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Assessing the impact of cyclical sequencing in make-to-stock production with sequence-dependent setup times

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Abstract

Cyclical sequencing is a well-known sequencing method in which the sequence of products is repeated cyclically. In make-to-stock production with sequence-dependent setup times, cyclical sequencing influences important logistical objectives in production as well as in the finished goods warehouse. We derive a simple model that enables companies to set the important parameters consistently. In simulation experiments, the model is validated for its influence on logistical objectives such as capacity requirements in production and mean finished goods inventories in the warehouse.

Keywords: make-to-stock manufacturing, inventory management, cyclical sequencing

1. Introduction

Setup times present a challenge as they negatively impact the achievement of logistical objectives [1,2,3]. When setup times are sequence-dependent, the sequence affects the setup effort. The setup effort results from the frequency of major setup times, which is the time to setup the workstation for a setup family change and minor setup times, which is the time to setup orders within a setup family. Thereby, determining the total setup effort required [4].

An approach to reduce setup efforts is the implementation of cyclical sequencing with setup families. This approach classifies orders in set up families based on similar setup requirements, allowing a structured and efficient sequencing that minimizes the total setup effort [5, 6]. And there are more advantages, such as the predictability of when a product will be produced again [7]. However, the negative consequence of cyclical sequencing is that it increases the variance in throughput times and requires high WIP levels on the workstation [4].

[4] models the impact of cyclical sequencing on logistic objectives. This enables the workstation's positioning to be determined with respect to logistical goals, such as mean WIP and mean throughput times [4].

However, the model is restricted to the effect of cyclical sequencing on workstations and does not reflect its impact on the required finished goods inventory in a make-to-stock production.

Consequently, this article introduces a modeling approach that extends model of [4] to finished goods inventories, allowing companies to assess the impact of cyclical sequencing on workstations and finished goods inventories [4]. The goal is to develop a model that describes the influence of cyclical sequencing (1) on the workstation, (2) on the finished goods inventories and (3) on the resulting interdependencies as a function of a common coupling variable.

2. Current state of research

2.1. Cyclical sequencing to cope with sequence-dependent setup times

According to [2], sequencing is a task of manufacturing control that determines the sequence in which orders are produced.

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Cyclical sequencing is a method of setup optimised sequencing that can be used in different specifications [8].

[4] specifies five rules for cyclical sequencing: (1) Orders are grouped into setup families, which are represented in a setup time matrix. (2) A fixed sequence of setup families is derived from a setup time matrix. Within a setup family, (3) production is exhaustive and (4) prioritised by an earliest operation due date sequencing. (5) Empty setup families are skipped.

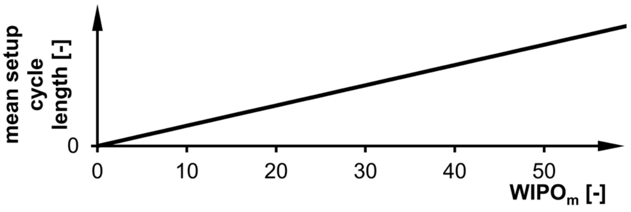


Figure 1 Influence of WIPO$_m$ on the mean setup cycle length

[4] as well as other authors distinguish between the mean setup cycle length (TSL$_m$), which describes the mean quantity of orders per cycle, and the mean setup cycle time (TSC$_m$), which indicates the time period between producing the same product again. [4] models the mean setup cycle length as a function of the mean work in process in orders (WIPO$_m$) and the proportion of setup family i in relation to all orders (p$_i$,cf. Equation 1).

Figure 1 shows that the mean setup cycle length and the maximum throughput time increase proportionally with the mean work in process [4], [9]. Therefore, a high mean work in process leads to long setup cycles [4].

$$TSL_m(WIPO_m) = WIPO_m * \frac{2}{\sum_{i=1}^{n}(1 - p_i) * p_i} \tag{1}$$

The required capacity for setups with cyclical sequencing depends on the setup effort for a setup cycle and on the mean setup cycle time (cf. Equation 2 and Figure 2) [4]. The setup effort per setup cycle (SE) results from major setup times (TS_i^+) for all setup families n and for all minor set times (TS_{ij}^-) for all products k (cf. Equation 3) [9]. Equation 3 assumes that orders for products within a setup family are scheduled consecutively if minor setup times are greater than zero. Furthermore, the mean setup cycle time (TSC$_m$) results from the mean cycle length in orders and mean output rate in orders (cf. Equation 4) [4].

The total capacity requirement consist of the capacity requirements for setups and for processing times [1].

$$CAPA_{req,setup}(TSC_m) = \frac{SE}{TSC_m} \tag{2}$$

$$SE = \sum_{i=1}^{n} TS_i^+ + \sum_{i=1}^{n}\sum_{j=2}^{k} TS_{ij}^- \tag{3}$$

$$TSC_m = \frac{TSL_m}{ROUT_m} \tag{4}$$

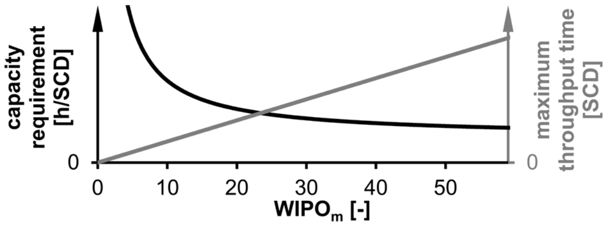


Figure 2 Conflict of objectives between capacity requirements and mean work in process in cyclical sequencing

[10] and [11] show that the performance of a manufacturing system can also be simulated and evaluated with Multiple System Dynamic Models.

2.2. Inventory models

A warehouse provides both temporal and quantitative decoupling between production processes and between production and customer [1]. Companies strive to reduce inventories, particularly in the finished goods inventory, as capital is tied up in order throughput and is maximised in the finished goods inventory [12].

The mean inventory is derived from the mean lot inventory and the safety inventory. The mean lot inventory results from half the lot size (IL$_{m,j,}$ cf. Figure 3) [2]. The required safety inventory in a warehouse is influenced by demand variations in the warehouse output and by delivery lateness and delivery quantity deviation in the warehouse input (cf. Figure 4) [2]. Equation 5 can be used to dimension the safety inventory due to demand deviation, which is impacted by the maximum and mean demand rate in units per period (DR$_{max}$, DR$_m$) during replenishment time (TRP, cf. Figure 4a). The safety inventory for delivery lateness is influenced by the maximum positive lateness (SI$_L$) and the mean demand rate in units per period (DR$_m$, cf. Figure 4b) and can be calculated by using Equation 6 [4], [9].

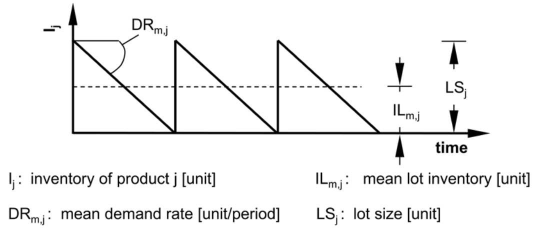


Figure 3 Lot inventory

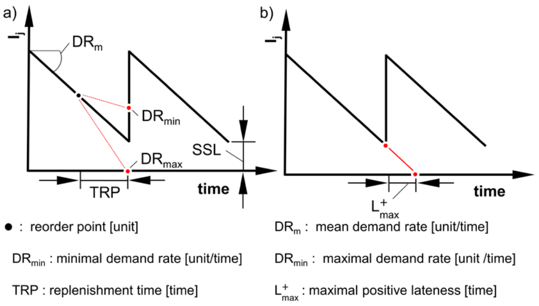


Figure 4 Safety inventory for demand deviation (a) and delivery lateness (b)

$$SI_{Dem,j} = \left(DR_{max,j} - DR_{m,j}\right) * TRP_j \quad (5)$$

$$SI_{L^{+}_{max},j} = (L^{+}_{max,j}) * DR_{m,j} \quad (6)$$

$$SI_{Dem,j}(SL_j) = SF_j\left(SL_j\right) * Dem_{s,j}\left(TRP_j\right) \quad (7)$$

The service level is the most important external logistic objective in make-to-stock production and is defined as the percentage of demands within a reference period that can be immediately satisfied from the warehouse or is defined as percentage of replenishment cycles with sufficient safety inventory [1], [2]. The service level is generally increasing with the mean inventory of a warehouse [12]. A variety of publications exist to determine the service level [13]. One possibility is to use safety factors to account for influences such as demand variation and delivery lateness [14]. Equation 7 considers only demand variation to dimension the safety inventory ($SI_{Dem,j}(SL_j)$) depending on the service level (SL): The service level can be determined by considering a safety factor that depends on the desired service level (SF(SL)) and the standard deviation of the demand during the replenishment time (Dem_s(TRP)) [1], [14].

3. Modeling the influence of cyclical sequencing on finished goods inventory levels and the workstation with sequence-dependent setup times

The idea of our modeling approach is to describe the impact of cyclical sequencing on the workstation and on the finished goods inventory as a function of the same influencing variable, which serves as a coupling variable between manufacturing and finished goods inventory. The term finished goods inventory refers to a warehouse that succeeds a workstation with sequence-dependent setup times.

We choose the mean setup time cycle as a coupling variable because of the following reasons:

1) The mean setup time cycle can be easily calculated from the WIP level of a workstation with Equation 1 and Equation 4.
2) The mean replenishment lead time is equivalent to the mean setup cycle time and directly connected to the lot size and the demand variation as drivers of the required finished goods inventory.
3) The mean setup time cycle is easy to understand.

This section presents a simple model that describes the influence of the mean setup cycle time on the finished goods inventory levels (subsection 3.1, 3.2 and 3.3) and on the workstation (subsection 3.4). Finally, we state the model assumptions (subsection 3.5).

3.1. Influence of mean cycle time on the lot size and lot inventory in finished goods inventories

If a product is produced exactly once during a setup cycle and the production quantity is determined at the time of production start, the maximum inventory level must cover the entire setup cycle time (cf. Figure 5). This implies that the replenishment time is equal to the setup cycle time [15].

Therefore, the mean lot size of a product j ($LS_{m,j}$) results from the mean demand rate of product j ($DR_{m,j}$) and the mean setup cycle time (TSC_m, cf. Equation 8) [15]. The mean lot inventory of a product j results from the mean lot size (cf. Equation 9). The integration of Equation 9 in Equation 8 enables the mean lot size to be represented as a function of the mean setup cycle time. Consequently, the sum of the mean lot inventory for all products is proportional to the mean setup cycle time (cf. Figure 6a).

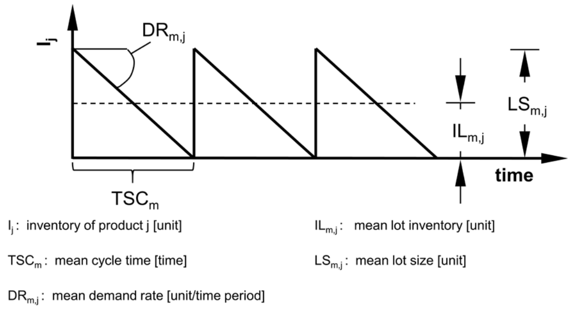


Figure 5 Characteristics of finished goods inventory with setup cycles

$$LS_{m,j} = TSC_m * DR_{m,j} \quad (8)$$

$$IL_{m,j} = \frac{LS_{m,j}}{2} \quad (9)$$

3.2. Influence of mean cycle time on the safety inventory for customer demand variation

Varying customer demands during setup cycles require safety inventory as a product is only replenished once in the setup cycle. [1] describes the well-known correlation that the variance of demand increases with the replenishment time.

As the replenishment time corresponds to the setup cycle time, the variance of demand increases with the setup cycle time. Therefore, the standard deviation of demand for a product j $Dem_{s,j}(TSC_m)$ is influenced by (1) the mean setup cycle time (TSC_m), (2) the statistical period (P_{stat}) and (3) the standard deviation during the statistical period ($Dem_{s,j}(P_{stat})$, cf. Equation 10).

Figure 6b describes the safety inventory for demand variation of product j as a function of the mean setup time cycle.

The safety inventory for demand variation of product j can be determined using the standard deviation of demand during the setup cycle time and a safety factor (SF, cf. Equation 11). Finally, the mean inventory level of product j is the integration of Equation 11 and Equation 9 to Equation 12 as a function of the mean setup cycle time.

Figure 6c depicts the influence of the mean setup cycle time on the mean inventory level. The longer the setup cycle, the greater the mean inventory level.

$$Dem_{s,j}(TSC_m) = \sqrt{\frac{TSC_m}{P_{Stat}}} \times Dem_{s,j}(P_{stat}) \tag{10}$$

$$IS_j = \mathrm{Dem}_s(TSC_m) * SF_j \tag{11}$$

$$I_{m,j} = IL_{m,j}(TSC_m) + IS_j(TSC_m) \tag{12}$$

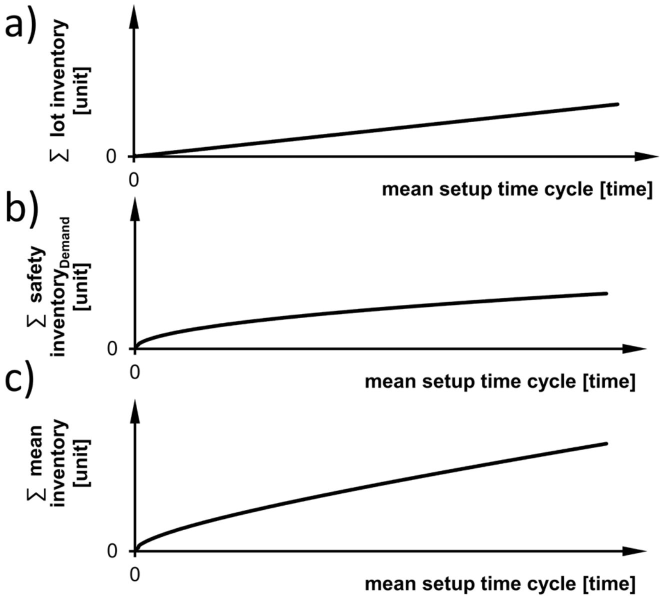


Figure 6 Influence of the mean setup time cycle on lot inventory (a), safety inventory for demand variance (b) and sum of mean inventory (c)

3.3. Influence of the setup cycle time variation on safety inventory levels

Workstations with setup optimized sequencing have often rigid capacities because they use the total capacity [8]. Combining cyclical sequencing with rigid capacities is problematic, because the setup cycle time varies due to variation in total demand. Deviations in the actual setup cycle time from the mean setup cycle duration have the effect of delivery lateness. This means that when demand is high, the setup cycle time increases.

The safety inventory for cycle time variation resp. delivery lateness is dependent on the mean demand rate (DR_m), the maximum setup cycle time (TSC_{max}) and the mean setup cycle time (TSC_m, cf. Equation 13).

Our assumption is that with flexible capacities and an active capacity control, such as the backlog control or with a very low variance of total demand, the variance of setup cycle times is usually small and can therefore be neglected.

$$SI_{L^+_{max}} = DR_m * (TSC_{max} - TSC_m) \tag{13}$$

3.4. Influence of mean cycle time on capacity demand for the workstation

The setup effort is an important performance indicator for companies as it impacts the capacity requirement of a workstation [1], [3]. The setup cycle time determines the setup effort and the major setup times per scheduled calendar day for a workstation. Therefore, capacity requirement of the workstation is determined in three steps:

1) Initially, the capacity requirement for setup efforts results from Equation 2.
2) The capacity requirement for the processing times ($CAPA_{req,process}$) results from the demand rate of all products ($Dem(SCD)_{m,j}$) and the mean processing time ($TP_{m,j}$) of all products (cf. Equation (14)) [9].
3) The total capacity requirement as a function of the mean setup cycle time equals the sum of the capacity requirement for setup efforts and the capacity requirement for the processing times (cf. Equation (15)) [9].

$$CAPA_{req,process} = \sum_{j=1}^{k} Dem(SCD)_{m,j} * TP_{m,j} \tag{14}$$

$$\begin{aligned} CAPA_{req}(TSC_m) = {} & CAPA_{req,setup}\,(TSC_m) \\ & + CAPA_{req,process}\,(TSC_m) \end{aligned} \tag{15}$$

3.5. Model assumptions

Since modelling always reduces the complexity, it is important to note that the model is based on the following premises:

1) No deviations from the planned processing and setup times.
2) No machine breakdowns resp. full availability of resources.
3) Raw material supply is guaranteed.

In general, longer processing and setup times and machine breakdowns will cause temporary backlogs and consequently will lead to longer than planned setup cycles requiring additional safety inventory. With an active capacity control, this effect will often be small compared to the safety inventory required for demand fluctuations. Also, raw material shortages will impact the required safety inventory.

4. Model integration

This section outlines how the models from Section 3 are integrated for determining the impact of cyclical sequencing on workstations with sequence-dependent setup times and on finished goods inventory. Based on the chosen setup cycle time, the capacity requirement for setups (Equation 14) and the influencing factors of the finished goods inventories are determined with the Equations 8 to 11.

Figure 7 shows two alternative positioning options. The positioning selected and therefore the mean setup cycle time determines (1) safety inventory levels, (2) lot inventories in finished goods warehouse and (3) the capacity requirement for setup effort. If companies opt for a low mean setup cycle time (position 1 in Figure 7), this has a positive effect on the mean lot inventory and safety inventory of all finished goods (cf. Figure 7a). However, a comparatively high capacity is required (cf. Figure 7b). If this is not possible, for example because capacity is limited, companies have to set a longer mean setup cycle time.

If the mean setup cycle time is increased (position 2 in Figure 7) accordingly, the setup effort and therefore the capacity requirement is reduced. However, the sum of the mean lot inventory and the necessary safety inventory significantly increases (cf. Figure 7a).

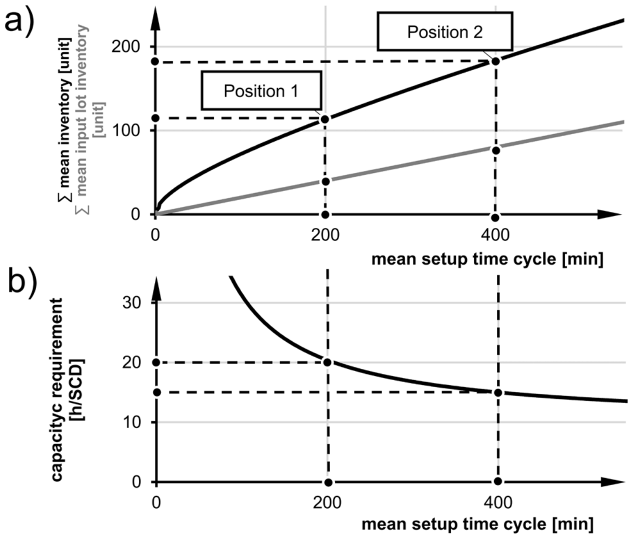


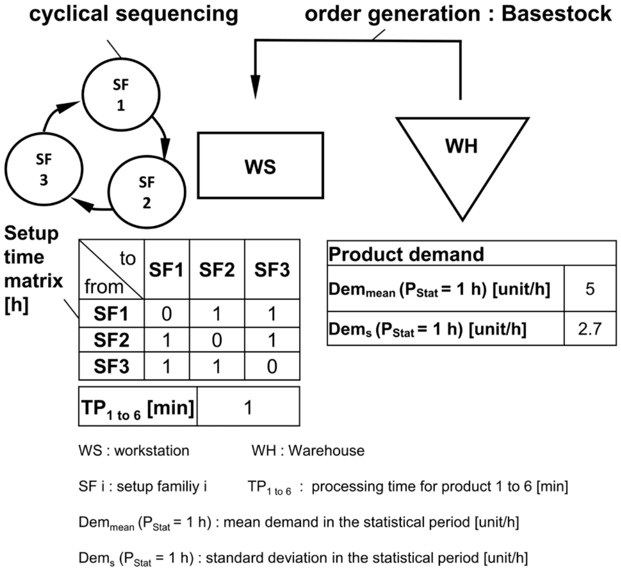
Figure 7 Model for positioning in objectives conflict of mean inventory (a) and capacity requirement (b)

5. Validation with simulation

The section validates the model with simulation experiments. We chose simulation experiments to validate because this allows to (1) selectively vary the influencing variables, (2) define the framework conditions and (3) conduct different experiments with acceptable effort [16].

Using the Plant Simulation software, we have created a make-to-stock production environment consisting of a workstation with sequence-dependent setup times and a finished goods warehouse (cf. Figure 8).

The simulation model uses basestock as the order generation method with an order lot size of one unit to smooth the input rate of the workstation (cf. Figure 8) [2]. As explained in section 2, we apply the cyclical sequencing according to [4]. The major setup times amount to one hour for each of the three setup families with two products each and minor setup times are zero (cf. setup time matrix in Figure 8). The fixed sequence of setup families is first setup family 1 (SF1), then SF2 and finally SF3 (cf. setup family cycle in Figure 8). The mean demand rate of all products is 5 units per hour. Each of the setup families has 2 products. The proportion of demand of product j in relation to all products is 0.17 for each product and the proportion of setup family i in relation to all orders is 0.33.



to / from	SF1	SF2	SF3
SF1	0	1	1
SF2	1	0	1
SF3	1	1	0

$TP_{1\text{ to }6}$ [min]	1

Product demand	
Dem_{mean} (P_{Stat} = 1 h) [unit/h]	5
Dem_s (P_{Stat} = 1 h) [unit/h]	2.7

WS : workstation WH : Warehouse

SF i : setup familiy i $TP_{1\text{ to }6}$: processing time for product 1 to 6 [min]

Dem_{mean} (P_{Stat} = 1 h) : mean demand in the statistical period [unit/h]

Dem_s (P_{Stat} = 1 h) : standard deviation in the statistical period [unit/h]

Figure 8 Simulation parameters

We conducted two simulation experiments, each with a duration of 500 scheduled calendar days: The first simulation experiment was conducted with rigid capacities of 24 hours per scheduled calendar day, a modeled mean setup cycle time of 6.40 hours and a modeled safety inventory (base stock) of 20 units. This results from calculating the standard deviation of demand for the mean setup cycle time with Equation 10 and multiplying the result with a safety factor of three, which corresponds to a service level of 99.9 % [1]. The second simulation experiment was conducted with rigid capacities of 23 hours per scheduled calendar day, a modeled mean setup cycle time of 7.02 hours and a modeled safety inventory of 21 (base stock) with a safety factor of three.

Since all products in the simulation experiments have the same safety inventory, mean demand rate and standard deviation of the demand rate, the lot sizes ($\varnothing\ LS_m$) and service levels ($\varnothing\ SL_{99.9\ \%}$) are summarised as mean values and the inventory as a sum ($\sum I_m$).

The simulation results for the mean setup cycle time and the mean lot size match the modeled values well (cf. Table 1 and Table 2). However, the inventory levels in the simulation experiments are 25.3 % (cf. Table 1) resp. 25.9 % (cf. Table 2) lower than values predicted by the model (cf. Table 1 and Table 2). Around 17 percentage points of this deviation can be explained by the fact that goods are removed from the finished goods warehouse during production, which is not considered in the modeling of mean inventory levels (cf. Equation 12). The deviation can be modeled with a simple model extension. However, it was decided not to include the effect in the model, because (1) the effect is smaller the more products are produced and (2) the model is simpler without the extension. The simulated and modeled service level match well because we selected the simulation conditions in such a way as to minimise total variation in demand and thus a very low variance of setup cycle times: In simulation experiment 1 the coefficient of variation for setup cycles is 0.07 and in simulation experiment 2 it is 0.08.

Table 1 Results of simulation experiment 1 with a mean setup time cycle of 6.4 hours

Denotation	Simulation	Modeling	Deviation [%]
TSC_m [h]	6.4	6.4	0.1
Ø LS_m [unit]	34	34	0.1
$\sum I_m$ [unit]	169	226	25.3
Ø $SL_{99.9\,\%}$ [%]	99.6	99.9	0.3

Table 2 Results of simulation experiment 2 with a mean setup time cycle of 7.0 hours

Denotation	Simulation	Modeling	Deviation [%]
TSC_m [h]	7.0	7.0	0.2
Ø LS_m [unit]	37	37	0.0
$\sum I_m$ [unit]	179	242	25.9
Ø $SL_{99.9\,\%}$ [%]	99.6	99.9	0.3

The theoretical implication is that the modeling can quantify the effects of cyclical sequencing on capacity requirements and the finished goods inventory using a simple model and the conflict of objectives between finished goods inventory and capacity requirement can be derived. Regarding the practical implications, the simple model enables the industry to set plan values for capacity requirements, WIP levels, replenishment lead times, safety inventory levels, finished goods inventory levels and service levels in a make-to-stock production for one workstation with cyclical sequencing.

6. Summary and outlook

The most important result of our research is the model that explains the conflict of objectives between the capacity requirement for a workstation with cyclical sequencing to reduce sequence-dependent setup efforts and the finished goods inventory levels. For this purpose, we integrated the model of [4] for setting up cyclical sequencing in a make-to-order production with approaches for setting up finished goods inventory levels in a make-to-stock production. Furthermore, we extended the existing models to set up safety inventory levels with a preceding workstation with cyclical sequencing. The model was validated with simulation experiments.

Future research should focus on the following three areas. (1) Combining an order generation method and sequencing is an useful approach as depicted in the simulation experiments. However, research should focus on creating a method that integrates the order generation and the sequencing in one method. (2) We only investigated the effect of cyclical sequencing on the succeeding inventory. The investigation of cyclical sequencing impacting the preceding warehouse is still missing. (3) Current research focuses on digitising methods from production planning and control [17]. Digitising this model appears to be a promising research direction.

Acknowledgements

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