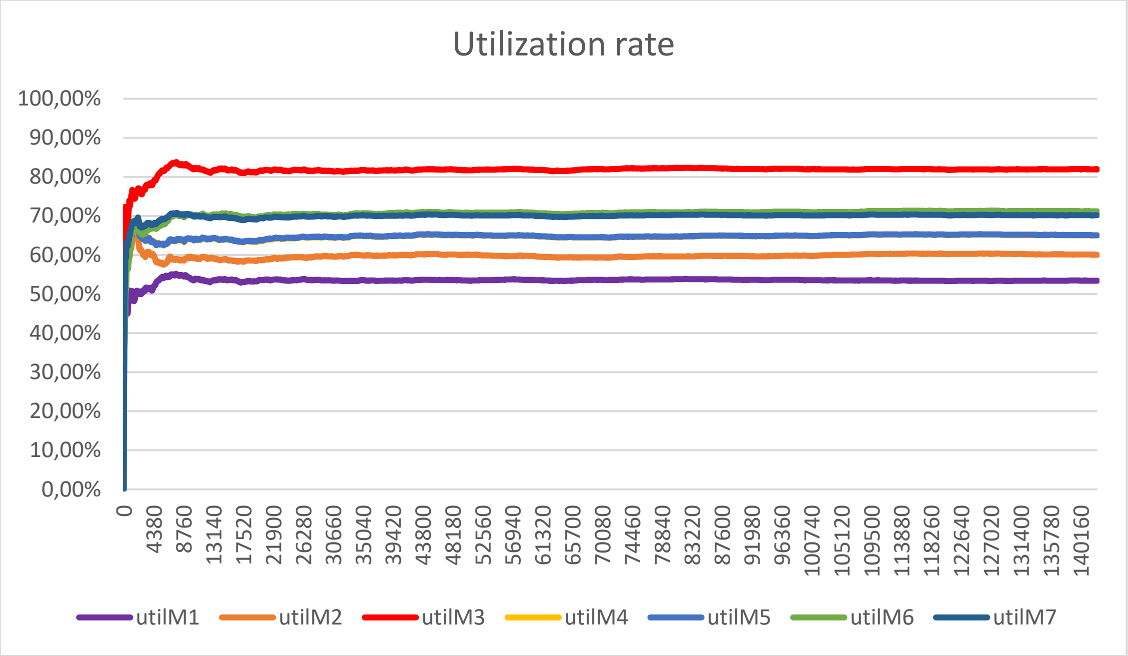


Figure 23 FIFO 0.2 S1 ja 0.15 S2 Utilization rate.

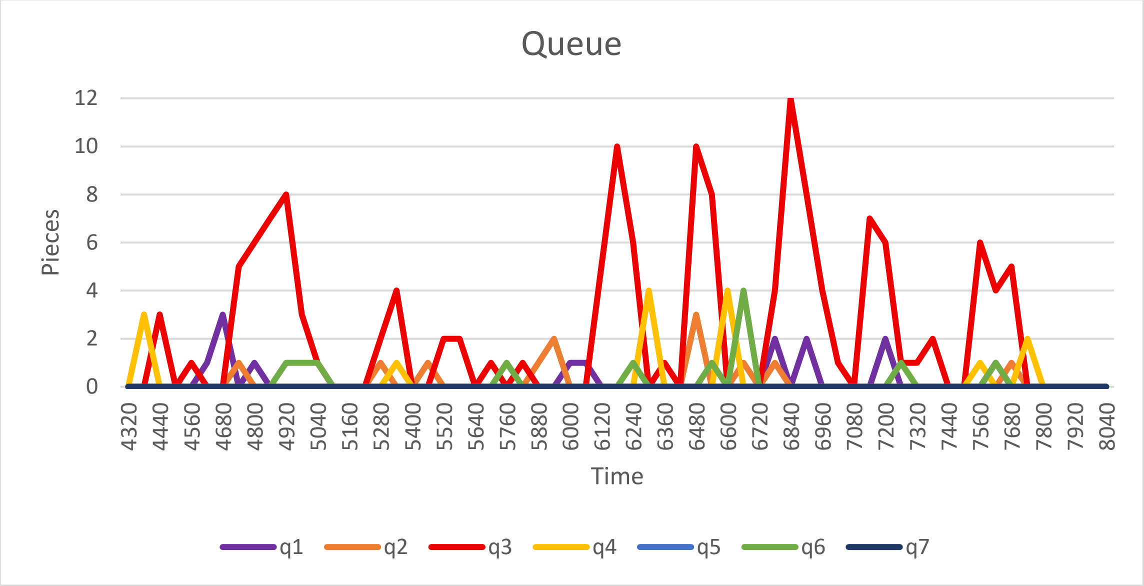


Figure 24 FIFO 0.2 and 0.15 Queue.

Figure 26 shows the production rate for this simulation. This is the first simulation where the WIP is other than 0, and it stays below the throughput line. The average throughput for this simulation was 20.95 products per hour, the median was 21.03 products per hour, and the standard deviation was 0.59 products. Compared to the previous simulation throughput results, the throughput is almost double, but the variation is still quite steady, and the throughput is constant throughout the simulation.

In Table 9 are the statistics of the beginning of this simulation. As in the previous simulation, the amount of data is significant, and only part of the statistics shown. Pictures 15 and 16 are taken at the end of the simulation, and Figures 24 and 26 show the simulation. Only the statistics and the queues illustrate the important parts.

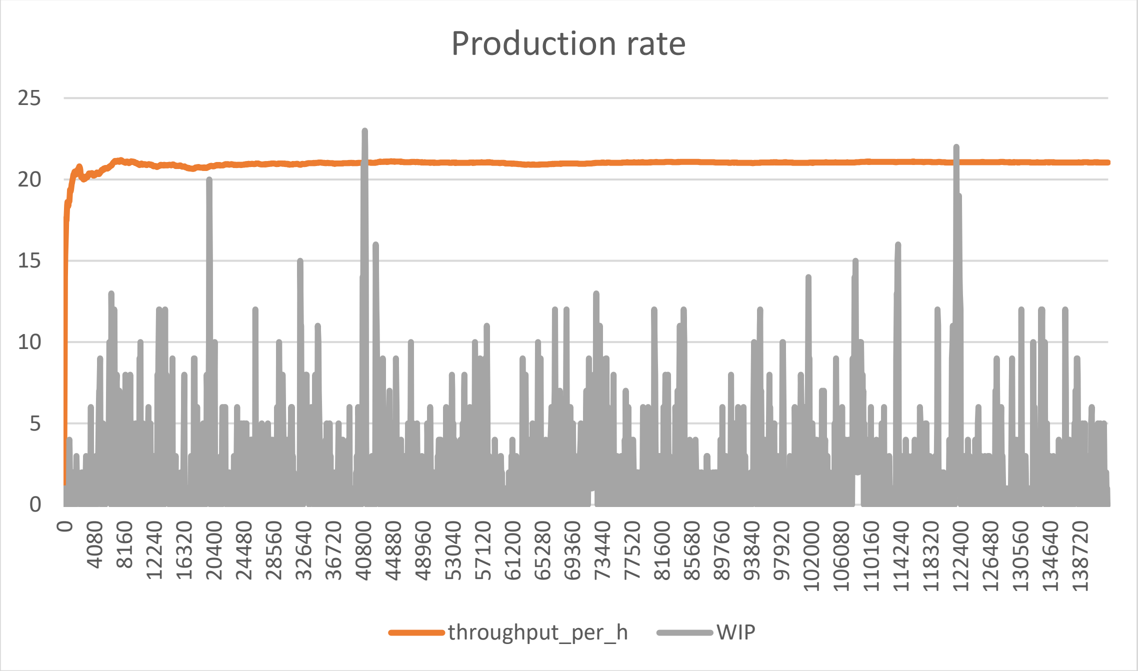
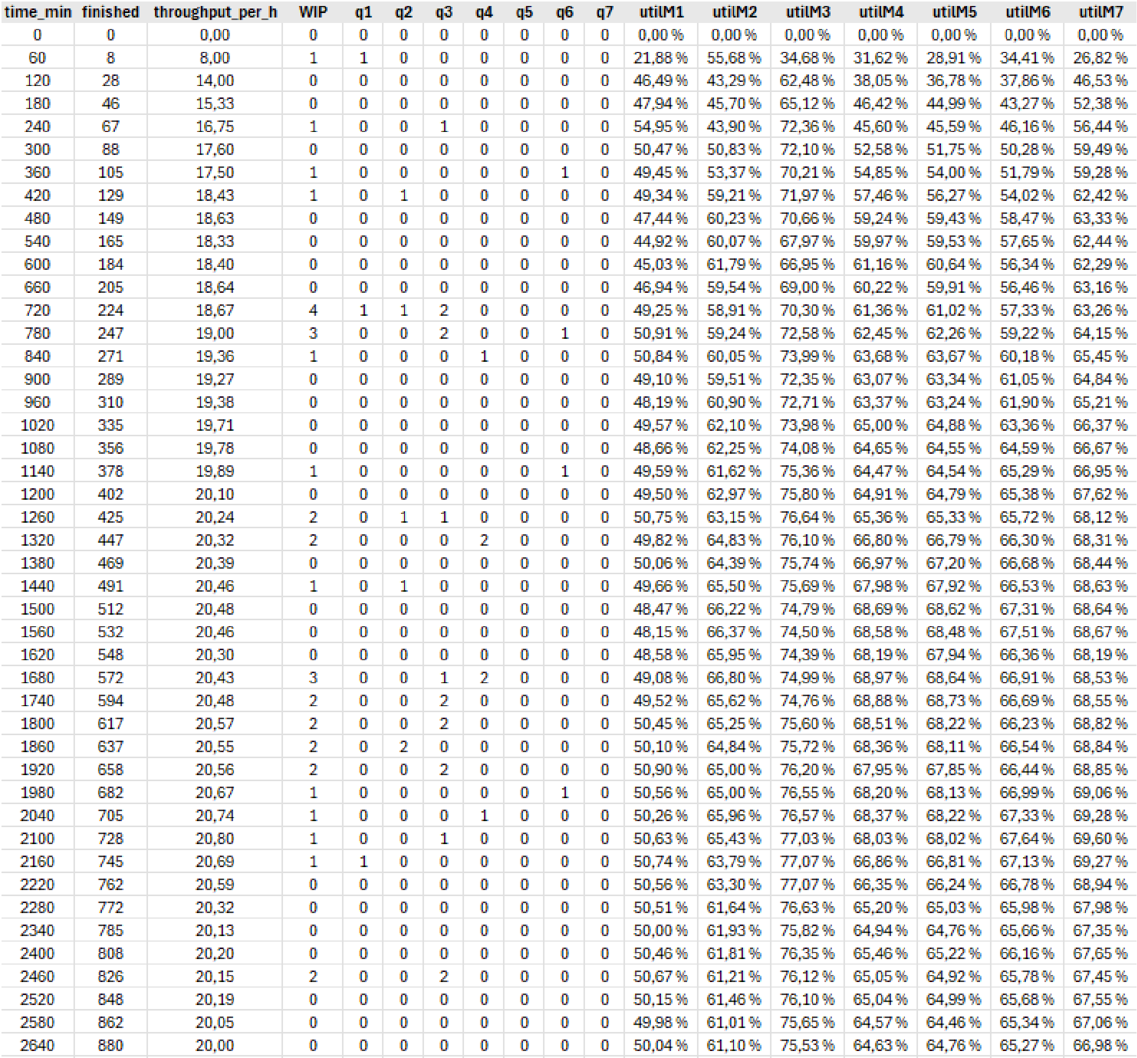


Figure 25 Production rate FIFO S1 0.2 and S2 0.15.

Table 9 FIFO 0.2 S1 and 0.15 S2 Statistic.

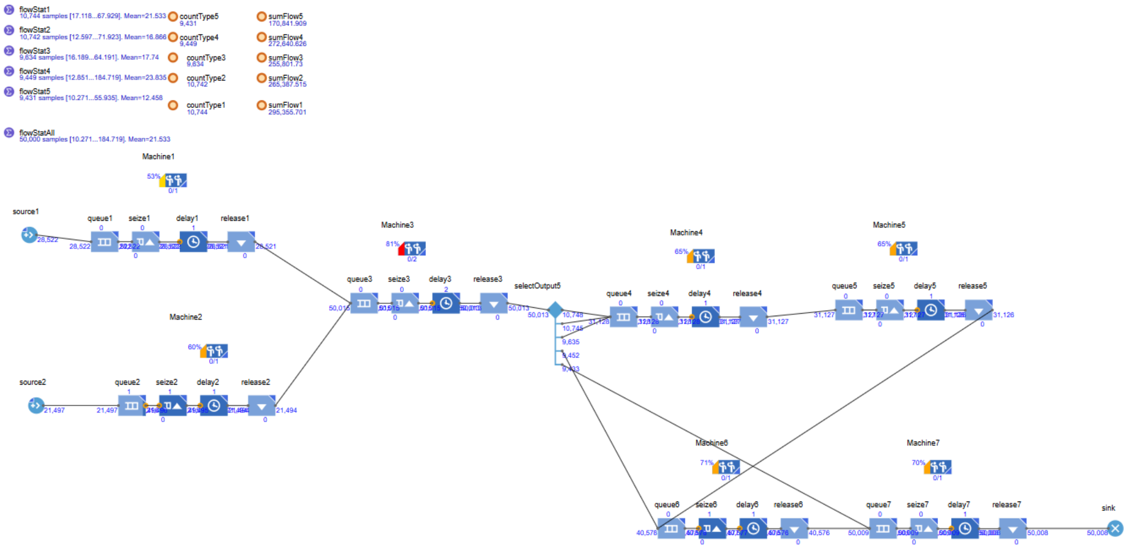


time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	8	8,00	1	1	0	0	0	0	0	0	21,88 %	55,68 %	34,68 %	31,62 %	28,91 %	34,41 %	26,82 %
120	28	14,00	0	0	0	0	0	0	0	0	46,49 %	43,29 %	62,48 %	38,05 %	36,78 %	37,86 %	46,53 %
180	46	15,33	0	0	0	0	0	0	0	0	47,94 %	45,70 %	65,12 %	46,42 %	44,99 %	43,27 %	52,38 %
240	67	16,75	1	0	0	1	0	0	0	0	54,95 %	43,90 %	72,36 %	45,60 %	45,59 %	46,16 %	56,44 %
300	88	17,60	0	0	0	0	0	0	0	0	50,47 %	50,83 %	72,10 %	52,58 %	51,75 %	50,28 %	59,49 %
360	105	17,50	1	0	0	0	0	0	1	0	49,45 %	53,37 %	70,21 %	54,85 %	54,00 %	51,79 %	59,28 %
420	129	18,43	1	0	1	0	0	0	0	0	49,34 %	59,21 %	71,97 %	57,46 %	56,27 %	54,02 %	62,42 %
480	149	18,63	0	0	0	0	0	0	0	0	47,44 %	60,23 %	70,66 %	59,24 %	59,43 %	58,47 %	63,33 %
540	165	18,33	0	0	0	0	0	0	0	0	44,92 %	60,07 %	67,97 %	59,97 %	59,53 %	57,65 %	62,44 %
600	184	18,40	0	0	0	0	0	0	0	0	45,03 %	61,79 %	66,95 %	61,16 %	60,64 %	56,34 %	62,29 %
660	205	18,64	0	0	0	0	0	0	0	0	46,94 %	59,54 %	69,00 %	60,22 %	59,91 %	56,46 %	63,16 %
720	224	18,67	4	1	1	2	0	0	0	0	49,25 %	58,91 %	70,30 %	61,36 %	61,02 %	57,33 %	63,26 %
780	247	19,00	3	0	0	2	0	0	1	0	50,91 %	59,24 %	72,58 %	62,45 %	62,26 %	59,22 %	64,15 %
840	271	19,36	1	0	0	0	1	0	0	0	50,84 %	60,05 %	73,99 %	63,68 %	63,67 %	60,18 %	65,45 %
900	289	19,27	0	0	0	0	0	0	0	0	49,10 %	59,51 %	72,35 %	63,07 %	63,34 %	61,05 %	64,84 %
960	310	19,38	0	0	0	0	0	0	0	0	48,19 %	60,90 %	72,71 %	63,37 %	63,24 %	61,90 %	65,21 %
1020	335	19,71	0	0	0	0	0	0	0	0	49,57 %	62,10 %	73,98 %	65,00 %	64,88 %	63,36 %	66,37 %
1080	356	19,78	0	0	0	0	0	0	0	0	48,66 %	62,25 %	74,08 %	64,65 %	64,55 %	64,59 %	66,67 %
1140	378	19,89	1	0	0	0	0	0	1	0	49,59 %	61,62 %	75,36 %	64,47 %	64,54 %	65,29 %	66,95 %
1200	402	20,10	0	0	0	0	0	0	0	0	49,50 %	62,97 %	75,80 %	64,91 %	64,79 %	65,38 %	67,62 %
1260	425	20,24	2	0	1	1	0	0	0	0	50,75 %	63,15 %	76,64 %	65,36 %	65,33 %	65,72 %	68,12 %
1320	447	20,32	2	0	0	0	2	0	0	0	49,82 %	64,83 %	76,10 %	66,80 %	66,79 %	66,30 %	68,31 %
1380	469	20,39	0	0	0	0	0	0	0	0	50,06 %	64,39 %	75,74 %	66,97 %	67,20 %	66,68 %	68,44 %
1440	491	20,46	1	0	1	0	0	0	0	0	49,66 %	65,50 %	75,69 %	67,98 %	67,92 %	66,53 %	68,63 %
1500	512	20,48	0	0	0	0	0	0	0	0	48,47 %	66,22 %	74,79 %	68,69 %	68,62 %	67,31 %	68,64 %
1560	532	20,46	0	0	0	0	0	0	0	0	48,15 %	66,37 %	74,50 %	68,58 %	68,48 %	67,51 %	68,67 %
1620	548	20,30	0	0	0	0	0	0	0	0	48,58 %	65,95 %	74,39 %	68,19 %	67,94 %	66,36 %	68,19 %
1680	572	20,43	3	0	0	1	2	0	0	0	49,08 %	66,80 %	74,99 %	68,97 %	68,64 %	66,91 %	68,53 %
1740	594	20,48	2	0	0	2	0	0	0	0	49,52 %	65,62 %	74,76 %	68,88 %	68,73 %	66,69 %	68,55 %
1800	617	20,57	2	0	0	2	0	0	0	0	50,45 %	65,25 %	75,60 %	68,51 %	68,22 %	66,23 %	68,82 %
1860	637	20,55	2	0	2	0	0	0	0	0	50,10 %	64,84 %	75,72 %	68,36 %	68,11 %	66,54 %	68,84 %
1920	658	20,56	2	0	0	2	0	0	0	0	50,90 %	65,00 %	76,20 %	67,95 %	67,85 %	66,44 %	68,85 %
1980	682	20,67	1	0	0	0	0	0	1	0	50,56 %	65,00 %	76,55 %	68,20 %	68,13 %	66,99 %	69,06 %
2040	705	20,74	1	0	0	0	1	0	0	0	50,26 %	65,96 %	76,57 %	68,37 %	68,22 %	67,33 %	69,28 %
2100	728	20,80	1	0	0	1	0	0	0	0	50,63 %	65,43 %	77,03 %	68,03 %	68,02 %	67,64 %	69,60 %
2160	745	20,69	1	1	0	0	0	0	0	0	50,74 %	63,79 %	77,07 %	66,86 %	66,81 %	67,13 %	69,27 %
2220	762	20,59	0	0	0	0	0	0	0	0	50,56 %	63,30 %	77,07 %	66,35 %	66,24 %	66,78 %	68,94 %
2280	772	20,32	0	0	0	0	0	0	0	0	50,51 %	61,64 %	76,63 %	65,20 %	65,03 %	65,98 %	67,98 %
2340	785	20,13	0	0	0	0	0	0	0	0	50,00 %	61,93 %	75,82 %	64,94 %	64,76 %	65,66 %	67,35 %
2400	808	20,20	0	0	0	0	0	0	0	0	50,46 %	61,81 %	76,35 %	65,46 %	65,22 %	66,16 %	67,65 %
2460	826	20,15	2	0	0	2	0	0	0	0	50,67 %	61,21 %	76,12 %	65,05 %	64,92 %	65,78 %	67,45 %
2520	848	20,19	0	0	0	0	0	0	0	0	50,15 %	61,46 %	76,10 %	65,04 %	64,99 %	65,68 %	67,55 %
2580	862	20,05	0	0	0	0	0	0	0	0	49,98 %	61,01 %	75,65 %	64,57 %	64,46 %	65,34 %	67,06 %
2640	880	20,00	0	0	0	0	0	0	0	0	50,04 %	61,10 %	75,53 %	64,63 %	64,76 %	65,27 %	66,98 %

4.2.2.3 SPT 0.2 S1 and 0.15 S2

Because the shortest processing time yielded the best results in case 1, the previous simulation is repeated, this time with the SPT prioritizing rule on machine 3. The results for this simulation are in Pictures 17 and 18. Also, this simulation was run to the maximum capacity of the produced products. The simulation time was 142 714,81 minutes, and during that time, there were 50 008 products manufactured.

Compared to the previous simulation, there is not much difference in the utilization rates (Figure 27) or the product amounts that were manufactured. However, there is a slight difference in the average waiting time where on machine 3 it previously was a bit over minute and here it is under a minute but in both cases it is very manageable.



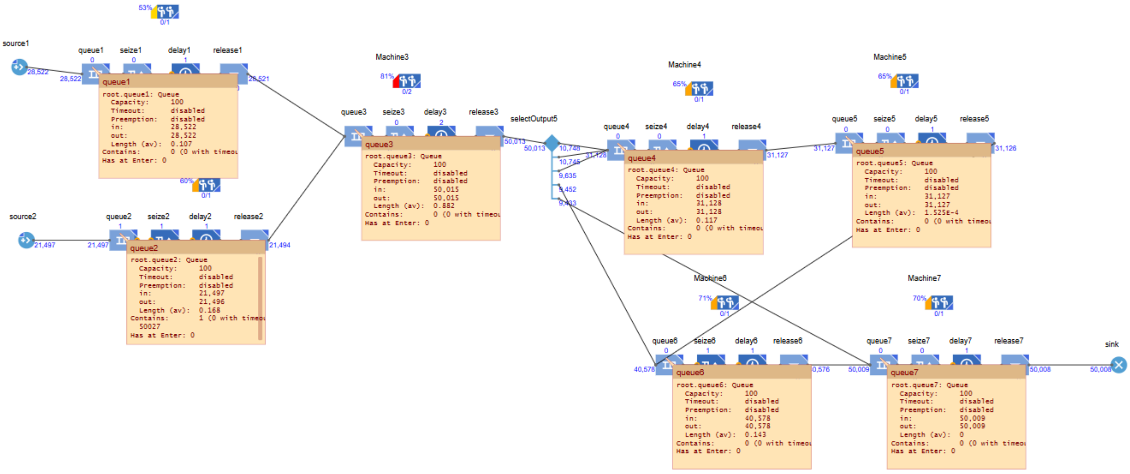
```
flowStat1
10,744 samples [17.118...67.929]. Mean=21.533
flowStat2
10,742 samples [12.597...71.923]. Mean=16.866
flowStat3
9,634 samples [16.189...64.191]. Mean=17.74
flowStat4
9,449 samples [12.851...184.719]. Mean=23.835
flowStat5
9,431 samples [10.271...55.935]. Mean=12.458

flowStatAll
50,000 samples [10.271...184.719]. Mean=21.533

countType5
9,431
countType4
9,449
countType3
9,634
countType2
10,742
countType1
10,744

sumFlow5
170,841.909
sumFlow4
272,640.626
sumFlow3
255,801.73
sumFlow2
265,387.515
sumFlow1
295,355.701
```

Picture 17 SPT S1 0.2 and S2 0.15.



```
queue1
root.queue1: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           28,522
  out:          28,522
  Length (av):  0.107
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
queue2
root.queue2: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           21,497
  out:          21,496
  Length (av):  0.168
Contains:       1 (0 with timeou
  50027
Has at Enter: 0
```

```
queue3
root.queue3: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           50,015
  out:          50,015
  Length (av):  0.882
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
queue4
root.queue4: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           31,128
  out:          31,128
  Length (av):  0.117
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           31,127
  out:          31,127
  Length (av):  1.525E-4
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           40,578
  out:          40,578
  Length (av):  0.143
Contains:       0 (0 with timeou
Has at Enter: 0
```

```
queue7
root.queue7: Queue
  Capacity:     100
  Timeout:      disabled
  Preemption:   disabled
  in:           50,009
  out:          50,009
  Length (av):  0
Contains:       0 (0 with timeou
Has at Enter: 0
```

Picture 18 SPT S1 0.2 and S2 0.15 waiting time.

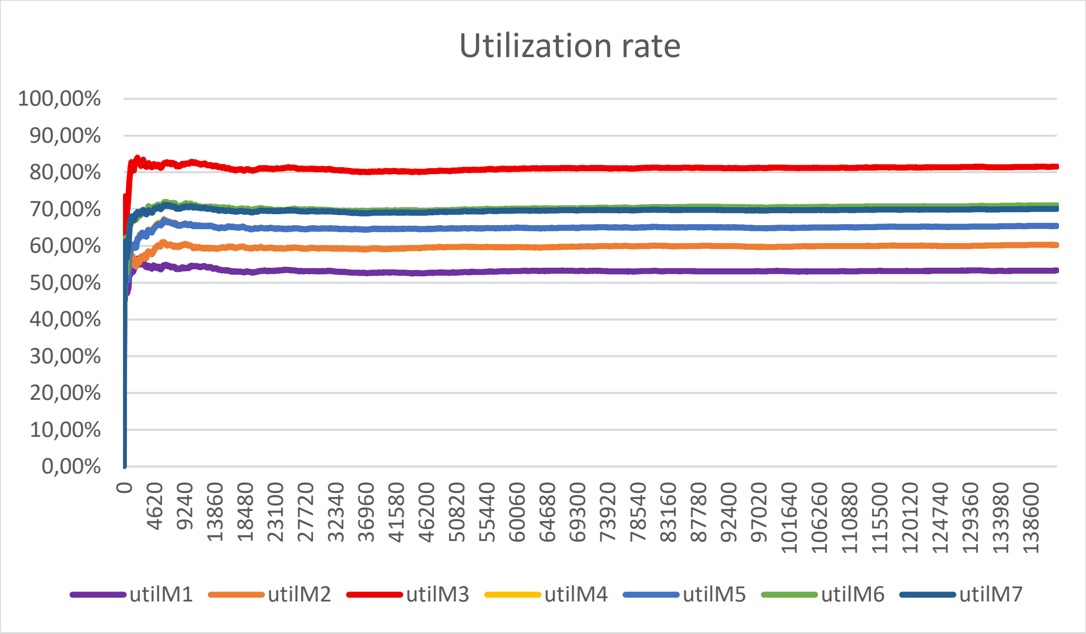


Figure 26 SPT S1 0.2 and S2 0.15 utilization rate.

The production rate was again good, and the WIP was slightly lower than in the previous simulation (Figure 28). The average throughput was 20,85 products per hour, and the median throughput was 20,91 products. With a standard deviation of 0,586 products, the production rate can again be considered highly stable and predictable for each hour.

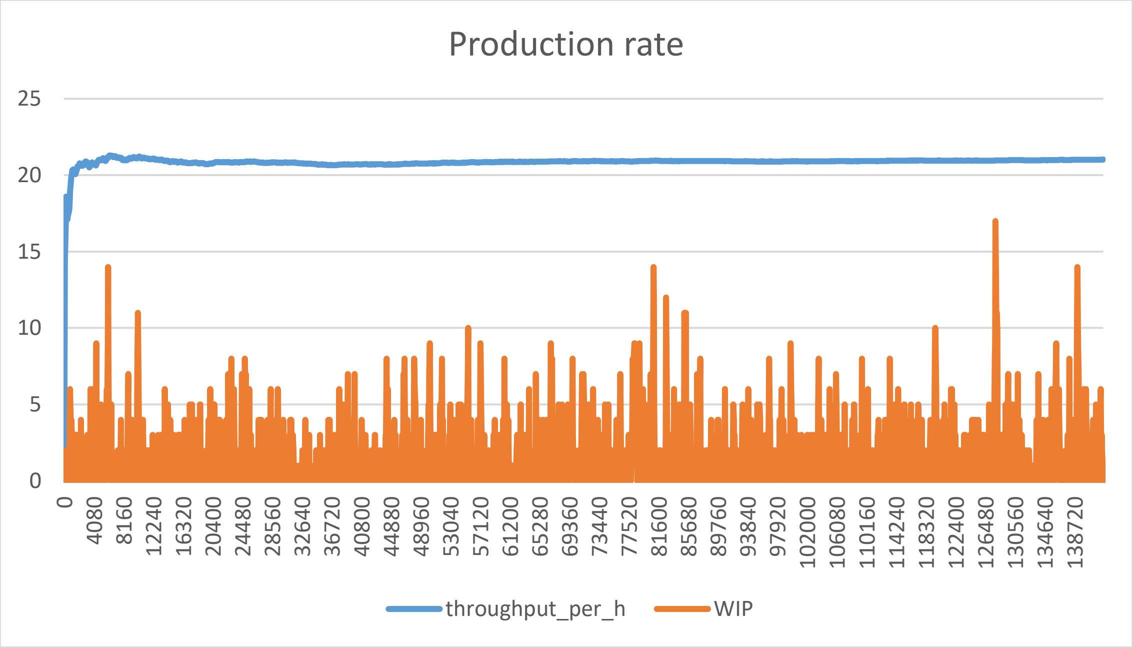
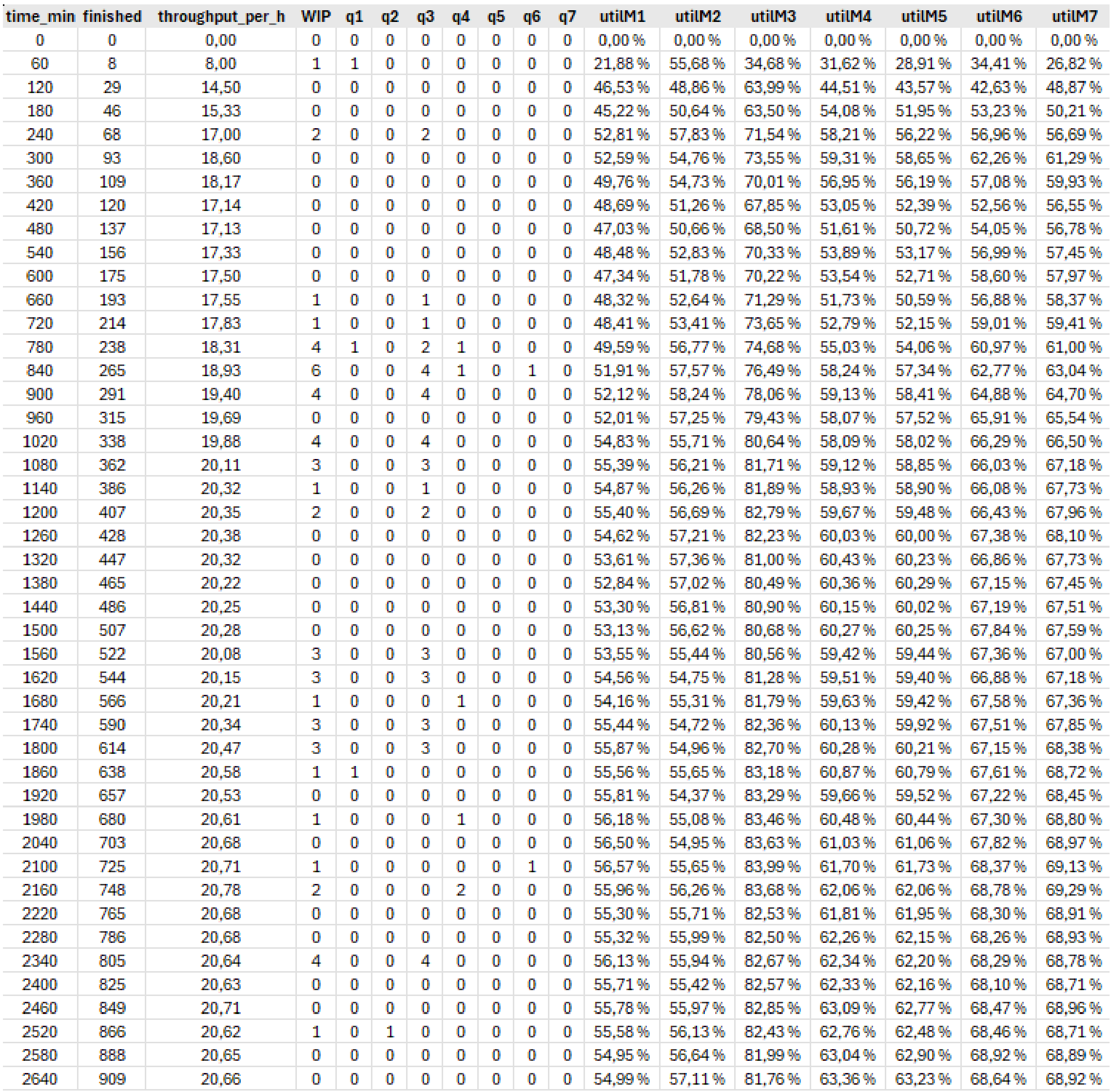


Figure 27 SPT S1 0.2 and S2 0.15 production rate.

Similarly to the previous simulation, there were not too large queues, and only queues that were formed from time to time were before machine 3. However, the queue did not exceed the amount of 10 products, and the queue was randomly timed from time to time and not constant. This can be seen from Table 10, where the statistics are from the beginning of the simulation, and also because the average waiting times were under a minute, so there must not be huge queues before the machine. Otherwise, the average waiting times would be much longer.

Table 10 SPT S1 0.2 and S2 0.15 Statistics.



time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	8	8,00	1	1	0	0	0	0	0	0	21,88 %	55,68 %	34,68 %	31,62 %	28,91 %	34,41 %	26,82 %
120	29	14,50	0	0	0	0	0	0	0	0	46,53 %	48,86 %	63,99 %	44,51 %	43,57 %	42,63 %	48,87 %
180	46	15,33	0	0	0	0	0	0	0	0	45,22 %	50,64 %	63,50 %	54,08 %	51,95 %	53,23 %	50,21 %
240	68	17,00	2	0	0	2	0	0	0	0	52,81 %	57,83 %	71,54 %	58,21 %	56,22 %	56,96 %	56,69 %
300	93	18,60	0	0	0	0	0	0	0	0	52,59 %	54,76 %	73,55 %	59,31 %	58,65 %	62,26 %	61,29 %
360	109	18,17	0	0	0	0	0	0	0	0	49,76 %	54,73 %	70,01 %	56,95 %	56,19 %	57,08 %	59,93 %
420	120	17,14	0	0	0	0	0	0	0	0	48,69 %	51,26 %	67,85 %	53,05 %	52,39 %	52,56 %	56,55 %
480	137	17,13	0	0	0	0	0	0	0	0	47,03 %	50,66 %	68,50 %	51,61 %	50,72 %	54,05 %	56,78 %
540	156	17,33	0	0	0	0	0	0	0	0	48,48 %	52,83 %	70,33 %	53,89 %	53,17 %	56,99 %	57,45 %
600	175	17,50	0	0	0	0	0	0	0	0	47,34 %	51,78 %	70,22 %	53,54 %	52,71 %	58,60 %	57,97 %
660	193	17,55	1	0	0	1	0	0	0	0	48,32 %	52,64 %	71,29 %	51,73 %	50,59 %	56,88 %	58,37 %
720	214	17,83	1	0	0	1	0	0	0	0	48,41 %	53,41 %	73,65 %	52,79 %	52,15 %	59,01 %	59,41 %
780	238	18,31	4	1	0	2	1	0	0	0	49,59 %	56,77 %	74,68 %	55,03 %	54,06 %	60,97 %	61,00 %
840	265	18,93	6	0	0	4	1	0	1	0	51,91 %	57,57 %	76,49 %	58,24 %	57,34 %	62,77 %	63,04 %
900	291	19,40	4	0	0	4	0	0	0	0	52,12 %	58,24 %	78,06 %	59,13 %	58,41 %	64,88 %	64,70 %
960	315	19,69	0	0	0	0	0	0	0	0	52,01 %	57,25 %	79,43 %	58,07 %	57,52 %	65,91 %	65,54 %
1020	338	19,88	4	0	0	4	0	0	0	0	54,83 %	55,71 %	80,64 %	58,09 %	58,02 %	66,29 %	66,50 %
1080	362	20,11	3	0	0	3	0	0	0	0	55,39 %	56,21 %	81,71 %	59,12 %	58,85 %	66,03 %	67,18 %
1140	386	20,32	1	0	0	1	0	0	0	0	54,87 %	56,26 %	81,89 %	58,93 %	58,90 %	66,08 %	67,73 %
1200	407	20,35	2	0	0	2	0	0	0	0	55,40 %	56,69 %	82,79 %	59,67 %	59,48 %	66,43 %	67,96 %
1260	428	20,38	0	0	0	0	0	0	0	0	54,62 %	57,21 %	82,23 %	60,03 %	60,00 %	67,38 %	68,10 %
1320	447	20,32	0	0	0	0	0	0	0	0	53,61 %	57,36 %	81,00 %	60,43 %	60,23 %	66,86 %	67,73 %
1380	465	20,22	0	0	0	0	0	0	0	0	52,84 %	57,02 %	80,49 %	60,36 %	60,29 %	67,15 %	67,45 %
1440	486	20,25	0	0	0	0	0	0	0	0	53,30 %	56,81 %	80,90 %	60,15 %	60,02 %	67,19 %	67,51 %
1500	507	20,28	0	0	0	0	0	0	0	0	53,13 %	56,62 %	80,68 %	60,27 %	60,25 %	67,84 %	67,59 %
1560	522	20,08	3	0	0	3	0	0	0	0	53,55 %	55,44 %	80,56 %	59,42 %	59,44 %	67,36 %	67,00 %
1620	544	20,15	3	0	0	3	0	0	0	0	54,56 %	54,75 %	81,28 %	59,51 %	59,40 %	66,88 %	67,18 %
1680	566	20,21	1	0	0	0	1	0	0	0	54,16 %	55,31 %	81,79 %	59,63 %	59,42 %	67,58 %	67,36 %
1740	590	20,34	3	0	0	3	0	0	0	0	55,44 %	54,72 %	82,36 %	60,13 %	59,92 %	67,51 %	67,85 %
1800	614	20,47	3	0	0	3	0	0	0	0	55,87 %	54,96 %	82,70 %	60,28 %	60,21 %	67,15 %	68,38 %
1860	638	20,58	1	1	0	0	0	0	0	0	55,56 %	55,65 %	83,18 %	60,87 %	60,79 %	67,61 %	68,72 %
1920	657	20,53	0	0	0	0	0	0	0	0	55,81 %	54,37 %	83,29 %	59,66 %	59,52 %	67,22 %	68,45 %
1980	680	20,61	1	0	0	0	1	0	0	0	56,18 %	55,08 %	83,46 %	60,48 %	60,44 %	67,30 %	68,80 %
2040	703	20,68	0	0	0	0	0	0	0	0	56,50 %	54,95 %	83,63 %	61,03 %	61,06 %	67,82 %	68,97 %
2100	725	20,71	1	0	0	0	0	0	1	0	56,57 %	55,65 %	83,99 %	61,70 %	61,73 %	68,37 %	69,13 %
2160	748	20,78	2	0	0	0	2	0	0	0	55,96 %	56,26 %	83,68 %	62,06 %	62,06 %	68,78 %	69,29 %
2220	765	20,68	0	0	0	0	0	0	0	0	55,30 %	55,71 %	82,53 %	61,81 %	61,95 %	68,30 %	68,91 %
2280	786	20,68	0	0	0	0	0	0	0	0	55,32 %	55,99 %	82,50 %	62,26 %	62,15 %	68,26 %	68,93 %
2340	805	20,64	4	0	0	4	0	0	0	0	56,13 %	55,94 %	82,67 %	62,34 %	62,20 %	68,29 %	68,78 %
2400	825	20,63	0	0	0	0	0	0	0	0	55,71 %	55,42 %	82,57 %	62,33 %	62,16 %	68,10 %	68,71 %
2460	849	20,71	0	0	0	0	0	0	0	0	55,78 %	55,97 %	82,85 %	63,09 %	62,77 %	68,47 %	68,96 %
2520	866	20,62	1	0	1	0	0	0	0	0	55,58 %	56,13 %	82,43 %	62,76 %	62,48 %	68,46 %	68,71 %
2580	888	20,65	0	0	0	0	0	0	0	0	54,95 %	56,64 %	81,99 %	63,04 %	62,90 %	68,92 %	68,89 %
2640	909	20,66	0	0	0	0	0	0	0	0	54,99 %	57,11 %	81,76 %	63,36 %	63,23 %	68,64 %	68,92 %

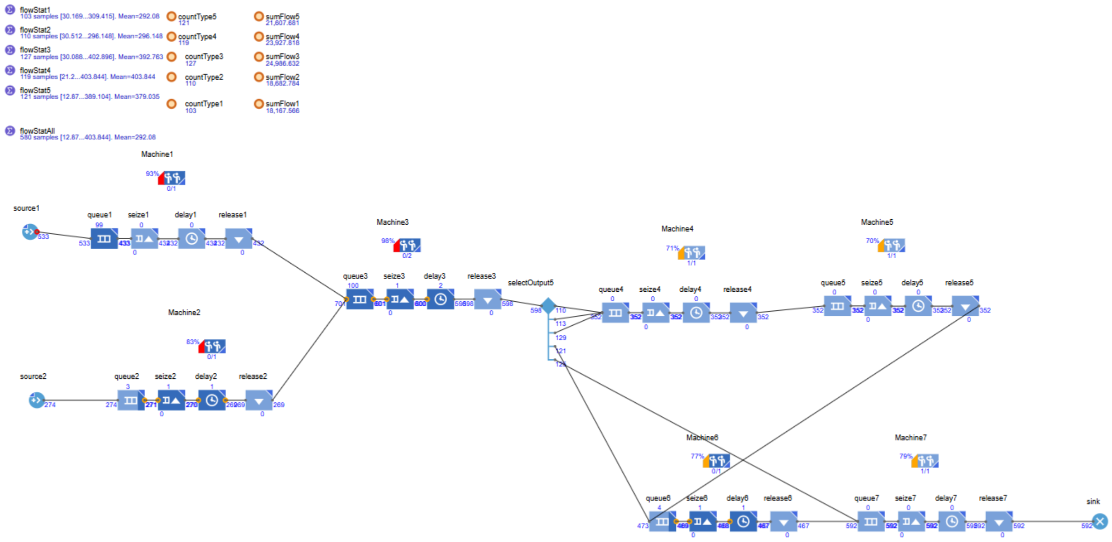
4.2.3 Case 3 Changing the variability

In this case all other values are the same as in the baseline scenario, but the variability is changed. In the first experiment, variability is increased by allowing processing times to vary between 0.5 and 1.5 times the nominal production time, in order to examine whether higher variability affects system performance and bottleneck formation.

In the second experiment, variability was introduced differently for each machine to better reflect the differences in processing times across the production system. In the first experiment, variability was modeled proportionally by allowing processing times to vary between 0.5 and 1.5 times the nominal production time. However, this approach may lead to unrealistic variation when processing times differ significantly between machines. For example, a 50% increase in a 24-minute process results in a much larger absolute change than a 50% increase in a 2-minute process. Therefore, in the second experiment, variability was defined in absolute terms by adjusting processing times using fixed time ranges in minutes, enabling a more balanced and realistic representation of variability across machines with different processing durations.

4.2.3.1 Increasing the relative variability on each machine

In this case, the original values are taken of the first simulation, and the variability is changed to higher. The variability that is set is a triangular distribution, with the fastest time is determined by multiplying the determined average time by 0.8, and the slowest time is determined by multiplying the average time by 1.2. The set delay times for each product can be found in Table 11. In the first experiment, the variability is increased so the fastest time is 0,5 times the average time, and the slowest time was 1.5 times the average time. The simulation was run several times to assess how much variation affected the simulation. Still, after 5 runs, the results were the same with the error time, utilization rates, and products produced. The results are presented below in Pictures 19 and 20. This simulation was run until the error occurred due to exceeding the maximum queue capacity. During the simulation, 592 products were manufactured within 1496.02 minutes.



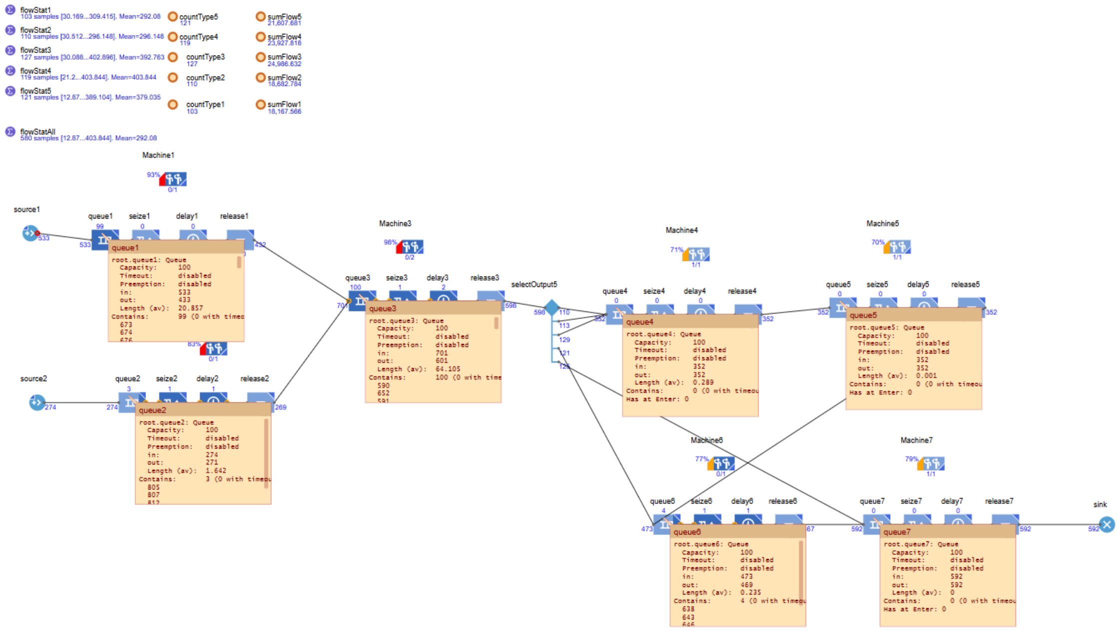
```
flowStat1
103 samples [30.169...309.415]. Mean=292.08
flowStat2
110 samples [30.512...296.148]. Mean=296.148
flowStat3
127 samples [30.088...402.896]. Mean=392.763
flowStat4
119 samples [21.2...403.844]. Mean=403.844
flowStat5
121 samples [12.87...389.104]. Mean=379.035

flowStatAll
580 samples [12.87...403.844]. Mean=292.08

countType5  121
countType4  119
countType3  127
countType2  110
countType1  103

sumFlow5  21,607.681
sumFlow4  23,927.818
sumFlow3  24,986.632
sumFlow2  18,682.784
sumFlow1  18,167.566
```

Picture 19 Relative variability.



```
flowStat1
103 samples [30.169...309.415]. Mean=292.08
flowStat2
110 samples [30.512...296.148]. Mean=296.148
flowStat3
127 samples [30.088...402.896]. Mean=392.763
flowStat4
119 samples [21.2...403.844]. Mean=403.844
flowStat5
121 samples [12.87...389.104]. Mean=379.035

flowStatAll
580 samples [12.87...403.844]. Mean=292.08

countType5  121
countType4  119
countType3  127
countType2  110
countType1  103

sumFlow5  21,607.681
sumFlow4  23,927.818
sumFlow3  24,986.632
sumFlow2  18,682.784
sumFlow1  18,167.566
```

```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            533
  out:           433
  Length (av):   20.857
Contains:        99 (0 with timeo
  673
  674
  676
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            274
  out:           271
  Length (av):   1.642
Contains:        3 (0 with timeou
  805
  807
  812
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            701
  out:           601
  Length (av):   64.105
Contains:        100 (0 with time
  590
  652
  591
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            352
  out:           352
  Length (av):   0.289
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            352
  out:           352
  Length (av):   0.001
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            473
  out:           469
  Length (av):   0.235
Contains:        4 (0 with timeou
  638
  643
  646
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            592
  out:           592
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

Picture 20 Relative variability waiting times.

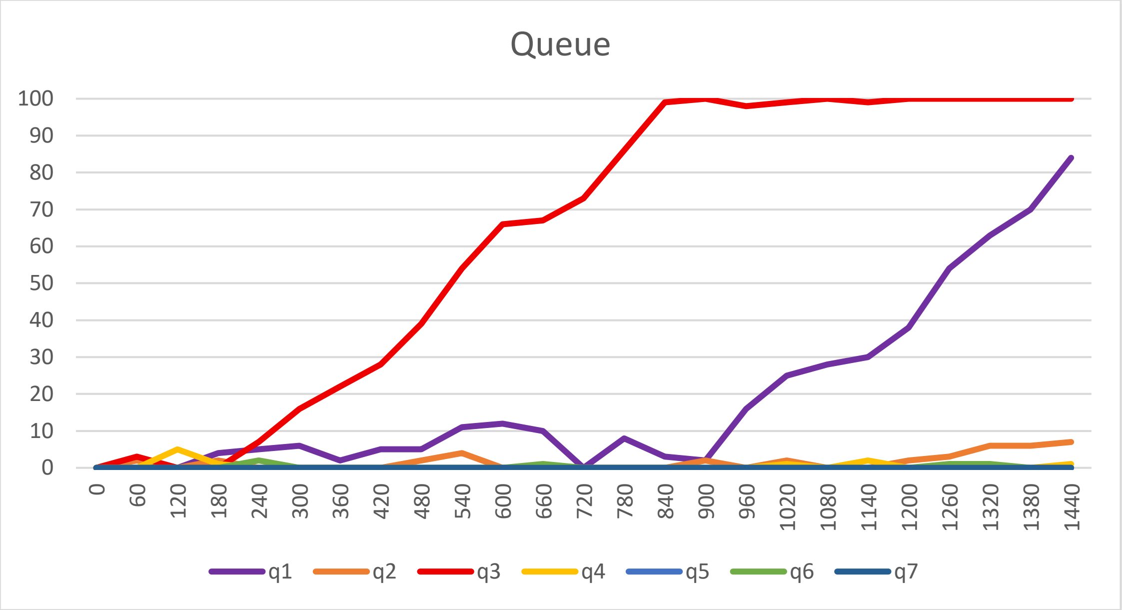


Figure 28 Relative variability queue.

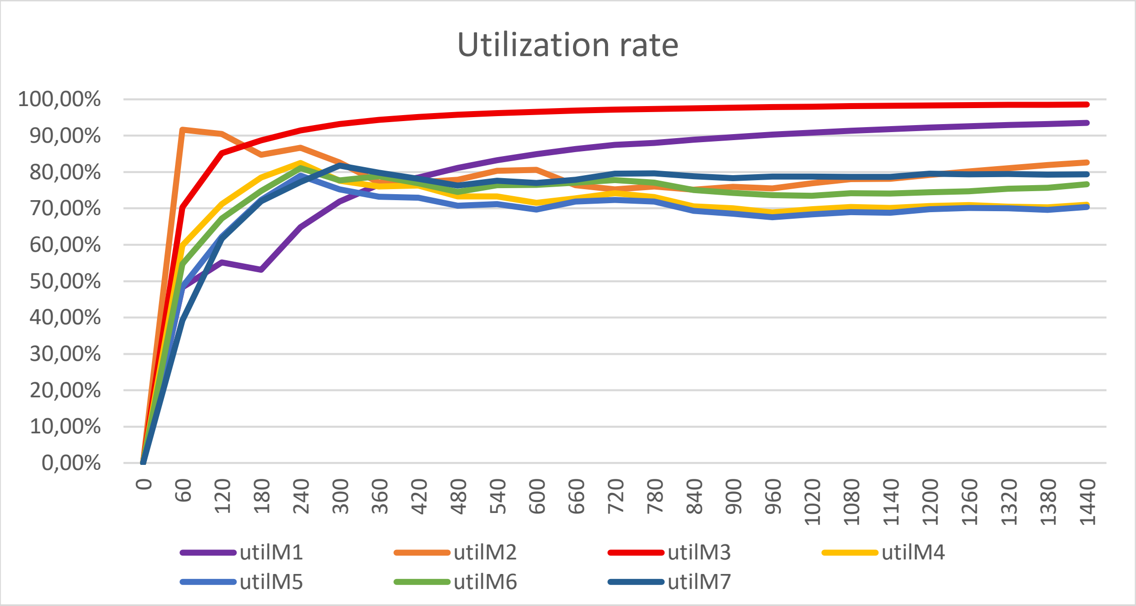


Figure 29 Relative variation utilization rate.

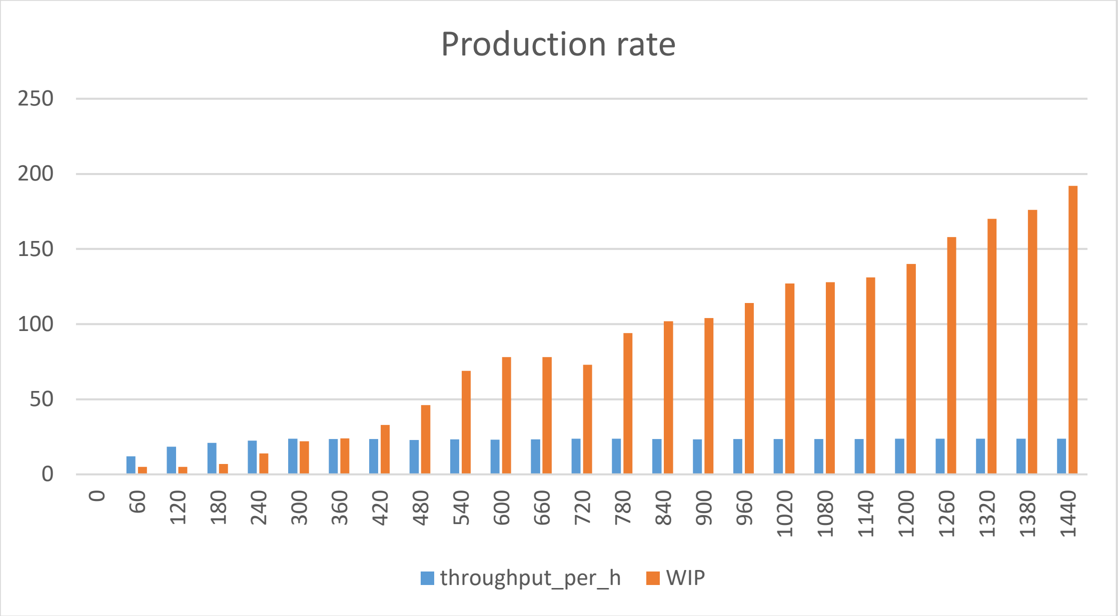


Figure 30 Relative variability production rate.

Table 11 Relative variability statistics.

time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	12	12,00	5	0	2	3	0	0	0	0	48,30 %	91,64 %	70,33 %	59,79 %	48,50 %	54,70 %	39,25 %
120	37	18,50	5	0	0	0	5	0	0	0	55,18 %	90,48 %	85,16 %	71,21 %	62,23 %	67,23 %	61,66 %
180	63	21,00	7	4	2	0	1	0	0	0	53,10 %	84,79 %	88,70 %	78,46 %	72,36 %	74,78 %	71,98 %
240	90	22,50	14	5	0	7	0	0	2	0	64,83 %	86,71 %	91,47 %	82,50 %	79,00 %	81,08 %	77,22 %
300	119	23,80	22	6	0	16	0	0	0	0	71,86 %	82,65 %	93,17 %	77,61 %	75,25 %	77,70 %	81,78 %
360	141	23,50	24	2	0	22	0	0	0	0	76,55 %	77,13 %	94,31 %	76,03 %	73,18 %	78,84 %	79,86 %
420	164	23,43	33	5	0	28	0	0	0	0	78,48 %	77,14 %	95,12 %	76,31 %	72,95 %	76,91 %	78,18 %
480	183	22,88	46	5	2	39	0	0	0	0	81,17 %	77,86 %	95,73 %	73,28 %	70,72 %	74,55 %	76,28 %
540	210	23,33	69	11	4	54	0	0	0	0	83,26 %	80,32 %	96,21 %	73,32 %	71,19 %	76,34 %	77,60 %
600	231	23,10	78	12	0	66	0	0	0	0	84,94 %	80,63 %	96,59 %	71,50 %	69,66 %	76,49 %	77,01 %
660	257	23,36	78	10	0	67	0	0	1	0	86,31 %	76,41 %	96,90 %	72,76 %	71,87 %	77,13 %	77,91 %
720	286	23,83	73	0	0	73	0	0	0	0	87,45 %	75,23 %	97,16 %	74,22 %	72,32 %	77,75 %	79,54 %
780	309	23,77	94	8	0	86	0	0	0	0	88,04 %	76,06 %	97,37 %	73,10 %	71,89 %	77,10 %	79,66 %
840	329	23,50	102	3	0	99	0	0	0	0	88,89 %	75,13 %	97,56 %	70,61 %	69,30 %	75,08 %	78,84 %
900	350	23,33	104	2	2	100	0	0	0	0	89,63 %	75,95 %	97,72 %	70,02 %	68,57 %	74,27 %	78,33 %
960	376	23,50	114	16	0	98	0	0	0	0	90,28 %	75,49 %	97,87 %	68,89 %	67,58 %	73,66 %	78,77 %
1020	399	23,47	127	25	2	99	1	0	0	0	90,85 %	76,89 %	97,99 %	69,79 %	68,37 %	73,48 %	78,74 %
1080	424	23,56	128	28	0	100	0	0	0	0	91,36 %	78,05 %	98,10 %	70,38 %	69,00 %	74,22 %	78,71 %
1140	447	23,53	131	30	0	99	2	0	0	0	91,82 %	78,15 %	98,20 %	70,14 %	68,81 %	74,05 %	78,67 %
1200	475	23,75	140	38	2	100	0	0	0	0	92,22 %	79,20 %	98,29 %	70,62 %	69,74 %	74,47 %	79,59 %
1260	498	23,71	158	54	3	100	0	0	1	0	92,59 %	80,19 %	98,37 %	70,90 %	70,10 %	74,73 %	79,35 %
1320	522	23,73	170	63	6	100	0	0	1	0	92,93 %	81,09 %	98,45 %	70,52 %	70,08 %	75,42 %	79,44 %
1380	544	23,65	176	70	6	100	0	0	0	0	93,24 %	81,91 %	98,52 %	70,29 %	69,61 %	75,65 %	79,25 %
1440	568	23,67	192	84	7	100	1	0	0	0	93,52 %	82,66 %	98,58 %	71,04 %	70,35 %	76,66 %	79,42 %

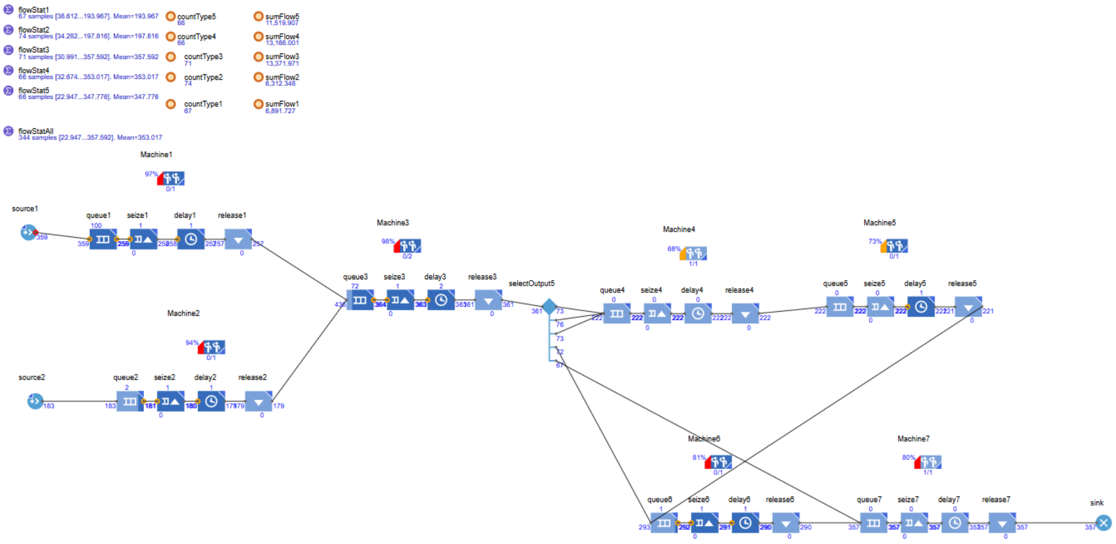
4.2.3.2 Changing the variability in each machine

In this experiment, the variability is changed from relative variability to absolute variability and it is determined for each product and step. This is done to compare the effect of the variability and make the variability differences closer to each other in minutes. The set variabilities are presented in Table 12. The used variability is triangular, and, in the table, the first number is the fastest possible time, the darkened middle number is the average manufacturing time, and the last number is the slowest set time. The min and max are determined by random, and they do not base on any statistics or have pattern.

Table 12 Absolut variabilities.

Machine	Product 1 (min)	Product 2 (min)	Product 3 (min)	Product 4 (min)	Product 5 (min)	Total (min)
1	0,**0**,0	0,**0**,0	2,**3**,6	1.5,**2**,4	2,**3**,7	5.5,**8**,17
2	2,**4**,9	3,**4**,7	0,**0**,0	0,**0**,0	0,**0**,0	5,**8**,16
3	2.5,**3**,4.5	0.5,**1**,1.5	3,**5**,7	7,**8**,10	6,**7**,9	19,**24**,32
4	2,**3**,4	1,**3**,5	1,**3**,4	0,**0**,0	0,**0**,0	4,**9**,13
5	2,**3**,4	2,**3**,4	2,**3**,4	0,**0**,0	0,**0**,0	6,**9**,12
6	3,**4**,6	0,5,**1**,2	1,**2**,3	2,**3**,4	0,**0**,0	6.5,**10**,15
7	1,**2**,4	1.5,**2**,2.5	1,**2**,3	1,**2**,3	1,**2**,3	5.5,**10**,15.5
Total (min)	12.5,**19,**31.5	8.5,**14**,22	10,**18**,27	11.5,**15**,21	7,**12**,19	

The times are set to the simulation, and the results are as follows. During the 909 minutes, there were 357 products manufactured. The error occurred due to exceeding the queue capacity before machine 1. More details from the simulation are in Pictures 21 and 22. Changing the variability made this production very front-heavy. The waiting times before machines 1 and 3 are noticeably longer than in the other machines. The utilization rates (Figure 32) are highest in machines 1, 2, and 3. In addition, compared to all the previous simulations, the time of the error was significantly earlier in this case.



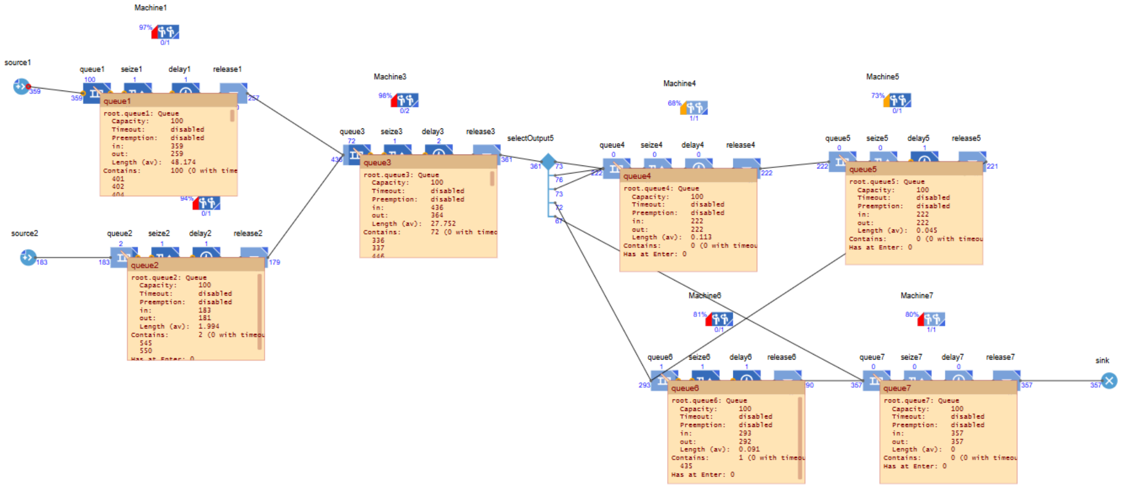
```
flowStat1
67 samples [38.612...193.967]. Mean=193.967
flowStat2
74 samples [34.282...197.816]. Mean=197.816
flowStat3
71 samples [30.991...357.592]. Mean=357.592
flowStat4
66 samples [32.674...353.017]. Mean=353.017
flowStat5
66 samples [22.947...347.776]. Mean=347.776

flowStatAll
344 samples [22.947...357.592]. Mean=353.017

countType5
66
countType4
66
countType3
71
countType2
74
countType1
67

sumFlow5
11,519.907
sumFlow4
13,166.001
sumFlow3
13,371.971
sumFlow2
6,312.348
sumFlow1
6,891.727
```

Picture 21 Absolute variability.



```
queue1
root.queue1: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            359
  out:           259
  Length (av):   48.174
Contains:        100 (0 with time
  401
  402
  404
```

```
queue2
root.queue2: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            183
  out:           181
  Length (av):   1.994
Contains:        2 (0 with timeou
  545
  550
Has at Enter: 0
```

```
queue3
root.queue3: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            436
  out:           364
  Length (av):   27.752
Contains:        72 (0 with timeo
  336
  337
  446
```

```
queue4
root.queue4: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            222
  out:           222
  Length (av):   0.113
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue5
root.queue5: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            222
  out:           222
  Length (av):   0.045
Contains:        0 (0 with timeou
Has at Enter: 0
```

```
queue6
root.queue6: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            293
  out:           292
  Length (av):   0.091
Contains:        1 (0 with timeou
  435
Has at Enter: 0
```

```
queue7
root.queue7: Queue
  Capacity:      100
  Timeout:       disabled
  Preemption:    disabled
  in:            357
  out:           357
  Length (av):   0
Contains:        0 (0 with timeou
Has at Enter: 0
```

Picture 22 Absolute variability average waiting times.

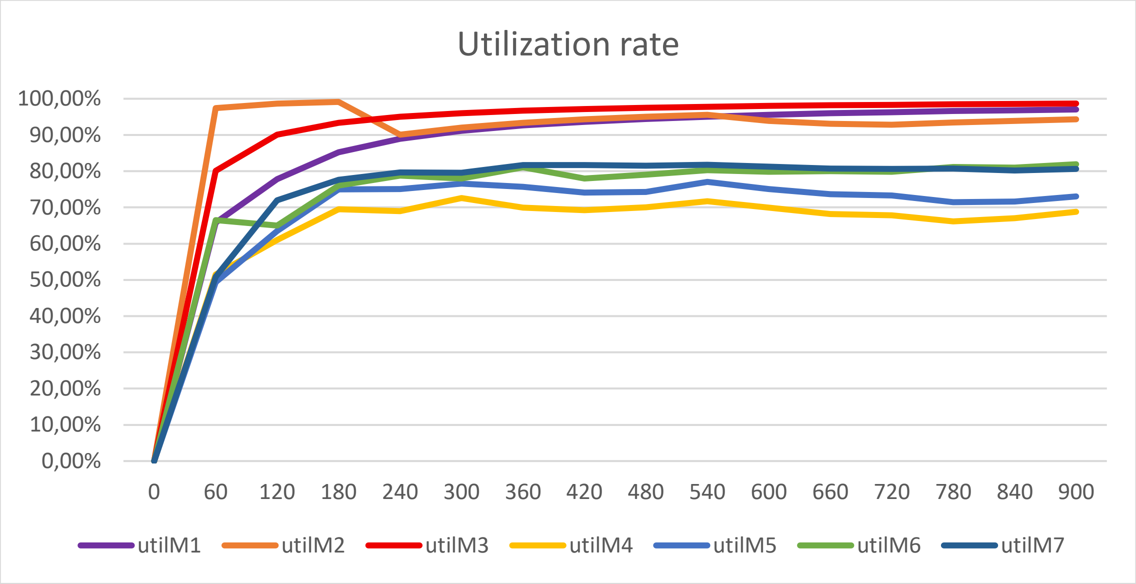


Figure 31 Absolute variability utilization rate.

The biggest difference in this simulation compared to all previous ones is that queue 1 increases faster than in machine 3. Previously, queue 3 was the one that caused queue formation in machine 1, but here, machine 1 is a bottleneck of its own at this arrival rate. The queue phases during the simulation can be seen in Figure 33.

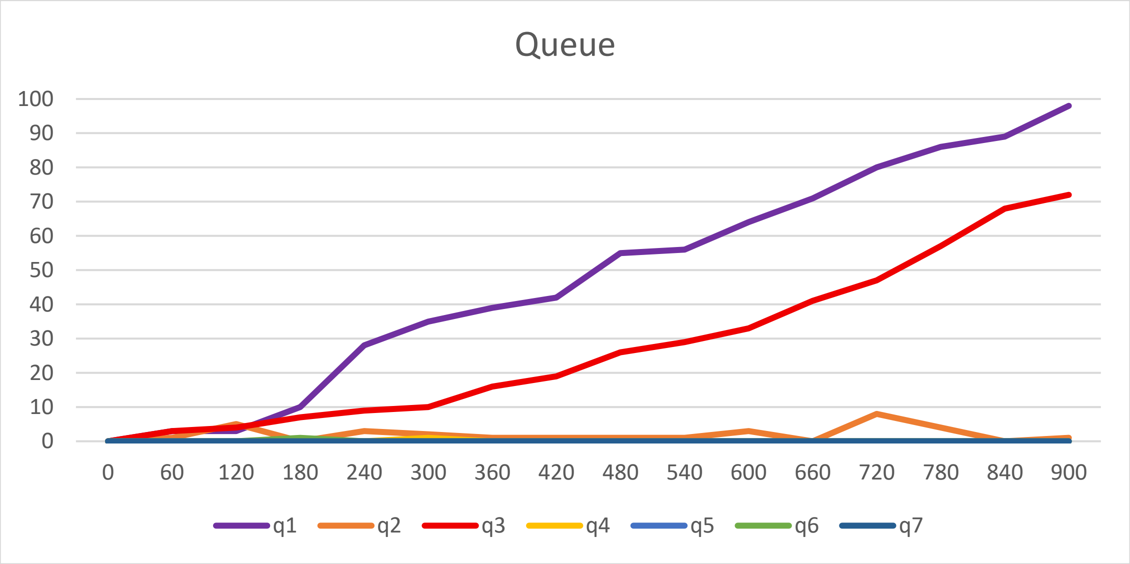


Figure 32 Absolute variability queues.

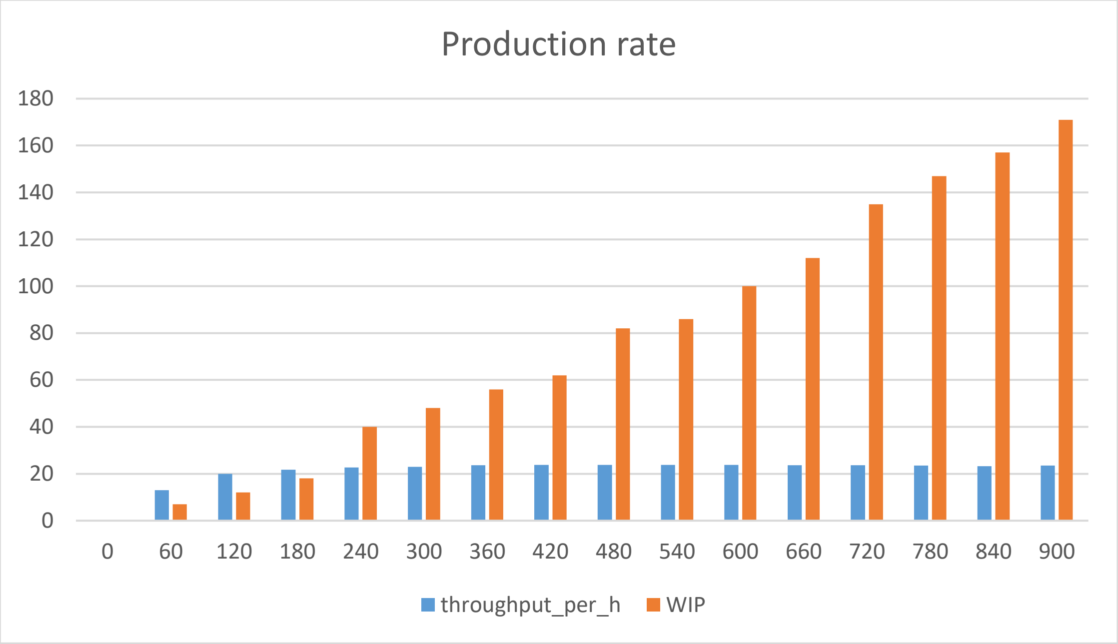


Figure 33 Absolute variability production rate.

In this simulation, the throughput is average when compared to all the previous simulations. In Figure 34 is the production rate for this simulation. The average throughput in this simulation is 21.04 products per hour. The median is 23.497 products, and the standard deviation is 6.231. The standard deviation is the highest in this simulation, which is expected as the variability was set to the highest. The statistics of this simulation are in Table 13.

Table 13 Absolute variability simulation results.

time_min	finished	throughput_per_h	WIP	q1	q2	q3	q4	q5	q6	q7	utilM1	utilM2	utilM3	utilM4	utilM5	utilM6	utilM7
0	0	0,00	0	0	0	0	0	0	0	0	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %	0,00 %
60	13	13,00	7	3	1	3	0	0	0	0	65,79 %	97,39 %	80,15 %	51,50 %	49,33 %	66,52 %	50,83 %
120	40	20,00	12	3	5	4	0	0	0	0	77,82 %	98,69 %	90,07 %	61,06 %	63,49 %	65,03 %	71,99 %
180	65	21,67	18	10	0	7	0	0	1	0	85,21 %	99,13 %	93,38 %	69,55 %	74,99 %	76,04 %	77,67 %
240	91	22,75	40	28	3	9	0	0	0	0	88,91 %	90,08 %	95,04 %	68,95 %	75,11 %	78,81 %	79,67 %
300	115	23,00	48	35	2	10	1	0	0	0	91,13 %	92,06 %	96,03 %	72,59 %	76,61 %	77,95 %	79,58 %
360	142	23,67	56	39	1	16	0	0	0	0	92,61 %	93,38 %	96,69 %	69,93 %	75,72 %	81,06 %	81,67 %
420	166	23,71	62	42	1	19	0	0	0	0	93,66 %	94,33 %	97,16 %	69,24 %	74,13 %	77,97 %	81,71 %
480	190	23,75	82	55	1	26	0	0	0	0	94,45 %	95,04 %	97,52 %	70,08 %	74,28 %	79,06 %	81,51 %
540	214	23,78	86	56	1	29	0	0	0	0	95,07 %	95,59 %	97,79 %	71,74 %	77,05 %	80,27 %	81,78 %
600	238	23,80	100	64	3	33	0	0	0	0	95,56 %	93,85 %	98,01 %	69,94 %	75,10 %	79,83 %	81,26 %
660	260	23,64	112	71	0	41	0	0	0	0	95,97 %	93,08 %	98,20 %	68,21 %	73,65 %	80,05 %	80,74 %
720	283	23,58	135	80	8	47	0	0	0	0	96,30 %	92,87 %	98,35 %	67,87 %	73,28 %	79,83 %	80,67 %
780	305	23,46	147	86	4	57	0	0	0	0	96,59 %	93,42 %	98,47 %	66,19 %	71,46 %	81,13 %	80,76 %
840	326	23,29	157	89	0	68	0	0	0	0	96,83 %	93,89 %	98,58 %	67,02 %	71,66 %	80,97 %	80,18 %
900	353	23,53	171	98	1	72	0	0	0	0	97,04 %	94,29 %	98,68 %	68,76 %	73,01 %	81,93 %	80,63 %

4.3 Analysis

In the first simulation, the utilization rate of machine 3 is clearly higher than the others. Additionally, the queue before machine 3 starts to rise relatively quickly, even though the machine has a higher capacity than the others, with ability to produce two items at the same time. In addition, when looking more closely at the average queue length on each machine, others in the halfway stop are under 5 minutes, but machine 3 has an average queue length of over 37 minutes. Based on the highest utilization rate of over 96%, the largest queue, and the highest average queue time, machine 3can be considered the bottleneck of this system.

To make an effort to improve production, the constraint machine 3 was changed with the goal of reducing the bottleneck and trying to improve the throughput while avoiding early errors. The first effort to minimize the bottleneck was changing the processing rule on machine 3. When only considering the throughput and Table 14, the SPT was the most effective method that created the most products and got the largest throughput with decent variation. However, the waiting times are still high when those are compared in Table 15 and the variation between finished product types and their mean lead times in Table 16 are still not great. When comparing only case 1 waiting times in table 15, LPT was the best choice, but in Table 16 LIFO gave the best result with the shortest lead times and the least variation between finished product types. The results of this simulation show that in the short term, production efficiency and capacity can be improved, but in the long term this approach is not sustainable.

In the following case, an attempt is made to influence and mitigate the bottleneck by reducing the level of WIP. In the first scenario the arrival rate was decreased close to 0 which deleted the problem of the bottleneck However, as the tables and figures show, this way the production is not efficient and the throughput is low, even though the waiting times and the lead times are close to being perfect. The bottleneck cannot be said to be removed. In the next scenarios the arrival rate was increased and tested on two different scheduling rules, which were FIFO and SPT. In these scenarios, there was not substantial difference between the scheduling rules, but there was a significant difference in the original simulation and compared to all simulations in case 1.

First, compared to the throughput results in Table 14, this production was able to manufacture all the 50 000 products that were set to limit. What is important is that the average throughput was better than in the baseline scenario, and still the deviation was under 1 product per hour. In addition, the waiting times are all significantly lower than in the baseline scenario or case 1 simulations. In addition, the results in mean lead times and variation between finished products are good.

In the last case, the effect of the variation was tested and its impact on the manufacturing line. First the variation was doubled and compared to the baseline scenario; the results on throughput and waiting times improved, which led to lower mean lead times but also smaller variations between the product types. However, when the relative values were changed into absolute values, the system performance deteriorated in several aspects. The time to error decreased significantly, indicating that the system reached instability faster under absolute variability conditions. Although the average throughput remained at a similar level compared to the baseline scenario, the variability of the system increased, as reflected by a higher standard deviation of throughput. Furthermore, while the average queue time at the bottleneck (Machine 3) decreased, the queue time at Machine 1 increased notably, and the bottleneck shifted from machine 3 to machine 1.

These findings demonstrate that bottleneck behavior is highly sensitive not only to the level of variability but also to how variability is modeled. Absolute variability introduces uneven disturbances across products, directly affecting the load and performance of the bottleneck resource. As a result, congestion is no longer consistently concentrated on a single resource but instead shifts between machines, leading to dynamic bottleneck behavior and less predictable system performance. This is further reflected in the variation of product-specific lead times, suggesting that the bottleneck does not remain stable but fluctuates in the system. Consequently, the production flow becomes unbalanced and more difficult to control, highlighting the effect of variability to correctly identify and manage bottlenecks in production systems. In real-life manufacturing systems, variation has a major impact on the system and should be minimized as much as possible.

Table 14 Simulation results on throughput.

Simulation	Description	Time of the error (min)	Finished products	Average throughput per h	Median throughput	std deviation throughput
Case 0	Baseline scenario	1476,65	569	20,47	22,11	5,06
	Changing the processing order					
Case 1.1	LIFO	1582.94	645	21,03	22,2	5,13
Case 1.2	SPT	2581.13	1149	24,95	26,92	4,91
Case 1.3	LPT	1172,77	393	16,33	17,28	4,59
	Reduced WIP					
Case 2.1	S1 0.15 and S2 0.05	251 236,78	50 015	11,87	11,94	0,26
Case 2.2	S1 0.2 and 0.15 S2 FIFO	142 622,14	50 011	20,95	21,03	0,59
Case 2.3	S1 0.2 and 0.15 S2 SPT	142 714,81	50 008	20,85	20,91	0,59
	Changing Variability					
Case 3.1	Increasing relative variability	1496,02	592	21,78	23,5	5,18
Case 3.2	Absolute variability	909,17	357	21,04	23,5	6,23

Table 15 Simulation results waiting times.

Case	Simulation	Machine 1	Machine 2	Machine 3	Machine 4	Machine 5	Machine 6	Machine 7
Case 0	Baseline scenario	32,7	6,8	70,51	0,072	0	0,15	0
	Changing the processing order							
Case 1.1	LIFO	40,41	9,81	74,22	0,25	0	0,22	0
Case 1.2	SPT	20,39	7,26	70,44	2,55	0,11	0,49	0
Case 1.3	LPT	9,95	1,883	59,99	0,02	0	0,06	0
	Reduced WIP							
Case 2.1	S1 0.15 and S2 0.05	0,03	0	0,06	0	0	0	0
Case 2.2	S1 0.2 and 0.15 S2 FIFO	0,11	0,19	1,4	0,16	0	0,14	0
Case 2.3	S1 0.2 and 0.15 S2 SPT	0,11	0,17	0,88	0,12	0	0,14	0
	Changing Variability							
Case 3.1	Increasing relative variability	20,86	1,64	64,11	0,29	0	0,24	0
Case 3.2	Absolute variability	48,17	1,99	27,75	0,11	0,05	0,09	0

Table 16 Simulation results: product manufacturing times.

Case	Metric	Product 1	Product 2	Product 3	Product 4	Product 5	All
Designed production time		19	14	18	15	12	
Case 0	Mean lead time	343	339,317	490,1	480,59	487,18	343
	Amount	113	108	97	126	125	569
Case 1.1	Mean lead time	145,92	142,8	297,92	295	292,92	142,8
	Amount	113	131	135	108	148	635
Case 1.2	Mean lead time	151,4	152,77	284,49	1233,26	270,44	284,49
	Amount	267	251	256	131	234	1139
Case 1.3	Mean lead time	417,05	0	135,7	120,17	129,84	135,7
	Amount	27	0	51	61	66	205
Case 2.1	Mean lead time	20,32	15,56	21,58	13,48	19,75	13,48
	Amount	6314	6296	12396	12533	12465	50006
Case 2.2	Mean lead time	20,36	13,67	22,36	20,12	12,26	12,26
	Amount	10774	10637	9500	9624	9468	50003
Case 2.3	Mean lead time	21,53	16,87	17,74	23, 835	12,46	21,53
	Amount	10744	10742	9634	9449	9431	50 000
Case 3.1	Mean lead time	292,08	296,15	392,76	404,84	379,04	292,08
	Amount	103	110	127	119	121	580
Case 3.2	Mean lead time	193,97	197,82	357,59	353,02	347,78	353,02
	Amount	67	74	71	66	68	344

5 Conclusion

This research aimed to investigate how bottlenecks are identified and how they behave in a job-shop production environment. The research was conducted using discrete-event simulation and simulation software AnyLogic. The first research question that this thesis aimed to answer was:

> RQ1: How can production system bottlenecks be identified and analyzed using discrete-event simulation?

The results showed that DES enables the identification of bottlenecks by comparing key performance indicators across workstations and analyzing their evolution over time and across scenarios. These key metrics were utilization rate, throughput, mean lead time, queue length, waiting times, and WIP. With these metrics, the bottlenecks in the system were effectively identified. Long lead times and high WIP indicate that there is a bottleneck or multiple bottlenecks somewhere in the production system. With machines' high utilization rates, combined with long queues and long waiting times, the location of the bottleneck was identified.

An example from the simulations, in the baseline simulation, Machine 3 consistently showed the highest utilization rate, reaching approximately 96–98%, while also having the longest queues and waiting times in the system. For example, at 700.6 minutes, the average waiting time at Machine 3 was approximately 38 minutes, whereas the waiting times at the other machines remained close to zero. In addition, the queue before Machine 3 reached maximum capacity significantly earlier than the queues at the other workstations. These indicators clearly demonstrated that Machine 3 acted as the main bottleneck in the production system.

The results also demonstrated that DES provides both a diagnostic and predictive tool for optimizing a production system. DES enables dynamic analysis over longer periods of time rather than only at single observation points. It is also easy to test and analyze different scenarios without interfering with production in real-life and to observe how the changes theoretically affect the systems. DES is an effective tool for identifying and analyzing bottlenecks in complex production systems. These findings are consistent with earlier research on bottleneck behavior in manufacturing systems. Similar to TOC presented by Goldratt (1990), the results demonstrated that system performance was strongly constrained by the bottleneck workstation. In addition, the observed relationship between long queues, high utilization, and bottleneck identification supports the findings of Roser et al. (2002) and Betterton and Silver (2012).

The second research question that this thesis aimed to answer was:

> RQ2: How do changes in production parameters influence bottleneck dynamics?

Changes in production parameters such as scheduling rules, WIP, and variability directly affect the location, intensity, and persistence of bottlenecks. The results showed that scheduling rules have a significant impact on bottleneck behavior, as they determine the order in which jobs are processed. This directly influences queue formation, waiting times, and the utilization of workstations. In this study, the results showed clear differences between the rules: SPT improved the overall flow and balanced the system, while LIFO led to faster congestion and increased pressure on the bottleneck. This demonstrates that even without changing the system structure, scheduling decisions alone can significantly affect production performance.

Another parameter examined in this study was the production load level and its effect on WIP. By lowering the arrival rates from the production sources, the overall load on the system was reduced in order to better match the processing capacity of the bottleneck workstation. The results showed that high load levels intensified bottlenecks by increasing queue lengths, waiting times, and WIP. In contrast, lower load levels reduced congestion and balanced the production flow more effectively. However, when the arrival rates were reduced excessively, the system became underutilized, which decreased throughput from 22 products per hour to 12 products per hour and overall production efficiency. In the lowest-load scenario, queues were eliminated, but machine utilization rates also dropped significantly as in all the machines except in Machine 3, the utilization rate was under 50%, indicating that the system capacity was no longer being used efficiently. Therefore, the results suggest that the most effective production performance was achieved when the workstation utilization remained above 80% but under 90% in the bottleneck machine to maintain throughput of 21 products per hour, while avoiding excessive queue accumulation before the bottleneck.

The last parameter that was studied was the variability and its effects on the system. Even though increasing the relative variability first initially improved system performance, changing the relative variability to absolute variability caused the bottleneck to shift from machine 3 to machine 1. The results showed that variability is something that should be minimized to have better control over the bottlenecks. This indicates that higher variability can destabilize the production flow and create shifting bottlenecks within the system. The findings suggest that as variability increases, bottleneck behavior becomes more difficult to predict and control, emphasizing the importance of minimizing unnecessary variation in processing times. This observation also supports the findings of Lima et al. (2008), who described bottlenecks as dynamic phenomena that may shift between workstations depending on system conditions and variability.

This study contributes to existing literature by providing a systematic approach to analyzing production bottlenecks using discrete-event simulation. The findings highlight that bottlenecks are not static but dynamic phenomena that can move through the system and change over time depending on production conditions. The bottleneck analysis and the detection methods also presented in the literature review were applicable for identifying bottlenecks in the simulation model. Furthermore, the results demonstrate that bottlenecks can be effectively managed by adjusting key production parameters, such as scheduling rules, load levels, and variability. When addressing the bottleneck, the simulation results support the Theory of Constraints presented by Goldratt (1984/2024), as improvements targeted at the bottleneck workstation led to improved production flow and overall system efficiency. Table 17 summarizes the best indicators for detecting bottlenecks based on this research.

Table 17 Indicators for identifying production bottlenecks.

High utilization rate over time	Workstation utilization remains consistently high
Long queue lengths	Queue accumulates continuously before a workstation
Long waiting times	Waiting times are significantly higher compared to other workstations
High WIP levels	Increasing unfinished production indicates unbalanced production flow
Machine starvation	Workstations remain idle due to insufficient incoming jobs. May indicate that the previous station is the bottleneck
Shifting congestion	Queue buildup and delays move between workstations

From a managerial perspective the findings of this study can be concluded with the following 3 bullet points:

- Monitor utilization, queue lengths, and waiting times continuously to identify emerging bottlenecks before they significantly disrupt production flow.
- Maintain high but controlled utilization at bottleneck workstations to maximize throughput while avoiding excessive queue accumulation and congestion.
- Control WIP levels and minimize unnecessary variability, since excessive WIP and unstable processing times may destabilize production flow and create shifting bottlenecks.

Additional observation from the results of this study indicates that production flow can temporarily be accelerated by increasing WIP levels, but excessive WIP in the long term will overload bottleneck workstations and negatively affect overall system performance. Therefore, maintaining balanced WIP levels is essential for stable and efficient production flow.

5.1 Limitations

The limitations of this study are mainly related to the simplified nature of the simulation model and the assumptions used in the analysis. While discrete-event simulation provides an effective tool for analyzing bottleneck behavior and production dynamics, the model used in this study represents a theoretical job shop production environment rather than a specific real-world manufacturing system. As a result, the model does not fully capture the complexity of real production environments. In particular, practical factors such as machine failures, setup variations, and order logs with due dates were not explicitly included in the simulation model. In addition, the results are dependent on the input data and assumptions used in the model. Since the processing times and system parameters were based on estimated and randomly generated values, they may not fully represent real production conditions.

Furthermore, the analysis is limited to the production perspective within a job shop manufacturing environment and does not account for broader operational or organizational factors. Also, the simulations are only experimented with in a job-shop environment and the results may not be extended to other production types. As a result, the findings of this study should be interpreted with caution, as they may not be directly transferable to real-world manufacturing systems without further validation and adaptation.

The simulations were conducted using the free version of AnyLogic, which introduces certain limitations that may affect the accuracy and scope of the results. The free license restricts data collection and model functionality, which limits the level of detail that can be obtained from the simulation. Specifically, it was not possible to extract the desired performance measures into a table or as a figure throughout the simulation runs, such as continuously updated average queue times or mean lead times. As a result, some of the analysis is based on partial or simplified data, which may reduce the precision of the findings.

5.2 Further research

Further research could focus on extending the analysis of bottleneck behavior to different types of production environments. While this study is limited to a job shop setting, other production systems, such as flow shop, batch production, or hybrid layouts, may exhibit different bottleneck dynamics. Investigating these environments would improve the generalizability of the findings and provide a broader understanding of how bottlenecks form and evolve under varying production structures.

Another important direction for further research is the inclusion of a wider range of scheduling rules. In this study, only a limited set of dispatching rules was analyzed, which restricts the scope of conclusions regarding scheduling performance. Future studies could incorporate additional rules, such as earliest due date (EDD) or critical ratio (CR), and evaluate their impact on system performance, bottleneck behavior, and production efficiency under different operating conditions. This would require applying the model in a real-world setting, which would provide empirical validation and improve the practical applicability of the results. This could enhance the realism of the model by incorporating due dates and order backlog into the simulation, as well as by implementing and validating the model in a real manufacturing environment. Including these factors would allow for a more comprehensive analysis of production performance, particularly in terms of delivery reliability and customer service.

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