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RESEARCH ARTICLE



# The key to improving the trade-off between service and inventory levels in make-to-stock production: sequencing and capacity control

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## ABSTRACT

Safety stocks play an important role in make-to-stock production, since they ensure supply to customers despite uncertainties in production and demand. A large literature exists on safety stock calculations, but it typically assumes exogenous stationary replenishment times. In most real-world settings, capacity is a constraint leading to non-stationary replenishment times that are under the control of management. In response, we design a new production planning and control approach for make-to-stock production based on cumulative quantity logic and show how companies can use sequencing and capacity control based on current demand to improve customer supply and to reduce safety stocks. Results from discrete event simulations highlight the potential of the new approach and indicate that the proposed manufacturing control reacts robustly against wrongly set planned demand rates. This contributes to theory, while the comparatively low information processing requirements and robustness of the approach make it an important potential solution for practice.

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## KEYWORDS

Sequencing; capacity control; cumulative quantity logic; make-to-stock; service level

## 1. Introduction

This study focusses on a make-to-stock context, where customer demand is fulfilled from a finished goods inventory replenished by a capacitated production system. This shop structure is omnipresent in practice and is consequently of high industrial relevance. Finished goods inventories are extensively used in practice to decouple production and demand (Nyhuis & Wiendahl, 2009; Vollmann et al., 2005), but despite decades of research, many firms struggle at the same time both with excess inventories and with their ability to deliver on time (Land et al., 2021).

A main means to control the trade-off between service and inventory levels is the setting of the safety stock in the applied replenishment policy. Given its importance, a large literature on safety stock calculation emerged, being the reader referred to Jonsson and Mattsson (2019), Schmidt et al. (2012), and Gonçalves et al. (2020) for a review. But the usefulness of these methods is often limited. Jonsson and Mattsson (2016), for example, found that using analytical methods to determine safety stocks may pay off in non-difficult contexts but not necessarily in more complex environments. This was further supported by Jonsson and Mattsson (2019), who showed that the simple number of days method may outperform more complex alternative methods for safety stock calculations.

A major shortcoming of existing methods is the assumption that replenishment times are stationary. But replenishment times are non-stationary, varying over time, when capacity is limited (Kanet et al., 2010) and demand varies (Jodlbauer & Dehmer, 2020). The estimation of lead or replenishment times constitutes therefore a second large stream of literature that seeks to improve the trade-off between service and inventory levels. Graves (2022) recently subdivided this literature in: literature that focuses on how to understand and manage the dynamics that planned lead times can induce within a planning system (e.g.

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Haeussler et al., 2021; Schneckenreither et al., 2021; Selçuk et al., 2006); literature that takes realized throughput times as exogenous random variables and then prescribes how to set the planned lead times, thereby ignoring any dependence between the throughput time and planned lead times (e.g. Ben-Ammar et al., 2020; Dolgui & Ould-Louly, 2002; Jansen et al., 2019); and literature that treats throughput times as endogenous (due to constrained resources) and seeks to control replenishment times. In this study, we argue that replenishment times should not be treated as an exogenous variable that needs to be estimated as good as possible, but as an endogenous variable under firm control that can be manipulated via manufacturing control. Manufacturing control thus emerges as a key to shape and potentially improve the trade-off between service and inventory levels.

The task of manufacturing control is the timely replenishment of the finished goods inventories (Lödding et al., 2013). Replenishment orders have to be generated and released for production (Thürer et al., 2025) and, on the shop floor, sequencing answers the question of which order to produce (Graves et al., 1995), while capacity control decides on the assignment of resources to regulate the production process (e.g. Berger et al., 2019; Costa et al., 2023; Wiendahl & Breithaupt, 2001) to ensure that replenishment orders are completed in time. Although these tasks are independent, they jointly realize the performance of the system. This study explores how manufacturing control can reduce the safety stocks required to ensure customer delivery.

Although there have been several studies that use some form of manufacturing control to improve the trade-off between service and inventory levels, these studies typically assume a make-to-order context or focus on order release (e.g. Enns & Suwanruji, 2004; Jodlbauer & Reitner, 2012; Missbauer & Uzsoy, 2020; Missbauer, 2020; Schneckenreither et al., 2021). Our focus is on sequencing and capacity control, since these tasks of manufacturing control particularly influence the safety stock that companies need in order to fulfill customer demand in the face of fluctuating demand. More specifically, we ask the following Research Questions (RQs):

RQ1: What is the impact of demand-driven sequencing on service and inventory levels?

RQ2: What is the impact of demand-driven capacity control on service and inventory levels?

RQ3: What is their combined effect?

RQ4: Are results robust to uncertainty in demand rates?

The basic idea is to use the information about current demand to coordinate replenishment and to perform sequencing and capacity control accordingly. This idea aligns with the contributions of e.g. Ardalan and Diaz, 2012, Ardalan and Diaz, 2012; Diaz and Ardalan (2010), Schönsleben (2007) and Beemsterboer et al. (2017), all highlighting the importance of aligning sequencing decisions with current demand information. Our research is especially influenced by the work of Schönsleben and the Capacity Oriented Materials Management methodology (CORMA; e.g. Schönsleben, 1995; Schönsleben, 2007), which is extended using cumulative quantity logic according to Heinemeyer (cf. 1988). Cumulative quantity logic was chosen since it is specifically suitable to represent material flows in complex manufacturing systems (Missbauer et al., 1998). The resulting manufacturing control will then be assessed using discrete event simulation to answer our research questions.

The remainder of this paper is structured as follows. Section 2 provides the background to our study, before Section 3 outlines the design of our new manufacturing control approach. The simulation model and the experiments used to evaluate its performance are described in Section 4, before results, a brief discussion and a robustness analysis are presented in Section 5. The paper concludes with a summary, limitations, and with an outlook on necessary and desirable future work, in Section 6. For ease of reference, a Nomenclature is provided in Table A.1 in the Appendix.

## 2. Background

### 2.1. The reference of an ideal replenishment process

Although modern inventory management research has evolved towards integrating multiple operational factors, such as energy utilization (Duong et al., 2026; Nguyen et al., 2025a), energy efficiency (Nguyen

et al., 2025b) and carbon emissions (Zemzami et al., 2026), the trade-off between service and inventory levels remains a key concern for many companies in practice. In an ideal replenishment process, production would finish a replenishment order exactly at the moment when a corresponding customer demand occurs, avoiding both stock-outs and warehouse inventories. In practice, this ideal replenishment process can usually not be realized, as information about the demand is not available in advance, at least not within a sufficient planning horizon. Nevertheless, the ideal replenishment process can serve as an ideal reference for design; the manufacturing control should approximate such an ideal replenishment process. Consider a simple example, in which demand varies over time and is distributed to just two products 1 and 2, as illustrated in Figure 1 using cumulative demand and cumulative output over time.

In practice, also the demand quantities will often differ, but even under the simplified conditions of constant demand quantities, the ideal replenishment is very difficult to achieve and creates challenges for capacity control and for sequencing:

- Capacity control: As the time between demands will vary due to the stochastic nature of demand, the ideal output will vary as well. Consequently, rigid capacities will not be able to match the ideal replenishment process. Instead, capacity control should align capacities with demand.
- Sequencing: Replenishment orders are generated before the related customer demand occurs in make-to-stock systems. With a First-Comes-First-Served (FCFS) sequencing policy at the workstations, the sequence in which the replenishment orders are generated will to a great extent determine the sequence, in which the replenishment orders are completed. Due to the stochastic demand, this will usually not match the sequence of the current demand. Consequently, a FCFS sequencing will not be able to match the ideal replenishment process. Instead, sequencing should be aligned more closely with the demand during the replenishment time.

Based on these considerations, concrete methods for sequencing and capacity control will be derived in Section 3. But first we review the relevant literature

## 2.2. Sequencing and determination of operation due dates

Sequencing determines which job in the queue at a workstation is processed next. The literature proposes numerous sequencing rules (Blackstone et al., 1982; Panwalker & Iskander, 1977), from very simple ones, such as FCFS, to somewhat more complex ones, such as Earliest Operation Due Date (EODD), which is

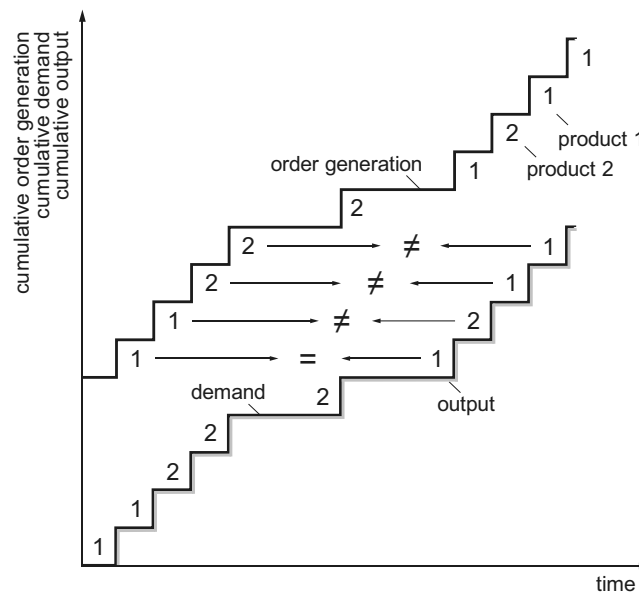


**Figure 1.** Sequence deviations of replenishment processes with random demand and FCFS sequencing.

widely applied in the literature since Kanet & Hayya (1982) and can be traced back as OPNDD in the pioneering work of Conway et al. (1967). It was shown to outperform leading dispatching rules in Kanet & Hayya (1982). In this study, we use EODD, which chooses the order with the earliest operation due date to accurately implement a planned sequence and reduce sequence deviations (Bertsch, 2015; Lödning & Piontek, 2017).

However, with static operation due dates, EODD sequencing cannot be coupled to the actual demand. Consequently, we develop a method for dynamically adjusting the due dates of the replenishment orders to the demand. Our starting point for this is CORMA's probable due dates (Schönsleben, 1995). Please note that also the contributions of Ardalan and Diaz (2012a), Ardalan and Diaz, 2012 and Beemsterboer et al. (2017) follow a similar pattern. Our paper differs by using the so-called cumulative quantity logic according to Heinemeyer as a basis for determining dynamic order due dates, which clearly depicts the essential actuating and control variables of make-to-stock production in the cumulative quantity diagram (cf. Heinemeyer, 1988).

### 2.3. Heinemeyer's cumulative production figures

Figure 2 shows the control points for the cumulative quantities of a product. These control points correspond to (1) order generation and thus, in the case of immediate order release, also to the input to production, (2) the output of the production and thus the input to the finished goods inventory, (3) the output from the finished goods inventory and thus the delivery to the customer, and (4) the customer demand.

A cumulative quantity is assigned to each control point for each product. If the order generation cumulative quantity CPF1 of a product takes the value  $Z$  at a certain point in time, then this means that orders for a total of  $Z$  units of the product have been generated since the start of counting. Similarly, the cumulative production quantity CPF2 describes the total units of the product manufactured and the cumulative delivery quantity CPF3 describes the total number of units delivered. If there is sufficient inventory in the warehouse, the delivery to the customer corresponds to the demand, so that the cumulative quantities CPF3 and CPF4 are congruent.

Figure 3 shows the cumulative quantities of a product at the control points of an exemplary replenishment process. CPF4 represents the demand for the product, which corresponds to an original straight line under the idealized conditions of continuous and constant demand. If there are no backlogs, it is also

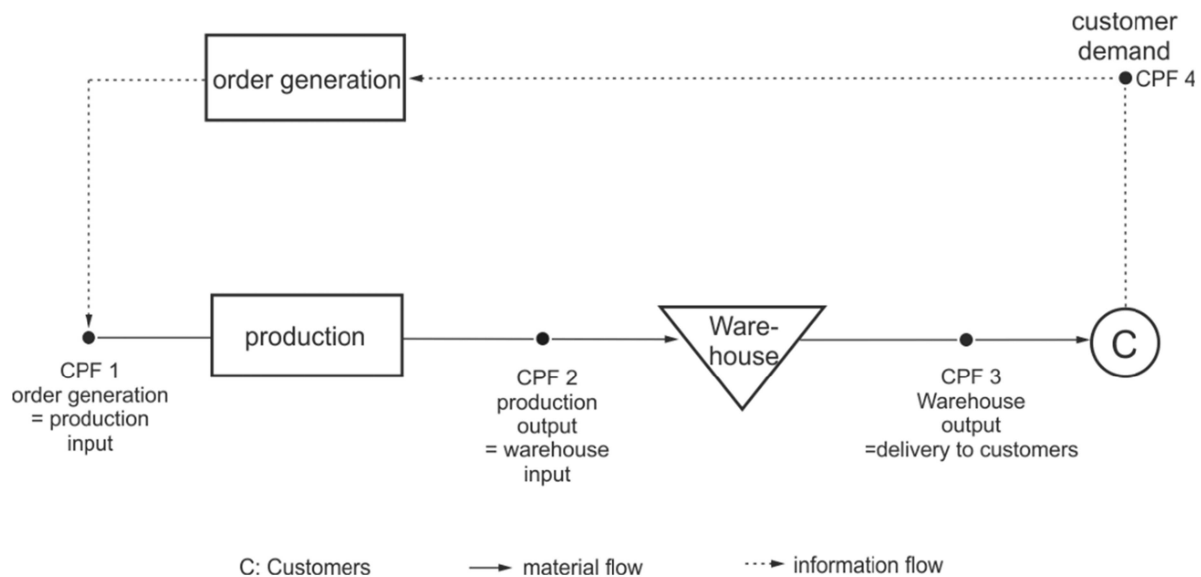


**Figure 2.** Representation of make-to-stock production with the counting points of the cumulative production figure logic.

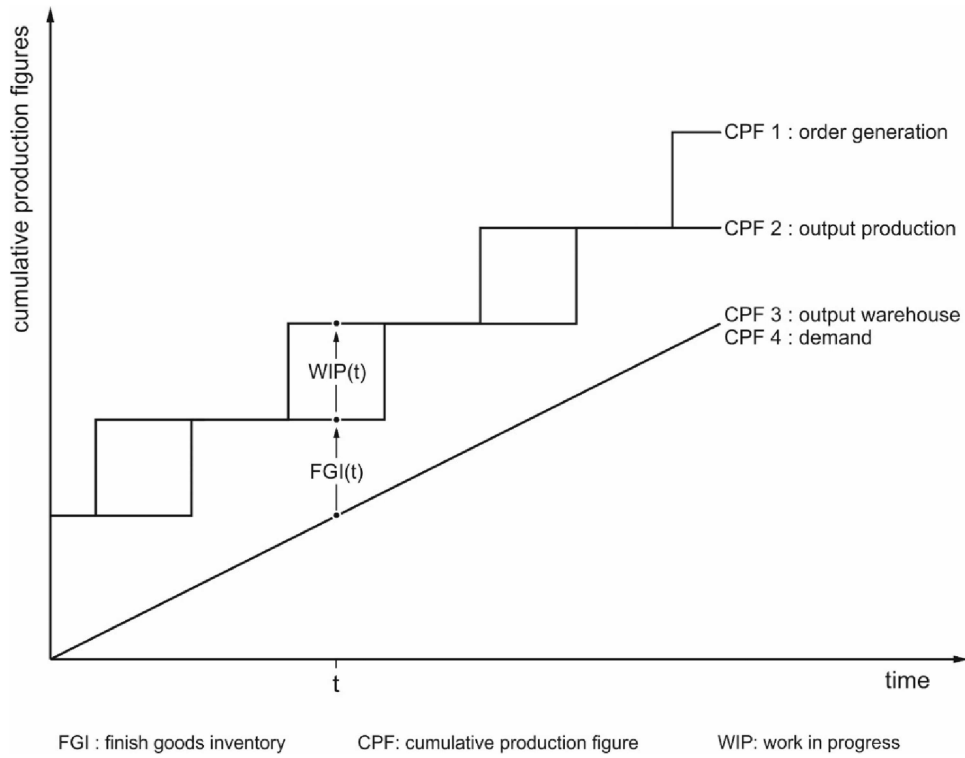


**Figure 3.** Cumulative quantity diagram of make-to-stock production.

identical to the cumulative production figure of the warehouse output (CPF3). The upper curve shows the cumulative production figure of order generation (CPF1). It jumps up by the lot size with the generation of a new replenishment order for the product. The middle curve shows the production output (CPF2), which at the same time corresponds to the input to the warehouse.

Elementary relationships can be derived from this representation:

- (1) The Work in Process (WIP) on the shop floor at any point in time is equal to the difference between the cumulative quantities for order generation and for production output.

$$WIP_j(t) = CPF\_order\_generation_j(t) - CPF\_production\_output_j(t) \quad (1)$$

- (2) The Finished Goods Inventory (FGI) of a product  $j$  is calculated analogously from the difference between the cumulative quantities for the production output (corresponds to the warehouse input) and the warehouse output.

$$FGI_j(t) = CPF\_production\_output_j(t) - CPF\_warehouse\_output_j(t) \quad (2)$$

- (3) The delivery backlog at any point in time is the difference between the cumulative demand and the cumulative warehouse output.

$$Delivery\_backlog_j(t) = CPF\_demand_j(t) - CPF\_warehouse\_output_j(t) \quad (3)$$

Finally, if demand and warehouse output match, as in Figure 3, then the delivery backlog is zero. With the help of Control CPFs, it is possible to implement common order generation procedures such as the order point system, Kanban control, or Base stock control (Lödding et al., 2013).

## 2.4. Capacity control

Essential control levers for capacity control are the working time of the production employees and their allocation to the workstations (Lödding et al., 2013). A *backlog control* (Lödding et al., 2013; Petermann, 1996) is an accepted good standard to decide when to adjust capacity (Land et al., 2015). In our study, the backlog is defined as the difference between the planned output (reference variable) and the actual output, which is the control variable (Wiendahl & Breithaupt, 2001). If the backlog exceeds an upper backlog limit (resp. falls below a lower backlog limit), capacities should be increased (resp. reduced) to achieve the planned output even under disturbances.

## 2.5. Assessment of the literature

In this study, we argue that replenishment times should not be treated as an exogenous variable that needs to be estimated as good as possible, but as an endogenous variable under firm control that can be manipulated via manufacturing control. This links the field of inventory management with the production planning and control literature. Although the necessary elements for sequencing and capacity control in make-to-stock environments exists and have been evaluated in isolation, there combined effect remains unknown. Our study addresses this shortcoming. It introduces an integrated framework for manufacturing control that allows for assessing the combined effect in a make-to-stock setting where order generation is driven by an inventory model. It further extends existing manufacturing control approaches by using cumulative quantity figures that create a better underlying model for manufacturing control decisions in this demand-driven context.

## 3. Proposed manufacturing control framework

How dynamic order sequencing and capacity control will be realized in our new manufacturing control framework will be outlined next.

### 3.1. Determining dynamic order due dates

In order to determine operation due dates, we first need a due date for the product. To link production and demand, order due dates are set as the point in time when the inventory of the product is expected to reach the safety stock, which is equivalent to Schönsleben's probable due date (Schönsleben, 2007). This is illustrated in Figure 4 and described next.

Figure 4a illustrates the situation at the time of order generation  $t_{gen}$ , where the due date corresponds to

$$due\_date_{j,i}(t_{gen}) = t_{gen} + planned\_replenishment\_time_j \quad (4)$$

For updating the order due date, it is helpful to record the order generation cumulative quantity for each replenishment order  $i$  of product  $j$ , excluding order  $i$  (because the urgency of order  $i$  is to be determined). Therefore, the lot size of order  $i$  is subtracted from the cumulative quantity if it already comprises order  $i$ :

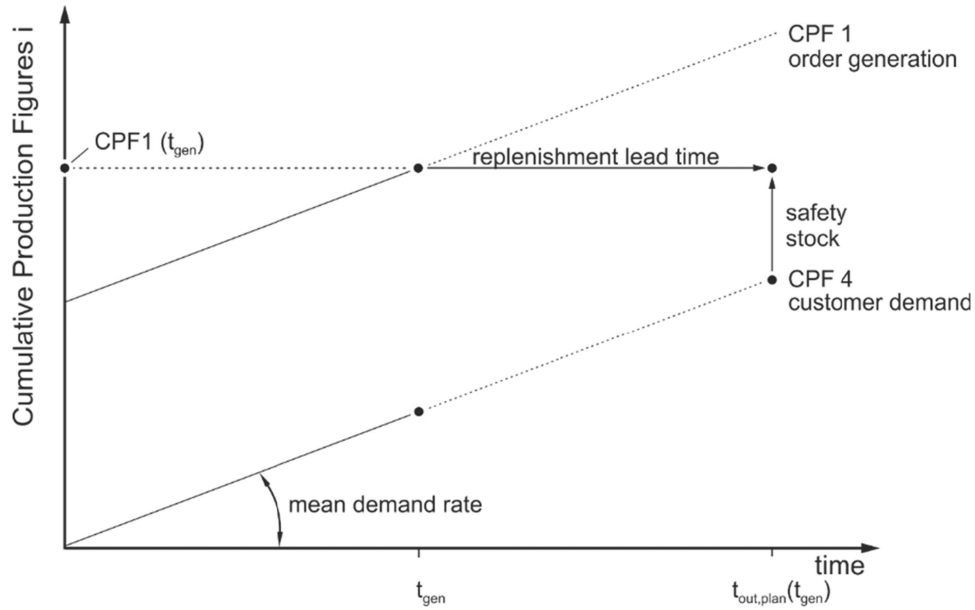
$$generation\_progress\_number_{j,i} = CPF\_order\_generation_j(t_{gen}) - lot\_size_i \quad (5)$$

If the company implements FCFS for the sequencing of products, then the current planned completion date of the order can be determined at any time  $t$  by estimating the length of time in which the inventory is expected to have fallen down to the safety stock (Schönsleben, 2007, cf. Figure 4b bottom). Accordingly:

$$due\_date_{j,i}(t) = t + \frac{generation\_progress\_number_{j,i} - safety\_stock_j - CPF\_demand_j(t)}{meandemandrate_j} \quad (6)$$

This dynamic determination of due dates has the following advantages. First, each replenishment order of a product can be given a different planned completion date because the equation takes the cumulative demand at the time of production into account. Second, the due date of an order may also be in the past.

### a) Determining the order due date at the time of order generation



### b) Updating the order due date at $t_1$

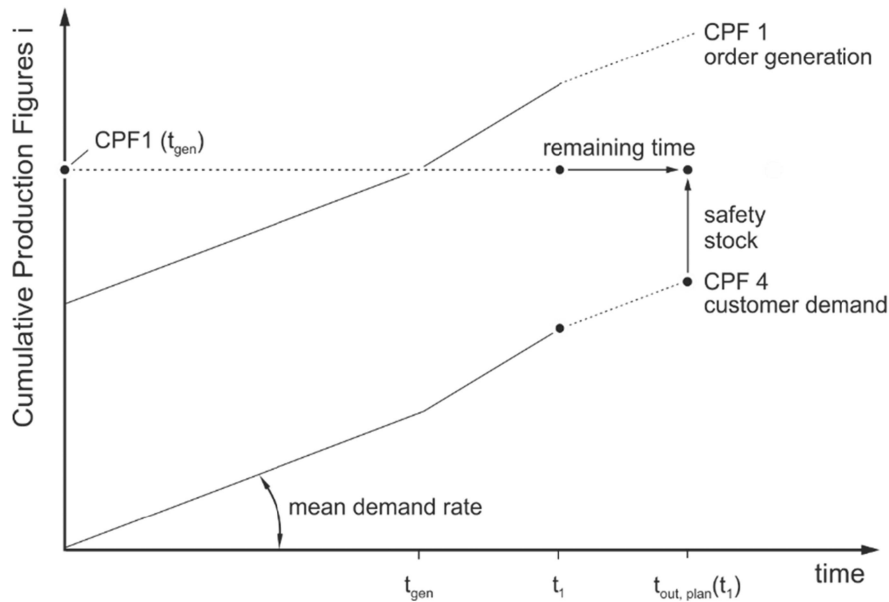


**Figure 4.** Determining the order due dates of replenishment orders.

This is the case as soon as the cumulative demand plus the safety stock exceeds the recorded generation progress number of the order. In this case, a delivery backlog is imminent or has already occurred. Sequencing can thus differentiate the urgency of backlogged products. Third, the order due date changes with the demand during the replenishment period. If demand is higher (resp. lower) than expected, the order due date moves backward (resp. forward) in time. Finally, the data requirements are very low and also coincide with the requirements that have to be fulfilled for order generation.

### 3.2. Determining operation due dates

Starting from the current planned completion date of the order, backward scheduling is applied to determine operation due dates using flow-rate oriented scheduling proposed by Ludwig and Nyhuis

(1992) and Nyhuis and Wiendahl (2009). The scheduling is based on workstation-specific planned transition times for the orders and order-specific operation times:

$$ODD_{i,j}(t) = due\_date_i(t) - \sum_{k=j+1}^n (Transition\_Time_{WS(k)} + Operation\_time_k) \quad (7)$$

The proposed determination of the operation due dates has the following advantages. First, by referencing the current order due date, the procedure also adapts the operation due dates to the current demand. Second, considering the product-specific routings adapts the due dates to the order flows through manufacturing. This makes the method suitable for both complex and simple, linear material flows. Third, the procedure simplifies sequencing in mixed production where both make-to-order and make-to-stock orders exist since both order types can be given the same criterion for prioritization with the operation due dates. For make-to-stock orders via the procedure developed and for make-to-order production via backward scheduling from the customer due date. Finally, backward scheduling is easy to perform.

The calculated dynamic operation due dates are then used for sequencing at the workstations. When an operation is completed, the order due dates and the operation due dates of all orders in the queue are updated, and then the order with the earliest operation due date is selected. The most important disadvantage of the method is this frequent updating of the operation due dates, which also requires information about the current demand of the products. Current planning systems in industry will usually not support the proposed sequencing method. However, technically it can be realized with relatively little effort.

### 3.3. Capacity control

With a static planned output, backlog control cannot be coupled to the actual demand. We consequently developed a new method for dynamically adjusting the planned outputs of the workstations to the actual demand. The resulting four-step procedure for regulating capacities can be described as follows.

*Step I: calculate the Plan Cumulative Production Figures (CPFs) of all products manufactured at a workstation.*

The planned cumulative production output is equal to the cumulative demand plus the planned finished goods inventory of the product.

$$CPF\_production_{plan,j}(t) = CPF\_demand_j(t) + FGI_{plan,j} \quad (8)$$

The planned cumulative production figure of the last workstation  $n$  corresponds to the planned cumulative production figure of production:

$$CPF\_WSn_{plan,j}(t) = CPF\_production_{plan,j}(t) \quad (9)$$

The planned cumulative production figure of the  $i^{th}$  workstation is offset from the planned cumulative quantity of production by the planned WIP of the following workstations:

$$CPF\_WSi_{plan,j}(t) = CPF\_production_{plan,j}(t) + \sum_{k=i+1}^n WIP_{plan,WS(k),j} \quad (10)$$

The planned WIPs are calculated using Little's Law, where the throughput time of an operation is the time of completion at the workstation minus the time of completion at the preceding workstation (resp. the time of order release at the first workstation), and the average demand rate of a product is the ratio of the demand for a product within a period and the length of the period:

$$WIP_{plan,WS(k),j} = TT_{plan,WS(k),j} \cdot DR_{j,plan} \quad (11)$$

Because planned inventories are constant, companies can store the planned WIP for each product and workstation in a matrix.

*Step II: calculate the Plan Output from the Plan Cumulative Production Figures*

The planned output of a workstation  $k$  is subsequently calculated by multiplying the CPFs for all products  $j$  by their processing times  $t_{p,j,k}$  and adding them up. Any set-up times are divided by the lot size and added to the processing times for each product unit.

$$Output\_hrs\_WSk_{plan}(t) = \sum_{j=1}^{nroffproducts} CPF\_WSk_{plan,j}(t) \cdot t_{p,j,k} \quad (12)$$

*Step III: calculation of the backlog*

In the third step, the current backlog of the working system is determined with the standard equation for the backlog (Petermann, 1996):

$$Backlog\_WSk(t) = Output\_hrs\_WSk_{plan}(t) - Output\_hrs\_WSk_{actual}(t) \quad (13)$$

*Step IV: conduct backlog control*

Based on the backlog determined in this way, a conventional backlog control can be implemented.

The proposed method has the following advantages. First, the backlog is directly linked to the current demand via the planned output. Second, the backlog definition takes into account the different capacity requirements of the products via the different processing times. Third, the backlog is also directly linked to the actual output, so that capacity control will also react to backlogs induced by disturbances in production. Fourth, the procedure simplifies capacity control in mixed production where both make-to-order and make-to-stock exist. The backlogs for both order types can be easily calculated and aggregated, providing a consistent base for decisions on capacity adjustments. Finally, the backlog is a simple and comprehensible criterion for capacity adjustments for production planners and workers. The obvious disadvantage of the method is that the planned outputs have to be recalculated more often than with a static approach.

Note that the control can also be extended by an abrasion and maintenance element (Berger et al., 2018), which is however, neglected in this study, since maintenance will not be considered.

## 4. Simulations

This study focuses on a make-to-stock context, where customer orders are fulfilled from a finished goods inventory, which is replenished by a capacitated production system. We are interested in the trade-off between inventory and delivery performance, which are measures related to individual flow items. Due to the resulting stochastic influences that will be modeled, the relationships between manufacturing control and the performance measures are too complex to be evaluated mathematically. We therefore use discrete event simulation to evaluate the proposed methods for sequencing and capacity control. Discrete event simulation was chosen since it is specifically suited to capture dynamic effects in complex systems that evolve over time (Melnik et al., 2024). Section 4.1 describes the simulation environment, before the simulated manufacturing control parameters are defined in Section 4.2. Section 4.3 presents the experimental design and the performance measures considered.

### 4.1. Simulation environment

Our simulation model is implemented using ARENA simulation software. The simulated shop produces 10 different products using six stations, where each station is a single constant capacity resource. Finished products are stored in a warehouse, with demand satisfied from this FGI. The simulation represents a production with linear material flow. Each of the ten products are assigned product-specific individual processing times (cf. Table A2 in the appendix). We would like to emphasize that the model does not assume identical processing times across all products and stations. Processing times vary both between products and between workstations, thereby introducing variability into the production system and contributing to stochasticity in the simulation experiments.

Deviating from usual company practice, we set the production lot size to 1 to prevent that a part of the demand is served from the lot inventory in case of replenishment delays or in case of demand fluctuations. The simulation generates customer demands of a quantity of 1 at random, exponentially distributed time

intervals (average overall demand rate: 1 per time unit). The demands are randomly assigned with equal probability to one of the ten products, resulting in product-specific demand rates of 0.1 units per time unit. This leads to strongly fluctuating durations between two demands and between the generation of replenishment orders for each of the products. It also leads to temporary bottlenecks. We do not consider stable bottlenecks since this would simplify the manufacturing control task.

The model was verified through a stepwise examination of entity flows, routing logic, synchronization behavior, and assignment decisions to ensure that the model correctly implements the intended system logic. Additionally, degenerate testing was performed under extreme conditions to confirm that system behavior aligned with theoretical expectations. Model validation was realized by comparing model outputs with expected qualitative system behavior and known operational rules. We ensured that the model responses under different scenarios were consistent with general manufacturing principles and literature benchmarks.

## 4.2. Manufacturing control parameters

Both order generation and order release are not the focus of our study. However, they have to be set to a defined and reasonable standard to make clear under which conditions the simulation experiments were conducted. For order generation, we use a base stock system. We consider six levels for the re-order points, from 4 to 9 items. The inventory position is given by the finished goods inventory (on hand) plus replenishment orders on their way (open orders) minus any open demand. It is compared with the final (rounded) re-order point for each product type, and when the inventory position is equal to the re-order point a production order is generated. Since we only consider demand quantities of 1, the inventory position cannot fall below the re-order point. Orders are released immediately to the shop floor where they are subject to sequencing and capacity control as introduced above.

Sequencing at the workstations follows FCFS, as a reference, or the EODD rule with operation due dates determined as explained in Section 3.2. Section 2.1. The planned transition times for calculating operation due dates are set to six time units for all stations based on preliminary simulation experiments. For capacity control, we consider rigid capacities, as a reference, and a backlog control with flexible capacities as explained in Section 3.3. For the backlog control, the following assumptions were made for all workstations: Upper backlog limit = 1 time unit, Lower backlog limit = - 1 time unit, Maximum capacity = 1.1 · Standard capacity, Minimum capacity = 0.9 · Standard capacity, and Standard capacity = 1. The backlog control was implemented as follows: If the backlog exceeds the upper backlog limit, then the processing time of the selected order is divided by 1.1, which is supposed to map the effect of a 10% increased capacity. If the backlog falls below the lower backlog limit, then the processing time is divided accordingly by 0.9 to produce the effect of a reduced capacity. The backlog of a workstation is recalculated with each sequencing decision.

We then calibrated the simulation model to ensure a good comparability of the different experiments. In particular, we wanted to avoid different mean replenishment times complicating the interpretation of the results. We therefore set the processing times of the products at the workstations in such a way that a planned value for throughput times (41.9 time units) was approximately achieved on average in the experiments with rigid capacities and EODD sequencing (see Table 2 in the appendix). In the experiments with flexible capacities, capacity control actively regulates these variables to the planned values with only small deviations (<1%). However, for the reference scenario with rigid capacities and FCFS sequences higher WIP levels (49.1) and throughput times (49.1 time units) result. Consequently, finished goods inventories at high service levels are somewhat lower in the reference scenario. We attribute this to an inherent load smoothing effect of the dynamic EODD sequencing applied, which is missing in the FCFS experiments. This hypothesis is supported by the analysis of the time between two completions of products of the same product type (inter-completion time) of two simulation experiments in which only the sequencing rule was varied. The standard deviation of the inter-completion times was smaller with EODD than with FCFS for all products. We assume that, in combination with varying processing times of the products at the workstations, the smaller standard deviation of EODD sequencing leads to a load smoothing effect, especially at the downstream workstations. As this is outside the scope of our study, we did not further validate our hypothesis.

Finally, note that the use of flexible capacities does not imply that more capacities are used in the simulation experiments with backlog control. Rather, less capacity is required, because capacity flexibility reduces the required WIP level for achieving a defined output rate (Nyhuis & Wiendahl, 2009).

### 4.3. Design of experiments and performance measures

The two main influencing factors of the experimental design are the sequencing and capacity control with two factor levels each (FCFS/EODD and rigid/flexible capacities). For each of the four factor level combinations, we also varied the safety stock at 6 levels (0,1,2,3,4,5), resulting in re-order points from 4 to 9. All parameters were set to realize the best discrimination between the performance of the different methods tested. Using a full factorial design,  $2 \times 2 \times 6 = 24$  different experiments were executed. Each simulation run includes 13,000 orders, of which 3000 orders are used as warm-up and consequently are not included in the analysis. The warm-up period was determined through the Welch method as presented in Mahajan and Ingalls (2004). Runs were replicated 100 times and common random numbers were applied. The main operational performance measures for make-to-stock are: (i) the service level, (ii) the inventory, and (iii) the delivery delay of orders that cannot be served from stock and are therefore delivered late, creating a customer waiting time. The service level refers to the share of customer demand that can be served directly from the warehouse. The higher the service level, the more reliably customers are supplied. The products in the warehouse form the inventory, which ties up capital and causes warehousing costs. For simplicity, we measure inventory in units. The customer waiting time of orders that cannot be supplied directly from inventory is given by the time of delivery minus the time when the demand of the order occurred.

To further analyze the results, we examined for each configuration of manufacturing control one simulation experiment in more depth. For this purpose, we selected simulation experiments with a safety stock of 3 units per product, while the due date of each replenishment order was set to the time of the related customer demand. This follows from the definition of the ideal replenishment process, in which all demands can be served without delays and without warehouse inventories. The lateness of each replenishment order was then calculated by comparing the actual completion date from the simulation with the due date of the ideal replenishment process. If this lateness is bigger than zero, then the order delivery is delayed and a customer waiting time arises. If the lateness is negative, then the order is completed early and increases the warehouse inventory until delivered to the customer. To be able to attribute lateness to backlog (i.e. capacity control) and sequence deviations (i.e. sequencing), we follow the proposal by Kuyumcu (2013) and Lödging et al. (2014) to further break down the lateness into a backlog-induced component and a sequence-induced component.

## 5. Results and discussion

In the following, we first present the results for the service level (section 4.1) and for the customer waiting times (section 4.2). There is an apparent conflict of objectives between the inventory level and these performance measures. Both are therefore depicted over the finished goods inventory. The resulting performance curves depict the conflict of objectives, being the objective of our study to change the shape of these trade-off curves, or operational frontiers (Schmenner & Swink, 1998). The numerical values of the simulation experiments can be found in Table A.3 in the appendix: Table A.4 to A.7 present the ANOVA and Scheffé multi-comparison results for FGI and service level. The third section is devoted to the robustness of the different manufacturing control setups and examines the different impacts of incorrect demand rates on the target variables (section 4.3).

### 5.1. Service level performance

Figure 5 shows the resulting service level curves. The horizontal axis represents the mean finished goods inventory across all products, and the y-axis the mean service level of all products. Note that quadrants 2,3, and 4 directly refer to the research questions 1–3.

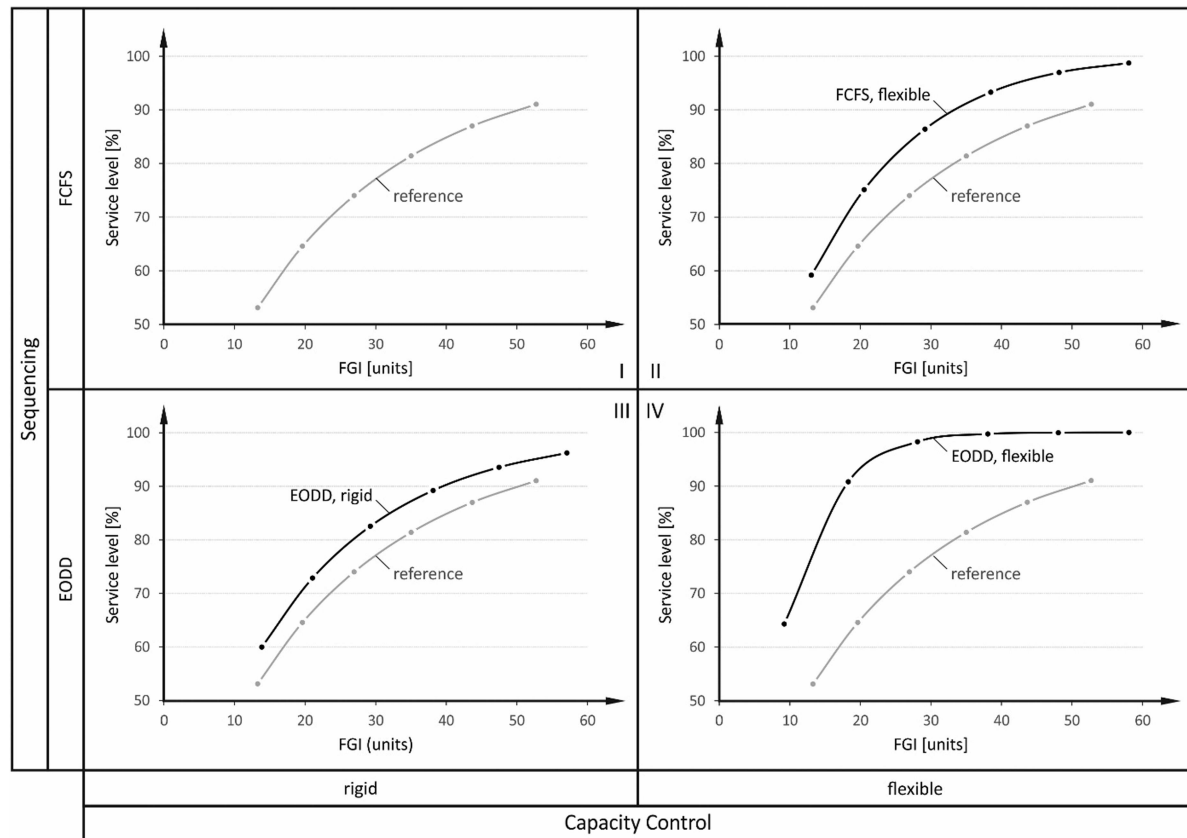


**Figure 5.** Performance results for service level.

### 5.1.1. Quadrant I

The reference experiments use rigid capacities and FCFS sequencing. This realizes a service level of 53.1% at a finished goods inventory of 13.3 (safety stock = 0). The highest service level of 91.0% is achieved with a finished goods inventory of 52.7 (safety stock = 5 units per product). From a scientific point of view, the comparatively poor performance of the reference configuration is understandable. First, capacity control cannot react to the varying capacity requirements induced by demand variance, which results in backlogs. Second, sequencing does not take into account the latest information on demand, which induces sequence deviations between demand and production. As a result, there are high backlog fluctuations and high sequence deviations compared to the ideal replenishment process. Accordingly, it would have been surprising if the service levels for a defined level of finished goods inventories had been as good as in the other configurations. This argumentation is supported by our in-depth analysis of a simulation experiment with a safety stock of 3 units per product. In this experiment, a service level of 78.2% was achieved. The standard deviation of backlog-induced lateness was 24.0 time units and the standard deviation of sequence-induced lateness was 26.1 time units.

### 5.1.2. Quadrant II

With flexible capacities and FCFS sequencing, a higher service level is achieved for each safety stock level than in the reference experiment (RQ 2). The service level increases from 59.2% with a finished goods inventory of 13.0 (Safety stock level = 0) up to 98.7% with a finished goods inventory of 58.0 (Safety stock level = 5 units per product). The influence of backlog control with flexible capacities on the service level is already very pronounced in the simulation experiments, even with FCFS sequencing. The results thus confirm the findings of Lohmann's dissertation (Lödding & Lohmann, 2012; Lohmann, 2009) for inventory-regulating capacity control and a single workstation. We attribute the increase in the service level to a reduced backlog and an improved synchronization of production output and demand. This is

enabled by the proposed calculation of the planned output, which updates the planned output with each customer demand. Moreover, the capacity flexibility of  $\pm 10\%$  implemented in the simulations experiments is relatively high and available without reaction time.

This line of arguments is further supported by our in-depth analysis, where the standard deviation of the backlog-induced lateness was reduced by 14.2 time units to 9.8 time units compared to the reference configuration with rigid capacities and FCFS sequencing. Because the impact of backlog on lateness does not depend on the type of material flow, this is a good indication that the suggested backlog control with a demand-driven planned output will also work for complex material flows, as shown by Koch (2018) in a make-to-order context for a planned output based on static due dates.

To the best of our knowledge, the use of a backlog control already corresponds to an above-average state of industry practice today. In contrast to our proposed method, however, the planned output in industry is likely to be derived from the due dates determined with the generation of a replenishment order. Thus, the link between the planned output and demand is rather loose compared to our method, which updates the planned output with every new demand. Our simulation results do not provide an answer to the extent to which this impacts the target achievement. However, it is well-known from control theory that a high sampling rate—as provided by our proposal—is helpful for the stability of the control.

### 5.1.3. Quadrant III

With EODD sequencing and rigid capacities, a higher service level is achieved for each safety stock level compared to the reference experiments (RQ1). The service level increases from 60.0% (finished goods inventory = 13.9; safety stock = 0) to 96.2% (finished goods inventory = 57.1; safety stock = 5). We attribute the increase in the service level to the dynamic due dates, which increase the priority of a replenishment order for a product with each demand that occurs for that product, such that the replenishment time is reduced if the demand for a product is higher than anticipated. This is in line with the arguments Schönsleben introduces with the development of CORMA (Schönsleben, 1995).

It is also supported by our in-depth analysis, where the standard deviation of the sequence-induced lateness was reduced by 7.8 time units to 18.3 time units compared to the reference configuration with rigid capacities and FCFS sequencing. Because the impact of sequence deviations on lateness does not depend on the type of material flow, this is a good indication that the suggested EODD sequencing with dynamic due dates will also work in complex material flows, as shown by Koch (2018) in a make-to-order context for an EODD sequencing with static due dates. The findings of Beemsterboer et al. (2017) for a job shop and a mixed production (MTO and MTS) also support this.

In industry, sequencing by due date is good practice. However, to the best of our knowledge, the due dates are usually not systematically adjusted after the order has been generated. This is a fundamental difference to our approach, which is based on CORMA's probable due dates. As under the very favorable framework conditions we simulated (linear material flow, no disruptions) the results of an FCFS sequencing and an EODD sequencing based on static plan dates will differ only slightly, our simulation results strongly indicate that companies can benefit significantly from the dynamic operation due dates proposed.

In comparison to a manufacturing control with FCFS sequencing and flexible capacities (Quadrant II), the service level increase is somewhat lower. This theoretically can result from the chosen experimental setting with its specific values for backlogs and sequence deviations. However, this is not supported by the data, as the discussion of the sequence- and backlog-induced lateness for the reference configuration (Quadrant I) shows with similar standard deviations of backlog-induced and sequence-induced lateness. We attribute the smaller effect to the fact that sequencing is decoupled from demand by the warehouse inventory. After completion, the replenishment orders go to the warehouse and can no longer be influenced by sequencing. However, demands still occur after completion, changing the urgency for the different products. Unlike sequencing, capacity control can be coupled directly to the demand and therefore offers a higher potential for reducing backlog-induced lateness.

### 5.1.4. Quadrant IV

The combination of an EODD sequencing with flexible capacities reaches the highest service levels across all FGI levels in the simulation (RQ3). They increase from 64.3% (finished goods inventory = 9.2; safety

stock = 0) to 100.0% (finished goods inventory = 58.1; safety stock = 5). The improvement is very big compared to the reference configuration with rigid capacities and FCFS sequencing (Quadrant I). However, the improvement is also big compared to manufacturing control configurations with flexible capacities and FCFS sequencing or with EODD sequencing and rigid capacities. We attribute the increase in the service level to a combination of the effects of flexible capacities and EODD sequencing. First, the planned output is updated with every demand. Therefore, a backlog control with flexible capacities can synchronize production with demand much better than a production with rigid capacities. Second, dynamic due dates increase the priority of a replenishment order for a product with each demand that occurs for that product. Therefore, the replenishment time is reduced if the demand for a product is higher than anticipated, which cannot be achieved with an FCFS sequencing.

This is further supported by our in-depth analysis, where the service level is increased by 22.7% compared to the reference configuration, to 99.9%. The standard deviation of the backlog-induced lateness is reduced by 13.9 time units to 10.1 time units. The standard deviation of the sequence-induced lateness is reduced by 7.1 time units to 19.0 time units. The analysis confirms the need for coupling sequencing and capacity control to the actual demand. Because the lateness models are not restricted to linear material flows, this is again a good indication that the proposed manufacturing control will also work with complex material flows, as shown by Koch (2018) in a make-to-order context for an EODD sequencing and a backlog control based on static due dates.

The big improvement in service level compared to Quadrants II and III, in which either capacity control or sequencing is set to the favorable factor level, can be traced back to the two sources of lateness, i.e. backlog-induced lateness and sequence-induced lateness. According to the manufacturing control model of Lödding et al. (2013), capacity control impacts backlogs and backlog-induced lateness, and sequencing has an effect on sequencing deviations and sequence-induced lateness.

Table 1 shows an overview of the effects and interactions for the four configurations of manufacturing control for the experiments used for the in-depth analyzes. The effect of capacity control on the service level (14.8%) is more than twice as big as the effect of sequencing (6.9%). Also, the division between capacity control and sequencing is quite strict as there is no relevant interaction between sequencing and capacity control (−0.1%). This is supported by the analysis of the standard deviations of the backlog- and sequence-dependent lateness. The effect of capacity control on the standard deviation of the backlog-induced lateness is large (−13.8%), while its effect on the standard deviation of the sequence-induced lateness is small (0.4 time units). Conversely, the effect of sequencing on the standard deviation of sequence-induced lateness is large (−7.5 time units) and small on the standard deviation of backlog-induced lateness (0.1 time units). The interaction between sequencing and backlog control is also small (standard deviation of backlog-induced lateness: 0.5 time units, standard deviation of sequence-induced lateness: 0.4 time units).

In industry, we do not know a single company that has implemented a manufacturing control with a backlog control based on dynamic planned outputs and a sequencing based on dynamic operation due dates, but of course our overview of industrial practice is very limited. The results clearly indicate that industry is failing to exploit a big potential for reducing inventories and increasing service levels.

## 5.2. Customer waiting time performance

Figure 6 shows the resulting performance curves for the customer waiting time. The horizontal axis represents the mean finished goods inventory across all products and the y-axis the mean customer waiting

**Table 1.** Effects and interactions of capacity control and sequencing.

| Systematic experiment (quadrant) | Capacity  | Sequencing  | Service level | Standard deviation of lateness from |                    |
|----------------------------------|-----------|-------------|---------------|-------------------------------------|--------------------|
|                                  |           |             |               | Backlog                             | Sequence deviation |
| I                                | Rigid     | FCFS        | 78.2%         | 24.0                                | 26.1               |
| II                               | Flexible  | FCFS        | 93.0%         | 9.8                                 | 26.1               |
| III                              | Rigid     | EODD        | 85.2%         | 23.4                                | 18.3               |
| IV                               | Flexible  | EODD        | 99.9%         | 10.1                                | 19.0               |
|                                  | Effect of | Capacity    | <b>14.8%</b>  | <b>−13.8</b>                        | 0.4                |
|                                  |           | Sequencing  | <b>6.9%</b>   | −0.1                                | <b>−7.5</b>        |
|                                  |           | Interaction | −0.1%         | 0.5                                 | 0.4                |

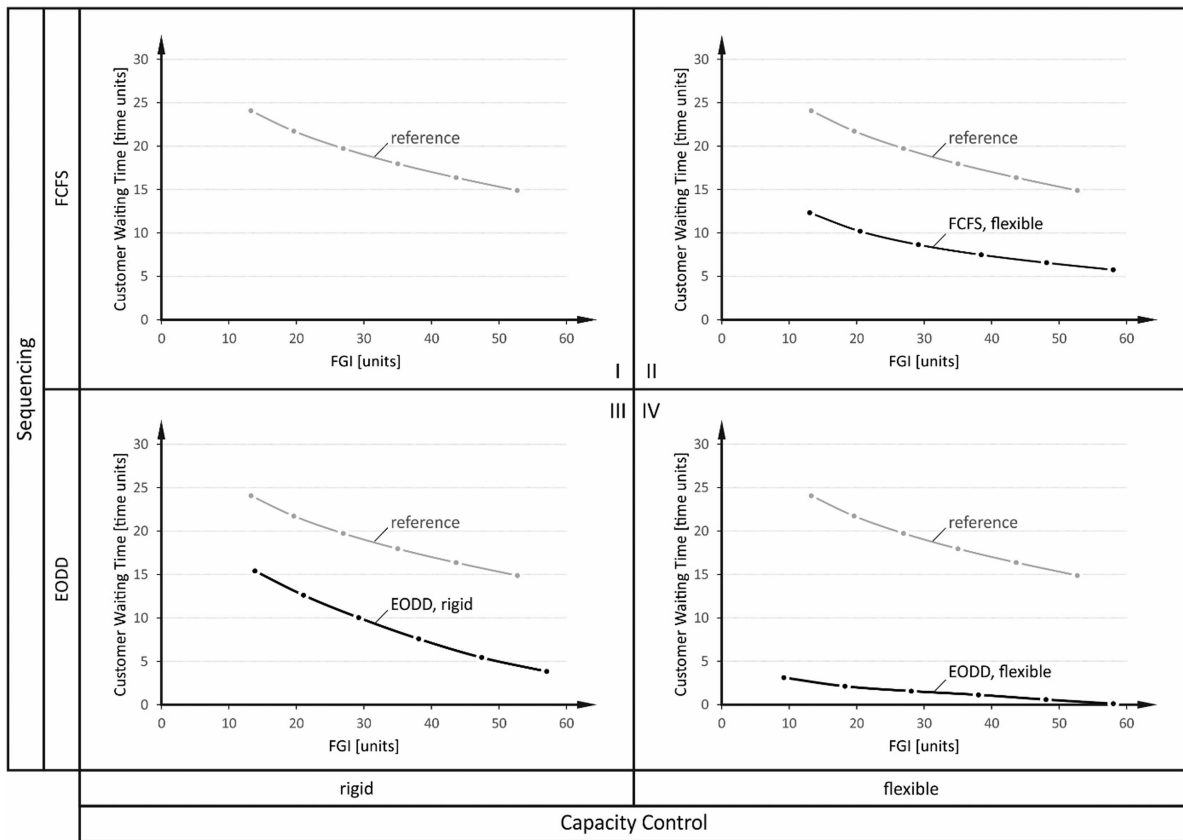


**Figure 6.** Performance results for customer waiting times.

times across all products. Note that in the calculation of the average customer waiting times only customer orders were considered that could not be served directly from the warehouse inventory.

### 5.2.1. Quadrant I

In the reference experiment with rigid capacities and FCFS sequencing, the deliveries were delayed by an average of 24.1 time units with a finished goods inventory of 13.3 (Safety Stock = 0). With a service level of 53.1%, this delay affects almost half of the customer orders. The delay decreases significantly as the finished goods inventory increases and also affects a smaller proportion of the orders due to the higher service level. Consequently, the lowest delay of 14.9 time units is achieved with the highest finished goods inventory (FGIm = 52.7) and the highest service level (SLm = 91.0%). It is well-known that the average customer waiting time is reduced with increasing service levels. The results therefore reflect the findings of, for example, Gläßner, (1994), Lutz (2002), and Nyhuis and Wiendahl (2009).

### 5.2.2. Quadrant II

With flexible capacity and FCFS sequencing, the mean customer waiting time is consistently reduced compared to the reference; from 12.3 time units with a finished goods inventory of 13.0 and a service level of 59.2% to a mean of 5.8 time units with a finished goods inventory of 58.0 and a service level of 98.7%. We attribute the positive impact of backlog control on the customer waiting times to the higher service levels achieved by a reduced backlog.

### 5.2.3. Quadrant III

In the experiments with rigid capacities and an EODD sequencing, the delay of orders delivered late is significantly reduced compared to the reference experiment. The mean delay decreases from 15.4 time units (finished goods inventory = 13.9, service level = 60.0%) to 3.8 time units (finished goods inventory =

57.1; service level = 96.2%). We attribute the positive impact of EODD sequencing to two different causes. First, EODD has a positive impact on the service level and a higher service level goes along with reduced customer waiting times. Second, late replenishment orders receive extra high priority with the proposed method for determining the due dates. Therefore, late orders are accelerated compared to FCFS sequencing, reducing their lateness. This result is consistent with the findings of Ardalan & Diaz for a flow shop (2012a) and for a jumbled flow shop (2012b). Please also note that the resulting customer waiting times for a given service level is lower in quadrant III (EODD sequencing, rigid capacities) than in quadrant II (FCFS sequencing, flexible capacities). This can be seen by comparing the simulations experiments with the highest resp. second highest FGI level.

#### 5.2.4. Quadrant IV

As already for the service level, the combination of flexible capacities with EODD sequencing also achieves the best results for the mean delay of delayed orders. The customer waiting times decrease from 3.1 time units (finished goods inventory = 9.2, service level = 64.3%) to 0.1 time units (finished goods inventory = 58.1; service level = 99.99%). Again, we attribute the high performance of a manufacturing control consisting of a backlog control with flexible capacities and an EODD sequencing with dynamic due dates to two causes. First, the very positive impact on the service levels pays off also for the customer waiting times. Second, late replenishment orders receive extra high priority.

What we find surprising is the magnitude of the possible reduction. The largest delay with flexible capacities and EODD sequencing (3.1 time units) is smaller than the smallest delay with all other manufacturing control configurations. The smallest delay in the reference configuration with FCFS sequencing and rigid capacities (14.9 time units) is almost five times higher and requires more than five times the finished goods inventory.

This positive effect of the proposed manufacturing control configuration on the customer waiting times is relevant for companies in several respects. On the one hand, the cost of a delayed order tends to increase with the delay. The significant reduction in delay therefore promises a significant reduction in these costs. On the other hand, the mean values of the delay are so low that companies can consider operating a form of make-to-stock production that is unusual today and that promises the customer a delivery within a short delivery time. In the example, a company could, for example, opt for an inventory of about 20 units with a delivery time of 6 time units. In this case, about 90% of the products could be served directly from stock. For the remaining 10% of cases, with a mean customer waiting time of 2.1 time units, the large majority of orders would be completed within 6 time units. Such a configuration would significantly reduce the required safety stocks.

As a final remark, we would like to refer to table A3 in the Appendix and to address the high consistency of throughput times, WIP levels and Finished Goods inventory to the set values, especially at high service levels. This indicates that the proposed combined use of demand-driven EODD sequencing and capacity control is realizing an effective closed-loop control.

### 5.3. Robustness against wrongly set average demand rates

A mostly implicit assumption of many simulation studies in the context of production planning and control methods is that input variables, such as the average demand rates of the products, are known and that therefore correct planning parameters can be determined. In practice, however, the average demand rates are often unknown, so that systematic deviations between the planned values and the actual values can occur. Our robustness analysis therefore evaluates how the proposed configuration of manufacturing control reacts to deviations between the planned and realized average demand rate, addressing (RQ 4).

We deliberately set the planned values for two of the ten products to a false value that deviates from the demand rate in the simulation experiments, which is equal for all products (0.1 units/time unit for each product). For product 1, half of the demand rate in the simulation was assumed as the planned value, so that based on a uniform safety stock of 3 the order point for product 1 was reduced from 7 to 5. For product 2, twice the simulated demand rate was planned, so that the order point for product 2 increased from 7 to 11 (see Table A.8 in the appendix). [Figure 7](#) shows the main simulation results in the usual

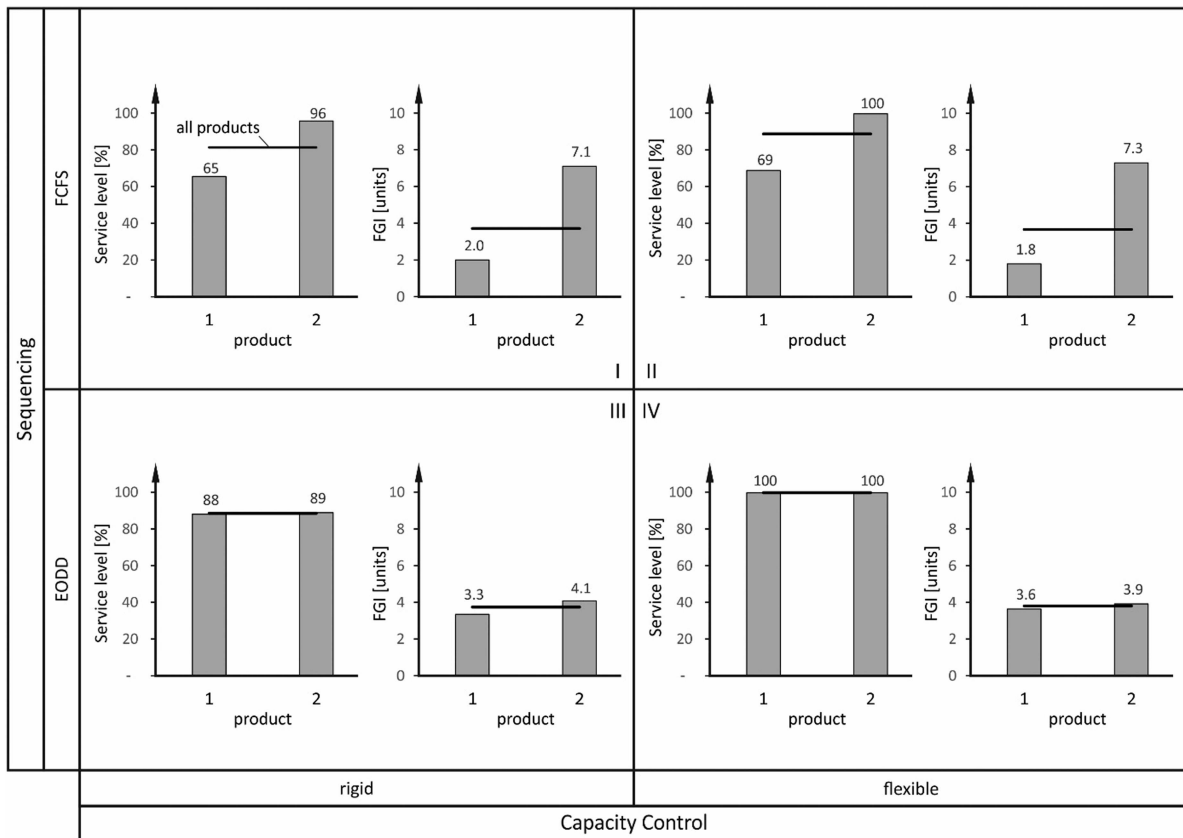


**Figure 7.** Evaluation of service levels and finished goods inventories for products with wrongly set average demand rates.

quadrant representation, with the service level and the finished goods inventory for products 1 and 2 shown as bars. The lines represent the average values for all ten products.

### 5.3.1. Quadrant I

For the reference configuration, service level and finished goods inventory are significantly below average for product 1 (service level = 65.5%; finished goods inventory = 2.0 units) and significantly above average for product 2 (service level = 95.7%; finished goods inventory = 7.1 units). The results are as expected. For product 1, the order point of 5 units is too low so that neither the required finished goods inventories nor the desired service level can be achieved. Conversely, the order point of 12 for product 2 is leading to above-average inventories and service levels. Manufacturing control cannot compensate for the wrongly set parameters. The important conclusion for industry practice is that it must carefully set the relevant input parameters to avoid problems in satisfying customer demands or excess inventories.

### 5.3.2. Quadrant II

For a configuration with FCFS sequencing and flexible capacities, the picture is the same, except that the service levels of the products are at a higher level overall. The average service level is increasing from 81.3% (rigid capacities) to 88.6% (flexible capacities). We attribute the improvement of the overall service levels on the reduced backlog-induced lateness of the replenishment orders for all products. However, backlog control cannot compensate the effect of the wrongly set order points for products 1 and 2.

### 5.3.3. Quadrant III

For EODD sequencing with rigid capacities, the service levels of product 1 and 2 converge: For product 1, the service level increases by 22.5 percentage points to 88.0% compared to the reference configuration, while for product 2 it decreases from 95.7% to 88.9%. Similar to quadrant II, the mean service level of

88.5% is significantly improved compared to the reference configuration. The finished goods inventories are hardly changed on average, but the inventories of product 1 and product 2 are significantly closer to the mean value than in the reference configuration.

EODD sequencing can almost completely compensate the effect of the wrongly set order points for product 1 and 2. Despite the clearly too low order point, product 1 achieves approximately the same service level as the other products. The reason for this is that the sequencing calculates planned completion dates with each demand for the product, so that the average throughput time for product 1 is reduced from 48.4 time units with FCFS sequencing to 28.4 time units. Conversely, the average throughput for product 2 is increasing from 49.7 time units (FCFS) to 80.8 time units with EODD sequencing. For industry, the simulation results indicate that EODD sequencing with dynamic due dates makes our approach robust against a mistakenly wrong setting of the average demand rate of a product.

#### 5.3.4. Quadrant IV

The combination of EODD sequencing with a backlog control increases the service level of product 1 to 99.7% (reference configuration: 65.5%) and for product 2 to the same value (reference configuration 95.7%), which also is the average service level of all products. The finished goods inventory of product 1 (3.6) and product 2 (3.9) only slightly deviate from the mean value of all products (3.7). A backlog control with dynamic planned outputs and EODD sequencing promises to make both service levels and inventory levels more robust against wrongly set planning parameters. EODD sequencing based on dynamic due dates can adjust replenishment lead times if the average demand rates of specific products are set to wrong values. The backlog control can compensate systematic deviations that arise if the average demand rate across all products deviates from planned value.

## 6. Conclusion

To ensure high service levels at low inventory, most companies rely on inventory control policies and demand forecasts. This ignores that the replenishment, and thus manufacturing control, also has a significant impact. We therefore asked: RQ1: What is the impact of demand-driven sequencing on service and inventory levels? RQ2: What is the impact of demand-driven capacity control on service and inventory levels? RQ3: What is their combined effect? RQ4: Are results robust to uncertainty in demand rates? To answer these questions, we proposed a new configuration for manufacturing control in make-to-stock production that consists of an EODD sequencing based on dynamic due dates and a backlog control based on the dynamic planned output of each workstation. This new configuration consistently outperforms a reference configuration with FCFS sequencing and rigid capacities and it is also performing better than configurations with EODD sequencing and rigid capacities resp. configurations with FCFS sequencing and flexible capacities. The new configuration of manufacturing control:

- achieves higher service levels for a defined safety stock (or reduced safety stocks for defined service levels),
- reduces customer waiting times for orders that cannot be served from inventory and
- reacts robustly to wrongly set demand rates of the products.

In general, the improvements will be most significant, if the deviation from average product demand and average overall demand are significant. With stable demands for the individual products and for the overall demand, the improvements will be minor. If the required safety stock is primarily driven by the demand variance of the individual products, sequencing will be especially important. Conversely, if the safety stocks are primarily driven by input lateness, the demand-driven capacity control will be important.

### 6.1. Theoretical implications

Apart from these findings, our study introduces some methods, that are primarily relevant for research. To the best of our knowledge, this paper provides the first application of the lateness model of Kuyumcu (2013) and Lödding et al. (2014) to make-to-stock production. The model enabled us to clearly separate

the effects of sequencing from the effects of capacity control, which will be helpful also in other research topics. Moreover, the use of CPF to couple both sequencing and capacity control to the current demand proved successful and may be used or adapted for different sequencing or capacity control applications. Finally, to the best of our knowledge, also the analysis of the robustness against deviations from the assumed average demand rates is new and highly relevant for the design of new manufacturing control methods. Consequently, it may be used in the evaluation of different inventory management approaches.

## **6.2. Managerial implications**

The proposed mechanisms are highly relevant for industry implementation. To the best of our knowledge, the combined application of demand-driven sequencing and demand-driven capacity control has not yet been applied in industry. Yet they offer a concrete perspective for reducing inventory levels and for improving service levels, with the evident improvements for customer service and employed capital. Moreover, data requirements are very limited, and the proposed methods are robust against wrongly set average demand rates. Implementation does introduce practical challenges. The proposed sequencing rule requires operation due dates to be updated frequently based on current demand, while capacity control requires planned outputs to be recalculated as demand changes. Existing production planning systems may not directly support these procedures. The computational burden of the calculations themselves is expected to be relatively low, since the rules rely on cumulative quantities, current demand, processing times, and planned WIP rather than on computationally intensive optimization. The more important challenge is therefore the availability, integration, and timely updating of the required information. Furthermore, the assumed capacity flexibility is not costless in practice. Increasing or reducing capacity may require overtime, temporary workers, cross-training, or changes in workforce allocation, and such adjustments may have monetary and organizational consequences. Consequently, the economic attractiveness of the proposed approach depends on the cost of capacity flexibility relative to the cost of holding finished goods inventory and the cost of delayed customer deliveries. Future research should explicitly incorporate these costs to determine when demand-driven capacity flexibility is economically preferable to additional safety stock.

## **6.3. Limitations and future research**

While we designed the rules for sequencing and capacity control to be as generic as possible, our simulation experiments reflect specific conditions and can therefore not evaluate the suitability of our configuration of manufacturing control for all the conditions found in practice. This concerns especially the following issues that open up potential venues for future research.

First, we have designed capacity control and sequencing rules for arbitrary lot sizes. However, in the simulation experiments we consistently used a lot size of 1, whereas in industry, the lot size is very often larger. We chose a lot size of 1 because we want to focus on the effect of manufacturing control on the required safety stocks, and a lot size of 1 simplifies the model-based in-depth analysis of the simulation experiments because each order can be attributed to a specific demand. We do not find our choice for a lot size of 1 problematic, but it should be reflected when interpreting the results. Lot sizes bigger than 1 will increase the inventory levels and will provide additional buffers against demand rate fluctuations and other disturbances. They will also have an impact on the required WIP levels, throughput times and setup efforts in production. Future research could explore the interplay between demand quantities and the actual lot sizing, and how phenomena as overshoot can be considered in the calculations. Second, we have designed the parameter settings for arbitrary routings and therefore all kinds of material flows. However, for simplicity we consistently use a linear material flow in the simulation experiments. Third, we have designed the setting of due dates and of the planned output in a way that is consistent also for make-to-order production. Therefore, we are confident that our configuration will be a good basis for manufacturing control in a mixed make-to-order/make to stock context. However, the simulation experiments are restricted to pure make-to-stock production and therefore cannot evaluate the performance in mixed production. Fourth, we have not varied some influencing variables, such as the number of products, the number of workstations in production and the WIP levels in production. Fifth, we assumed

an instantaneous availability of capacity for flexible capacity adjustment, which in practice is seldom realized. It also comes at a monetary and human cost that future research could consider. Meanwhile, we have also not mapped other influencing variables, such as disturbances at the workstations or special features as workstations with sequence-dependent set-up times. In general, future research should include applications to more complex manufacturing systems, stochastic environments, digital manufacturing, and sustainable production planning. Finally, implementation in industry is the ultimate litmus test for any manufacturing control method and configuration, and it is still missing.

### Author contributions

CRedit: **Hermann Lödding**: Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing; **Nuno O. Fernandes**: Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing; **Matthias Thürer**: Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing.

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### Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Ethics approval statement

This study did not require any ethics approval or consent to participate.

### Consent for publication

This study did not require any consent for publication.

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## Appendix

**Table A1.** Nomenclature.

| Symbol/abbreviation | Definition                                                                                 | Unit                |
|---------------------|--------------------------------------------------------------------------------------------|---------------------|
| $i$                 | Replenishment order index                                                                  | –                   |
| $j$                 | Product index                                                                              | –                   |
| $k$                 | Workstation index                                                                          | –                   |
| $t$                 | Current time                                                                               | time units          |
| $n$                 | Number of workstations in the production route                                             | –                   |
| $D_j(t)$            | Cumulative demand for product $j$ up to time $t$                                           | units               |
| $d_j$               | Average demand rate of product $j$                                                         | units/time unit     |
| $q_i$               | Quantity of replenishment order $i$                                                        | units               |
| $SS_j$              | Safety stock of product $j$                                                                | units               |
| $ROP_j$             | Reorder point of product $j$                                                               | units               |
| $CPF_j(t)$          | Cumulative Production Figure of product $j$ at time $t$                                    | units               |
| $CPF_{j,k}(t)$      | Cumulative Production Figure of product $j$ at workstation $k$                             | units               |
| $WIP_{j,k}$         | Planned work-in-process of product $j$ at workstation $k$                                  | units               |
| $FGL_j$             | Finished goods inventory of product $j$                                                    | units               |
| $FGL_m$             | Mean finished goods inventory across products                                              | units               |
| $SL_j$              | Service level of product $j$                                                               | %                   |
| $SL_m$              | Mean service level across products                                                         | %                   |
| $TT_j$              | Throughput time of product $j$                                                             | time units          |
| $TT_m$              | Mean throughput time across products                                                       | time units          |
| $CW_j$              | Customer waiting time for product $j$ when demand cannot be served directly from inventory | time units          |
| $CW_m$              | Mean customer waiting time for orders delivered late                                       | time units          |
| $t_{p,j,k}$         | Processing time of product $j$ at workstation $k$                                          | time units/unit     |
| $C_k$               | Capacity of workstation $k$                                                                | units/time unit     |
| $C_k^{std}$         | Standard capacity of workstation $k$                                                       | units/time unit     |
| $C_k^{max}$         | Maximum capacity of workstation $k$ under capacity control                                 | units/time unit     |
| $C_k^{min}$         | Minimum capacity of workstation $k$ under capacity control                                 | units/time unit     |
| $B_k(t)$            | Backlog at workstation $k$ at time $t$                                                     | time units          |
| $B_k^{upper}$       | Upper backlog limit at workstation $k$                                                     | time units          |
| $B_k^{lower}$       | Lower backlog limit at workstation $k$                                                     | time units          |
| $PO_k(t)$           | Planned output of workstation $k$ at time $t$                                              | time units/workload |
| $CPF_k^{plan}(t)$   | Planned cumulative production figure at workstation $k$                                    | units               |
| $L_i$               | Lateness of replenishment order $i$ relative to the ideal replenishment process            | time units          |
| $L_i^{backlog}$     | Backlog-induced component of lateness of replenishment order $i$                           | time units          |
| $L_i^{sequence}$    | Sequence-induced component of lateness of replenishment order $i$                          | time units          |
| $SD(L^{backlog})$   | Standard deviation of backlog-induced lateness                                             | time units          |
| $SD(L^{sequence})$  | Standard deviation of sequence-induced lateness                                            | time units          |

**Table A2.** Processing times of the products at the workstations (time units).

| Workstation | Product |      |      |      |      |      |      |      |      |      |
|-------------|---------|------|------|------|------|------|------|------|------|------|
|             | 1       | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   |
| 1           | 1.65    | 0.24 | 0.47 | 1.41 | 0.94 | 0.94 | 1.41 | 0.47 | 0.24 | 1.65 |
| 2           | 0.24    | 1.65 | 1.41 | 0.47 | 0.94 | 0.94 | 0.47 | 1.41 | 1.65 | 0.24 |
| 3           | 1.65    | 0.24 | 0.47 | 1.41 | 0.94 | 0.94 | 1.41 | 0.47 | 0.24 | 1.65 |
| 4           | 0.24    | 1.65 | 1.41 | 0.47 | 0.94 | 0.94 | 0.47 | 1.41 | 1.65 | 0.24 |
| 5           | 1.65    | 0.24 | 0.47 | 1.41 | 0.94 | 0.94 | 1.41 | 0.47 | 0.24 | 1.65 |
| 6           | 0.24    | 1.65 | 1.41 | 0.47 | 0.94 | 0.94 | 0.47 | 1.41 | 1.65 | 0.24 |

**Table A3.** Simulation results.

| Simulation parameters |            |                          | Results shop floor |      | Results warehouse          |               |                       |
|-----------------------|------------|--------------------------|--------------------|------|----------------------------|---------------|-----------------------|
| Sequencing            | Capacities | Safety stock per product | Throughput Time    | WIP  | Finished Goods Inventories | Service level | Customer waiting time |
| FCFS                  | Rigid      | 0                        | 49.1               | 49.1 | 13.3                       | 53.1          | 24.1                  |
|                       |            | 1                        | 49.1               | 49.1 | 19.6                       | 64.6          | 21.7                  |
|                       |            | 2                        | 49.1               | 49.1 | 27.0                       | 74.0          | 19.7                  |
|                       |            | 3                        | 49.1               | 49.1 | 35.0                       | 81.4          | 18.0                  |
|                       |            | 4                        | 49.1               | 49.1 | 43.7                       | 87.0          | 16.4                  |
| EODD                  | Rigid      | 5                        | 49.1               | 49.1 | 52.7                       | 91.0          | 14.9                  |
|                       |            | 0                        | 43.5               | 43.4 | 13.9                       | 60.0          | 15.4                  |
|                       |            | 1                        | 43.5               | 43.4 | 21.1                       | 72.9          | 12.6                  |
|                       |            | 2                        | 43.5               | 43.4 | 29.2                       | 82.5          | 10.0                  |
|                       |            | 3                        | 43.5               | 43.4 | 38.1                       | 89.2          | 7.6                   |
| FCFS                  | Flexible   | 4                        | 43.5               | 43.4 | 47.5                       | 93.6          | 5.4                   |
|                       |            | 5                        | 43.5               | 43.4 | 57.1                       | 96.2          | 3.8                   |
|                       |            | 0                        | 42.1               | 42.0 | 13.0                       | 59.2          | 12.3                  |
|                       |            | 1                        | 42.1               | 42.0 | 20.5                       | 75.1          | 10.2                  |
|                       |            | 2                        | 42.1               | 42.0 | 29.2                       | 86.4          | 8.6                   |
| EODD                  | Flexible   | 3                        | 42.1               | 42.0 | 38.5                       | 93.3          | 7.5                   |
|                       |            | 4                        | 42.1               | 42.0 | 48.2                       | 97.0          | 6.6                   |
|                       |            | 5                        | 42.1               | 42.0 | 58.0                       | 98.7          | 5.8                   |
|                       |            | 0                        | 42.0               | 41.9 | 9.2                        | 64.3          | 3.1                   |
|                       |            | 1                        | 42.0               | 41.9 | 18.3                       | 90.8          | 2.1                   |
|                       |            | 2                        | 42.0               | 41.9 | 28.1                       | 98.3          | 1.6                   |
|                       |            | 3                        | 42.0               | 41.9 | 38.1                       | 99.7          | 1.1                   |
|                       |            | 4                        | 42.0               | 41.9 | 48.1                       | 100.0         | 0.6                   |
|                       |            | 5                        | 42.0               | 41.9 | 58.1                       | 100.0         | 0.1                   |

**Table A4.** ANOVA results FGI.

| Source                | Sum of squares          | df   | Mean square | F        | Sig.  |
|-----------------------|-------------------------|------|-------------|----------|-------|
| Corrected model       | 114284,414 <sup>a</sup> | 23   | 4968,888    | 167,240  | <.001 |
| Intercept             | 218755,776              | 1    | 218755,776  | 7362,772 | <.001 |
| Rule                  | 43504,915               | 1    | 43504,915   | 1464,267 | <.001 |
| Capacity              | 50453,753               | 1    | 50453,753   | 1698,147 | <.001 |
| ROP                   | 16020,434               | 5    | 3204,087    | 107,842  | <.001 |
| Rule × capacity       | 1271,090                | 1    | 1271,090    | 42,782   | <.001 |
| Rule × ROP            | 24,609                  | 5    | 4922        | 166      | .975  |
| Capacity × ROP        | 2330,561                | 5    | 466,112     | 15,688   | <.001 |
| Rule × capacity × ROP | 679,052                 | 5    | 135,810     | 4571     | <.001 |
| Error                 | 70593,481               | 2376 | 29,711      |          |       |
| Total                 | 403633,672              | 2400 |             |          |       |

**Table A5.** ANOVA results service level.

| Source                | Sum of squares           | df   | Mean square  | F          | Sig.  |
|-----------------------|--------------------------|------|--------------|------------|-------|
| Corrected model       | 503,089,624 <sup>a</sup> | 23   | 21873,462    | 427,725    | <.001 |
| Intercept             | 16,805,257,085           | 1    | 16805257,085 | 328618,649 | <.001 |
| Rule                  | 31,261,526               | 1    | 31261,526    | 611,304    | <.001 |
| Capacity              | 57,217,422               | 1    | 57217,422    | 1118,859   | <.001 |
| ROP                   | 398,626,431              | 5    | 79725,286    | 1558,989   | <.001 |
| Rule × capacity       | 010                      | 1    | 010          | 000        | .989  |
| Rule × ROP            | 54,98,849                | 5    | 1099,770     | 21,505     | <.001 |
| Capacity × ROP        | 8,018,795                | 5    | 1603,759     | 31,361     | <.001 |
| Rule × capacity × ROP | 2,466,591                | 5    | 493,318      | 9647       | <.001 |
| Error                 | 121,506,466              | 2376 | 51,139       |            |       |
| Total                 | 17,429,853,175           | 2400 |              |            |       |

**Table A6.** Scheffé multi comparison results: FGI.

| (I) ROP | (J) ROP | Mean difference (I-J) | Sig.  | 95% Confidence Interval |             |
|---------|---------|-----------------------|-------|-------------------------|-------------|
|         |         |                       |       | Lower bound             | Upper bound |
| 4       | 5       | 2.06598*              | <.001 | 0.78                    | 3.35        |
|         | 6       | 3.73521*              | <.001 | 2.45                    | 5.02        |
|         | 7       | 5.18538*              | <.001 | 3.90                    | 6.47        |
|         | 8       | 6.48629*              | <.001 | 5.20                    | 7.77        |
|         | 9       | 7.58325*              | <.001 | 6.30                    | 8.87        |
| 5       | 4       | -2.06598*             | <.001 | -3.35                   | -0.78       |
|         | 6       | 1.66923*              | .002  | 0.39                    | 2.95        |
|         | 7       | 3.11940*              | <.001 | 1.84                    | 4.40        |
|         | 8       | 4.42030*              | <.001 | 3.14                    | 5.70        |
|         | 9       | 5.51727*              | <.001 | 4.23                    | 6.80        |
| 6       | 4       | -3.73521*             | <.001 | -5.02                   | -2.45       |
|         | 5       | -1.66923*             | .002  | -2.95                   | -0.39       |
|         | 7       | 1.45016*              | .015  | 0.17                    | 2.73        |
|         | 8       | 2.75107*              | <.001 | 1.47                    | 4.03        |
|         | 9       | 3.84804*              | <.001 | 2.56                    | 5.13        |
| 7       | 4       | -5.18538*             | <.001 | -6.47                   | -3.90       |
|         | 5       | -3.11940*             | <.001 | -4.40                   | -1.84       |
|         | 6       | -1.45016*             | .015  | -2.73                   | -0.17       |
|         | 8       | 1.30091*              | .044  | 0.02                    | 2.58        |
|         | 9       | 2.39787*              | <.001 | 1.11                    | 3.68        |
| 8       | 4       | -6.48629*             | <.001 | -7.77                   | -5.20       |
|         | 5       | -4.42030*             | <.001 | -5.70                   | -3.14       |
|         | 6       | -2.75107*             | <.001 | -4.03                   | -1.47       |
|         | 7       | -1.30091*             | .044  | -2.58                   | -0.02       |
|         | 9       | 1.09697               | .151  | -0.19                   | 2.38        |
| 9       | 4       | -7.58325*             | <.001 | -8.87                   | -6.30       |
|         | 5       | -5.51727*             | <.001 | -6.80                   | -4.23       |
|         | 6       | -3.84804*             | <.001 | -5.13                   | -2.56       |
|         | 7       | -2.39787*             | <.001 | -3.68                   | -1.11       |
|         | 8       | -1.09697              | .151  | -2.38                   | 0.19        |

**Table A7.** Scheffé multi comparison results: service level.

| (I) ROP | (J) ROP | Mean difference (I-J) | Sig.  | 95% Confidence Interval |             |
|---------|---------|-----------------------|-------|-------------------------|-------------|
|         |         |                       |       | Lower bound             | Upper bound |
| 4       | 5       | -16.69886*            | <.001 | -18.38                  | -15.01      |
|         | 6       | -26.16257*            | <.001 | -27.85                  | -24.48      |
|         | 7       | -31.75684*            | <.001 | -33.44                  | -30.07      |
|         | 8       | -35.21726*            | <.001 | -36.90                  | -33.53      |
|         | 9       | -37.35219*            | <.001 | -39.04                  | -35.67      |
| 5       | 4       | 16.69886*             | <.001 | 15.01                   | 18.38       |
|         | 6       | -9.46371*             | <.001 | -11.15                  | -7.78       |
|         | 7       | -15.05798*            | <.001 | -16.74                  | -13.37      |
|         | 8       | -18.51840*            | <.001 | -20.20                  | -16.83      |
|         | 9       | -20.65332*            | <.001 | -22.34                  | -18.97      |
| 6       | 4       | 26.16257*             | <.001 | 24.48                   | 27.85       |
|         | 5       | 9.46371*              | <.001 | 7.78                    | 11.15       |
|         | 7       | -5.59427*             | <.001 | -7.28                   | -3.91       |
|         | 8       | -9.05469*             | <.001 | -10.74                  | -7.37       |
|         | 9       | -11.18961*            | <.001 | -12.87                  | -9.51       |
| 7       | 4       | 31.75684*             | <.001 | 30.07                   | 33.44       |
|         | 5       | 15.05798*             | <.001 | 13.37                   | 16.74       |
|         | 6       | 5.59427*              | <.001 | 3.91                    | 7.28        |
|         | 8       | -3.46042*             | <.001 | -5.14                   | -1.78       |
|         | 9       | -5.59534*             | <.001 | -7.28                   | -3.91       |
| 8       | 4       | 35.21726*             | <.001 | 33.53                   | 36.90       |
|         | 5       | 18.51840*             | <.001 | 16.83                   | 20.20       |
|         | 6       | 9.05469*              | <.001 | 7.37                    | 10.74       |
|         | 7       | 3.46042*              | <.001 | 1.78                    | 5.14        |
|         | 9       | -2.13493*             | .003  | -3.82                   | -0.45       |
| 9       | 4       | 37.35219*             | <.001 | 35.67                   | 39.04       |
|         | 5       | 20.65332*             | <.001 | 18.97                   | 22.34       |
|         | 6       | 11.18961*             | <.001 | 9.51                    | 12.87       |
|         | 7       | 5.59534*              | <.001 | 3.91                    | 7.28        |
|         | 8       | 2.13493*              | .003  | 0.45                    | 3.82        |

**Table A8.** Re-order points used for the experiments with wrongly set demand rates.

| Product |    |   |   |   |   |   |   |   |    |
|---------|----|---|---|---|---|---|---|---|----|
| 1       | 2  | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 5       | 11 | 7 | 7 | 7 | 7 | 7 | 7 | 7 | 7  |