Wageningen University - Department of Social Sciences

Operations Research and Logistics

MSc Thesis

Setting order-up-to levels for perishable products in a multi-product system

The purpose of this research was to assess the use of an average constrained system to reduce product waste of perishable items in a multi-product inventory system using a Base Stock Policy (BSP). The average service level ensures that an overall service level is obtained, while individual product service levels may be lower. This model was compared to a multi-product inventory system of perishable items that has individual service levels for each product, in which all products adhere to the same service level. Two simulation based optimisations were done to assess the use of an average constrained system compared to an individual constrained system.
The results showed a slight decrease in both waste levels and obtained service levels when an average constraint was used. The decrease in waste levels was accompanied by a decrease in obtained service level. It is therefore concluded that the use of an average constrained system is not a promising tool to reduce product waste in perishable products in the settings used in this research.
This was not in line with the decrease in inventory that was observed in previous literature. However, previous literature used an aggregated service level instead of an average service level. It is therefore suggested to further research the proposed model using an aggregated service level to assess whether this can reduce product waste.

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1. Introduction

1.1 Background information

1.1.1 Food waste

Globally, around a quarter of the produced food is lost within the food supply chain (Kummu et al., 2012). In high income countries, food wasted at the retail level is estimated as high as 13 kg/capita/year (Forbes et al., 2021). The causes of food waste at the retail level have been researched by Teller et al., (2018). Their research has shown that demand patterns, in-store behaviour (including customer commitment to the First-In-First-Out (FIFO) policy) and inventory management policies have a significant influence on the waste produced by retailers (Teller et al., 2018).

Limiting waste on the retail level could be achieved by using a well-adjusted inventory management policy. To this end, the parameters involved in the inventory management policy need to be optimised. In order to find these optimal parameter settings, an approach would be to build models that can simulate the outcome of different settings of the parameters. These models yield optimal decisions based on the input parameters. This is either done by minimising the total costs subjected by a fill-rate constraint or by minimising the total costs and setting a penalty for out-of-stock situations or using a service level constraint (van Donselaar et al., 2021). The objective of minimising the total costs ensures the cost effectiveness, whilst the fill-rate constraint or the service level constraint ensures enough demand is met. Meeting demand requires a certain amount of inventory to be able to fulfil orders from stock, however, higher inventory levels will also lead to more waste in times of lower demand, since food products have a short shelf life.

1.1.2 Service level

As mentioned above, models can be used to find a balance in an order policy between (waste) costs and the service level that is provided. The service that is provided is expressed as a service level constraint.

A retailer with a product category of N stock keeping units (sku's) is considered. Each sku $n \in \{1, \ldots N\}$ has an individual obtained service level α_n that should be above some minimum level α_n. If each sku is kept at a high service level, high inventory positions will be needed to fulfil orders from stock. In turn, this will result in high product waste. However, if some sku's are kept at a lower service level, lower inventory levels will be acceptable and less products will be wasted. In order to compensate for the lower service level, another product in the same product category can be assigned a higher service level. This way each of the sku's has its own differentiated service level, instead of individual service levels for all products in the product category. In this scenario, it is assumed that unmet demand for the former product can be compensated with the latter product (i.e. product substitution). In addition to the differentiated service levels a weighted average service level α, weighted over all sku's can be implemented. This ensures that an overall service level is provided, whilst the individual service levels per sku may differ. Since each sku is allowed a different service level, each sku needs a different order-up-to level to provide this service level.

Van Donselaar et al., (2021) suggested four heuristics to determine the order-up-to levels for aggregated constrained multi-item systems. In this research it is shown that differentiation in individual service levels can decrease inventory levels up to 28.7%. However, this research does not account for product perishability, rendering it suboptimal for use in stock-keeping of perishable products like food.

Other groups have described research on the determination of order-up-to levels for perishable products. Pauls-Worm et al., (2014) provided an Mixed Integer Linear Programming (MILP) model to determine order-up-to levels for perishable products, taking into account product waste levels as a result of product perishability. The model presented tracks the age of the products in stock and discards products from stock that have reached their shelf life. The model first assumes a FIFO issuing policy and later on shows the impact of the FIFO constraint relaxation.

This model was not made for a multi-product inventory system, but for a single product system.

1.2 Research objective

As alternatives to individual service level constraints show promising results in previous research, this research aims to provide insight on the effect of an average service level constraint on product waste in a multi-product inventory Base Stock Policy (BSP), compared to a BSP with individual service level constraints.

In doing so, this research combines two aspects of previous research: 1.) the determination of order-up-to levels for aggregated constrained multi-product inventories and 2.) the determination of order-up-to levels for perishable products in models that incorporate product waste. This research will contribute to literature by assessing the application of an average service level as a means to reduce food waste at the retail level.

1.3 Research approach

In order to assess the effect of an average service level on food waste, two simulation based optimisations will be developed. In this optimisation-simulations, multiple settings can be run to assess the influence of the use of an average service level constraint on the resulting product waste in a multi-product BSP.

A literature study is done to determine how the average service level is to be translated into individual order-up-to levels in the simulation model for perishable products as is presented in Section 2. In Section 3 the formulated simulation based optimisation models will be discussed. The results obtained by these models will be discussed in Section 4. Finally, Section 5 discusses the implications of the results found and describes recommendations for future research.

2. Literature review

In this research the use of an average service level constraint for a multi-product inventory of perishable products in order to reduce product waste is investigated. This literature research provides an overview of how order-up-to levels are determined in simulation in previous research.

2.1 Multi-product inventory

When considering the retail situation, one might investigate the performance of each sku separately. This single-item approach then considers the key performance indicators (KPIs) of each of the items separately. However, research has shown that it is preferable to use a system approach instead of the single-item approach in terms of for instance inventory and waste levels (De Schrijver et al., 2013). Instead of considering each sku individually, the system approach considers multiple sku's as a multi-product inventory. In this approach, the interactions between the products can be considered and the performance of the system as a whole can be estimated. A widely used performance indicator is the service level that is provided. In a multi-product inventory system, the service level that is provided can be measured over multiple sku's. In contrast to a single-item system, in which the service level that is provided is measured over each sku separately.

2.2 Service level types

In literature, two main types of service levels are used: 1) An alpha service level, which measures the chance that the demand in a period is lower than the inventory at the beginning of the period. 2) A beta service level, also known as fill-rate service level, which measures the amount or percentage of demand that is delivered from stock without delay (Stadtler & Meistering, 2019). An alpha service level indicates the amount of stock-outs in a given period and is therefore an event-oriented requirement. In contrast, the beta service level also looks at the size of the demand that was not met.

2.3 Ordering policies

The decisions made on inventory levels, such as ordering quantities and frequencies are defined in the inventory management policy. One of these policies is the (s, S) policy:

Given:

I_0 : actual inventory

S: order-up-to-level

s: reorder point

If $I_0 \geq s$, no reorder is needed. If $I_0 < s$, the optimal policy is to reorder $S - I_0$, provided that the revenue associated with reordering is greater than the revenue expected with not reordering. Otherwise, no order has to be placed (Ghiani et al., 2013).

Algorithms have been developed to determine the optimal (*s*, *S*) policy minimising the total costs. The algorithm developed by Federgruen & Zipkin, (1984) assumes stationary data, well-behaved one-period costs, discrete demand, full backlogging and the long-run-average cost criterion. This algorithm determines the optimal (*s*, *S*) policy minimising the costs for a given demand, lead time, fixed cost and penalty cost (for out-of-stock situations).

A specific use of a (*s*, *S*) system is the Base Stock Policy (BSP). In this policy, operating on a single item, a replenishment order that fills up the inventory to a level *S* is placed when the inventory level is below the reorder point *s*. When demand is discrete, after each demand a replenishment order is to be placed equal in magnitude to the size of the demand. Therefore, the base-stock policy can be written as (*S-1*, *S*) model. This policy is applied when the ordering costs are negligible compared to holding costs or in situations in which the demand for the item is infrequent (Anbazhagan et al., 2013). Furthermore, the BSP is easily implemented and therefore widely used in retail situations.

When determining the value of the order-up-to level, one must consider multiple factors. A higher order-up-to level will lead to higher inventory levels and in turn lead to more waste if products are perishable. However lower inventory levels will lead to a lower service (i.e. less products sold from stock, or less products sold in total in case of a lost-sale), since not all demand can be met from stock.

2.4 Simulation models

The determination of the optimal order-up-to levels is dependent on multiple factors, such as demand, prices and the desired service level. To assess the optimal setting of the order-up-to levels, simulation models can be used. Simulation models are used to assess how multiple factors such as demand, purchasing costs and inventory costs influence factors such as provided service and profits made. These models are either deterministic or stochastic. Deterministic models are used for situations in which the demand and the lead time are known with certainty. They can be applied in situations where companies use large quantities of products in their warehouse and stock is replenished at hourly or daily intervals. In stochastic models, demand and lead time are uncertain. Simulation models can simulate multiple ways of inventory management policies.

2.5 Product perishability

In order to assess the product waste as result of product perishability, this factor has to be incorporated into the simulation model. In order to do so, the product age has to be known. Multiple categories of product age are used in models: 1) fixed lifetime, i.e. deterministic lifetime, 2) age-dependent lifetime or inventory-level-dependent deterioration rate and 3) time-dependent deterioration rate. (Chaudhary et al., 2018).

The addition of product age into models has been previously reported by Haijema & Minner, (2018). In their research, the use of product age (or stock-age) information as a means to find a cost-optimal order policy is investigated. Stock-age is used to assign values to products in stock according to their age, so out-of-stock situations may be predicted. This has shown to be more cost effective as compared to a policy obtained by stochastic dynamic programming. In case of perishable products, stock-age information is also needed to describe the age of the products that are sold first. This is described in the issuing policy.

2.6 Issuing policies

Three main issuing policies are described in literature: 1) A First-In, First-Out (FIFO) policy, in which the oldest products are sold first. 2) A Last-In, First-Out (LIFO) policy, in which the youngest products are sold first. 3) A combination of FIFO and LIFO policy, in which both are implemented at different points in time.

In the model described by Pauls-Worm et al., (2014) simulates the situation of a food retailer that uses a FIFO policy. This policy is applied because it is easy to implement and it is assumed that it keeps waste due to outdating low. In a second scenario, the FIFO policy constraints are replaced with inventory balance constraints, simulating no predetermined issuing policy. In the latter situation, orders are fulfilled in a cost optimal way. It is observed that the FIFO policy is more costly than when no issuing policy is implemented. In their specific instance, the product waste in both situations is the same.

A model using a LIFO issuing policy was made in the research done by Zhou & Yang, (2003). The LIFO policy was adopted since it is a more realistic policy when looking at a retail situation. In this situation, customers have a free choice to pick which item they want. Since customers have a preference towards fresher products, a LIFO policy is more realistic than a FIFO policy.

A comparison of the FIFO and LIFO policies was carried out by Parlar et al., (2011). Their research showed that for all possible combinations of unit revenue, penalty costs and demand intensity the expected maximum profit of the LIFO policy is always lower than that of the FIFO policy. However, at high values for holding costs or low values for purchase costs, the LIFO policy will yield a higher expected maximum profit.

2.7 Setting order-up-to levels for aggregated constrained systems

Multiple research has been done on setting order-up-to levels in aggregated constrained multi-product inventory systems using BSP. Table 1 provides an overview of some research done on finding order-up-to levels using different parameters. In the research presented in Table 1, differences are found in objective function, review system, service level, type of weighted average and the methods to solve the problem. The objective of the research is either to minimise product investments or minimising holding costs. Most research uses a beta service level constraint, only one example of an alpha service level is observed. All publications use a Poisson distribution in the demand simulation. These researches use different simulation models that find order-up-to levels. Different approaches are used to find order-up-to levels: 1) marginal analysis 2) iterative procedure 3) using a Lagrangian multiplier combined with an algorithm to find and optimal reorder level.

Table 1: overview of publications that investigate ways to find order-up-to levels for aggregated constrained multi-product inventory systems using BSP.

Objective	Review system	Service level	Weighted average based on	Problem solved using	Reference
Minimise investment in product		Beta		Marginal analysis	Sherbrooke, (2004)
Minimise inventory investment	Continuous	Beta	Demand	Marginal analysis	Thonemann et al., (2002)
Minimise investments in product	Continuous	Beta		Iterative procedure	Hill & Pakkala, (2007)
Minimise investments in product	Continuous	Beta		Heuristics provide lower bound and an approximate solution	(Kranenburg & van Houtum, 2007)
Minimise holding costs	Periodic	Alpha	Generic, volume and turnover	Function of a Lagrangian multiplier obtained, for which optimal reorder levels are found using Van Wijngaarden-Dekker-Brent algorithm	Van Donselaar et al., (2021)
Minimise holding costs	Periodic	Beta			

In the simulation using marginal analysis considers the costs incurred by adding one unit to the order-up-to level compared to the increase in average fill rate (i.e. service level). Some publications refer to the marginal analysis as 'greedy heuristic'. This method starts by calculating the minimum base-stock level so that the minimum service level is reached. Then, for each product, the increase in the weighted average service level as result of raising the stock level by one unit (ΔD) is calculated. The product with the smallest cost/ΔD ratio is selected. This product will have the largest contribution to the weighted average service level per monetary unit spent.

The iterative procedure described by Hill & Pakkala (2007) incorporates possible interaction between products. This interaction can be beneficial when these products can share costs of the initial dispatch. The recommended solution is the 'iteration from above'. It starts by an initialisation that sets each order-up-to level (S) to a large integer value. The second step is to find an order-up-to level for each product that minimises the total costs, using a set of 'Rules for optimality'.

2.8 Substitution

As mentioned previously, the concept of allowing different individual service levels is based on the assumption that product substitution takes place. Implementing substitutions into the model can improve the performance of the inventory system (Tan & Karabati, 2012). It can influence the obtained product waste values and order-up-to levels, since demand that cannot be fulfilled by an out-of-stock product can then be fulfilled by another product in the same product category.

As previously observed, substitution can be applied in different ways. Firstly, 'one-way-substitution' is applied in situations where one assumes that products are divided into different categories. In this case, products from higher categories can be used as a substitute for products from lower categories, but not the other way around. In this case, when demand is uncertain and setup costs are associated with product substitution it is optimal to divide the products in subcategories and stock only the product with the highest grade within each subgroup.

The next approach on product substitution is more complex. It considers different customer requests and dynamic customer arrivals within the period. This approach causes great complexity in model analysation.

In the third approach each of the products can be used as a substitute for all other products in the inventory with a certain probability. It considers the cumulative effect of the substitution by considering total product demand at the end of the period (Rajaram & Tang, 2001) .

Alternatives to using individual service levels have shown to reduce inventory levels. In this research the application of an average service level on the waste levels is assessed as compared to the use of individual service levels. To do so, two simulation based optimisation models are formulated, in which multiple settings are simulated.

3.Methodology

The determination of order-up-to levels is done using two simulation based optimisation models. First, the simulation model is described in section 3.1. The optimisation models are described in sections 3.2 and 3.3 on waste minimisation and profit maximisation respectively.

3.1 Simulation model

The models considers a product group with multiple perishable products, with deterministic lifetime of M periods. Products have a shelf life of $M \geq 2$ periods. The ages of the products are indexed by b=1,..,M. Unsold products that have reached age M at the end of the period are considered waste and are removed from inventory. The total product waste is the percentage of acquired products that is wasted.

The service level is determined by calculating the percentage of periods in which an out-of-stock situation occurs (i.e. an alpha service level).

Table 2: Explanation of the symbols used in the equations

Symbol	**Meaning**
T	Maximum amount of periods
t	Index denoting the period
N	Maximum amount of sku's
n	Index denoting sku
M	Maximum shelf life in amount of periods
b	Index denoting age of the sku
$IE_{b,n,t}$	Inventory level of sku n with the age b at the end of period t
$Q_{n,t}$	Order quantity of sku n at the beginning of period t
S_n	Order-up-to level for sku n
A	Target service level
$d_{n,t}$	Demand for sku n in period t
$UD_{n,t}$	Unmet demand for product n in period t
$ED_{n,t}$	Extra demand for product n in period t
p_n	Price for sku n
s_n	Sales of sku n
c_n	Cost of sku n
TP	Total profit

Since holding and ordering costs are shared over multiple sku's, these costs are negated in this model. In the simulation model, the values for S_n are given as input and yield an output of obtained alpha, profit and waste values.

Determination of order quantity for product n at time t:

$$Q_{n,t} = max\left\{S_n - \sum_{b=1}^{M-1} IE_{b,n,t-1} - Q_{n,t-1}, 0\right\} \ \forall n, t$$

(1)

The order quantity $Q_{n,t}$ of each product n in each period t is determined at the start of the period, before demand occurs and is delivered with lead time 1 at the start of the next period. The order quantity is determined in Eq. (1), subtracting the inventory of the previous period $IE_{b,n,t}$ that has not reached shelf life and the amount that was ordered in the previous period $Q_{n,t-1}$ from the order-up-to level.

Inventory dynamics when LIFO policy is applied:

For each product n in each period t, demand ($d_{n,t}$) is generated according to a Poisson distribution. After the demand, stock levels are recalculated. The inventory dynamics for a LIFO policy are formulated in Eqs. (3) – (4), ensuring the demand is met from the youngest products first, then by the older products.

$$IE_{n,t,b} = max\{0, Q_{n,t-1} - d_{n,t}\} \forall n, t, b = 1$$

(2)

$$IE_{n,t,b} = max\left\{0, IE_{n,t-1,b-1} - max\left\{0, d_{n,t} - \sum_{1}^{b-2} IE_{n,t-1,b} - Q_{n,t}\right\}\right\} \forall n, t, b \geq 2, \dots, M$$

(3)

Determination of substitution:

When demand $d_{n,t}$ for product n cannot be met from stock, some substitution may take place as is described in the substitution matrix. The unmet demand can be fulfilled by one of the other products, if these are still in stock. When the customers that opted for a substitution product encounter a second stock-out, no second substitution will take place. The percentage of customers that opt for product substitution is set in the substitution matrix. It should be noted that in this model, the possible substitution is calculated after all initial demand has taken place. This approach to product substitution is chosen due to programming constraints.

$$UD_{n,t} = max\left\{0, d_{n,t} - \sum_{1}^{M-1} IE_{n,t-1,b} - Q_{n,t-1}\right\} \forall n, t$$

(4)

$$ED_{n,t} = UD_{n,t} * SR_n \ \forall t$$

(5)

Substitution is determined by Eqs. (4) and (5). Eq. (4) determines whether there is extra demand for a product, Eq. (5) translates this demand into extra demand for other products. The demand matrix *SR* looks as follows:

$$SR = \begin{bmatrix} 0 & 0.2 & 0.1 \\ 0.2 & 0 & 0.2 \\ 0.05 & 0.2 & 0 \end{bmatrix}$$

In this situation, the alternative products are represented in the rows, the original customer preference is represented in the columns. In all cases some substitution takes place however, not all customers are as likely to buy an alternative. For instance, customers that wanted the cheapest product (product 1) are least likely to buy the most expensive product when encountering a stock-out.

Recalculation of final inventory:

After the determination of the amount of product substitution, the final inventory levels for the period are calculated.

$$IE_{n,t,b} = max\left\{0, IE_{n,t-1,b} - max\left\{0, ED_{n,t} - \sum_{1}^{b-1} IE_{n,t,b}\right\}\right\} \forall n, t, b$$

(6)

Eq. (6) recalculates the final inventory of each product, subtracting the extra demand from the inventories of the respective products.

3.2 Simulation based optimisation models

3.2.1 Waste minimisation

In the following simulation based optimisation model the objective is to minimise the total product waste, given an average service level constraint or individual service level constraints.

$$min\left\{\sum_{t=1}^{T}\sum_{n=1}^{N} IE_{M,n,t}\right\}$$

(7)

subject to

Average service level constraint:

$$\frac{\sum_{n=1}^{N} P\left(\sum_{b=1}^{M} IE_{b,n,t}\right)}{n} \geq A$$

(8)

Individual service level constraint:

$$P\left(\sum_{b=1}^{M} IE_{b,n,t} \geq 0\right) \geq A \; \forall n$$

(9)

The objective function Eq. (7) minimises the amount of products that reach their shelf life of *M* periods and are considered waste. Eqs. (8) and (9) are not used at the same time. Eq. (8) is used when individual service levels are allowed to be lower than the minimum aggregated service level *A*. Eq. (9) is used when all individual service levels are required to be above the minimum aggregated service level *A*.

The optimal order-up-to levels are found using a two step iterative procedure. In the first step, optimal values for *S* are found by running values of the order-up-to level *S* for each product through the simulation model. The simulation then provides a value for the total waste level with the used *S* values. When the obtained waste value is an improvement on the previous value and meet the constraint requirements, the input of *S* values and corresponding output values are saved (Figure 1).

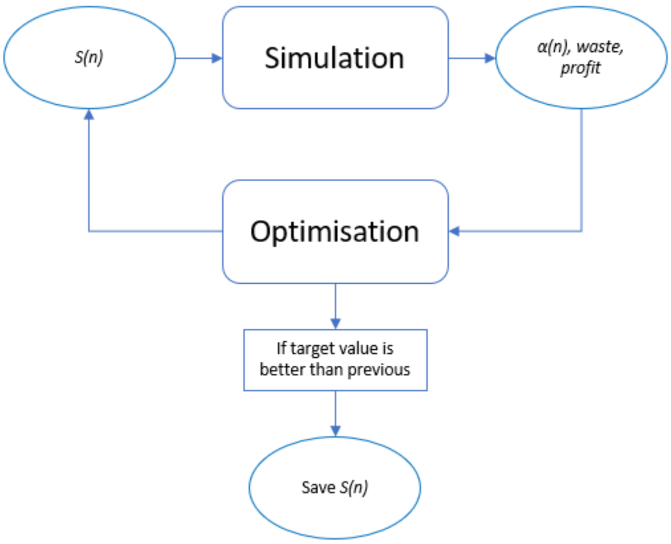

Figure 1: graphic overview of the simulation based optimisation procedure.

Values in the range of 0-50 are run through the simulation, using increments of 5 units. The optimal S values $S_{n,opt1}$ that are found in this first step are used to find upper and lower search limits values $S_{n,upp}$ and $S_{n,low}$.

$$S_{n,upp} = S_{n,opt1} + 5 \; \forall n \tag{10}$$

$$S_{n,low} = S_{n,opt1} - 5 \; \forall n \tag{11}$$

In the second step, values in the range of S_{upp} up to and including S_{low} are run through the simulation using increments of 1 unit. The same demand values that were generated in the first step are also used in the second step. Again, the simulation provides the waste level obtained with the used S values. If the waste level is an improvement on the previous level, the value is saved. Finally, this yields the optimal values for S for each product, with corresponding alpha values, waste values and profit.

3.2.2 Profit maximisation

The second model maximises profit, whilst providing a minimum average service level and keeping product waste under a given maximum percentage.

$$TP = \sum_{t=1}^{T} \sum_{n=1}^{N} \left(p_n s_{n,t} - Q_{n,t} c_n \right) \tag{12}$$

subject to:

Eq. (8) or Eq. (9)

$$\frac{\sum_{t=1}^{T} \sum_{n=1}^{N} IE_{n,t,M}}{\sum_{t=1}^{T} \sum_{n=1}^{N} Q_{n,t}} * 100\% \leq WL \tag{13}$$

This simulation based optimisation is also required to meet the service level constraints as put in Eq. (8), the average service level, or in Eq. (9), the individual service levels. Eq. (12) describes the total profit summed over all products and over all periods. The profit is calculated by subtracting the costs of the acquired product from the sales.

Optimal order-up-to levels are found using the same two-step procedure as described for the waste minimalization. However, in this situation the obtained profit is used to determine which values for *S* are optimal.

4. Results

4.1 Design of experiments

In order to assess the impact of an average service level on the product waste as compared to an individual service level, four simulation based optimalisation models are run.

Both simulation based optimalisation models are run for multiple values of different parameters, Table 4 gives an overview of the parameters used in each experiment. Each experiment is simulating a period of 3650 days. The simulations have a warm-up period of ten days. All experiments simulate an inventory of three products, with a shelf life of seven days. The demand for each product is simulated using a Poisson distribution with an average of 10 products per day. The gross profit margin for all products is 40%. An overview of these data can be found in Table 3.

Table 3: Product properties of simulated products

Product	buying price (EUR) (c)	Selling price (EUR) (p)	Gross profit margin(%)	Shelf life (days)	Demand per day
1.	1.68	2.80	40	7	10
2.	2.40	4.00	40	7	10
3.	2.58	4.30	40	7	10

All experiments are done once using Eq. (8) and once using Eq. (9). The former allowing for individual service levels to be lower than the minimum average service level and the latter requiring all individual service levels to be higher than the minimum average service level.

Table 4: Overview of the settings used in the different experiments.

Experiment	Objective	Service level constraint	Minimum service level (%)	Maximum waste level (%)
A1	Waste minimisation	Average	75	100
A2	Waste minimisation	Average	85	100
A3	Waste minimisation	Average	95	100
B1	Waste minimisation	Individual	75	100
B2	Waste minimisation	Individual	85	100
B3	Waste minimisation	Individual	95	100

C1	Profit maximisation	Average	70	4
C2	Profit maximisation	Average	80	4
C3	Profit maximisation	Average	85	4
C4	Profit maximisation	Average	70	100
C5	Profit maximisation	Average	80	100
C6	Profit maximisation	Average	85	100
C7	Profit maximisation	Average	95	100
D1	Profit maximisation	Individual	70	4
D2	Profit maximisation	Individual	80	4
D3	Profit maximisation	Individual	85	4
D4	Profit maximisation	Individual	70	100
D5	Profit maximisation	Individual	80	100
D6	Profit maximisation	Individual	85	100
D7	Profit maximisation	Individual	95	100

Preliminary simulation runs have shown that when minimising waste, *A* value of approximately 0.85 yields a waste level just below 4%, an alpha of approximately 0.95 yields a waste level around 7%. The maximum waste level of 4% was chosen to use in the profit maximisation model as a maximum waste level. In order to simulate three different products from the same product group, three different buying and selling prices are used.

Experiments yield order-up-to levels (*S*), obtained service levels, waste levels and profit. From these data the safety factor (*z*) is calculated using the obtained average demand per period of the review period plus lead time (μ_{R+L}), the order-up-to level (*S*) and the standard deviation (σ_{R+L}).

$$z = \frac{S - \mu_{R+L}}{\sigma_{R+L}} \tag{14}$$

For Poisson distribution the standard deviation (σ) is described as:

$$\sigma = \sqrt{\mu} \tag{15}$$

The performance of the model is determined based on the obtained service level, profit and waste. The safety factor is calculated to be able to compare outcomes of experiments with different demands.

4.2 Sensitivity analysis

From Eq. (15) it can be derived that with increasing demand the standard deviation will be smaller compared to the value for μ , implying that a larger demand will lead to less uncertainty. Therefore, a

sensitivity analysis is done to investigate the influence of the demand on the order-up-to levels, profit, obtained service levels and waste levels.
To this end, experiments are repeated using a different average demand compared to the base scenario of 10 units per period per product. An overview of the repeated experiments is given in Table 5.

Table 3: overview of different product demand in different scenarios

	Base scenario	**Scenario 1**	**Scenario 2**
		Average demand	
Product 1	10	50	6
Product 2	10	50	18
Product 3	10	50	6

A demand value of 50 items per product per period was chosen to investigate the effect of a much higher demand. The demand values of 6, 18 and 6 for the first, second and third product respectively were chosen to investigate the effect of a different demand distribution among the products. The total demand of this scenario is the same as in the base scenario.

4.3 Results

In this section, the outcome of different parameter settings on the outcomes of the models are discussed. Two settings are compared: 1) the base setting in which individual service levels may be lower than the average service level and 2) the setting in which all individual service levels have to be above the same service level. The outputs that are compared are the obtained service levels, waste levels and profits.

4.3.1 Waste minimisation

The first model has the objective of minimising product waste. As can be observed from Figure 2, with increasing obtained service levels, the product waste increases. Furthermore, increasing the service levels from a minimum of 0.85 average to a minimum of 0.95 average leads to a steeper increase of waste levels than raising service level from 0.75 to 0.85. This effect is confirmed by the effect the safety factor has on the obtained service level. When the minimum alpha is increased from 0.85 to 0.95, the increase in safety factor is higher than when the minimum alpha is increased from 0.75 to 0.85. This indicates that, in the former situation a larger increase in stock is needed to provide an increase in alpha.

Additionally, Figure 2 shows that the using individual service levels slightly increases the average obtained service level. This follows from the requirement that all individual service levels should be higher. The use of individual service levels also results in a higher waste value.

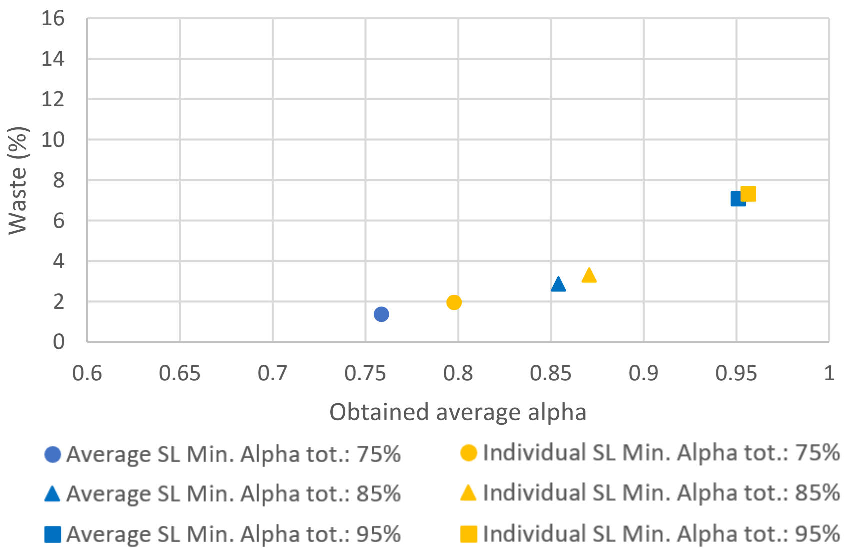

Figure 2: obtained average alpha versus waste value for waste minimisation

When comparing the obtained average alpha with the obtained profit, it can be observed that increasing the minimum average alpha from a minimum of 0.85 to 0.95 leads to a steep reduction in the total profit (Figure 3). The profitability of the experiments done with an average service level does not differ distinctly from the experiments done with individual service levels.

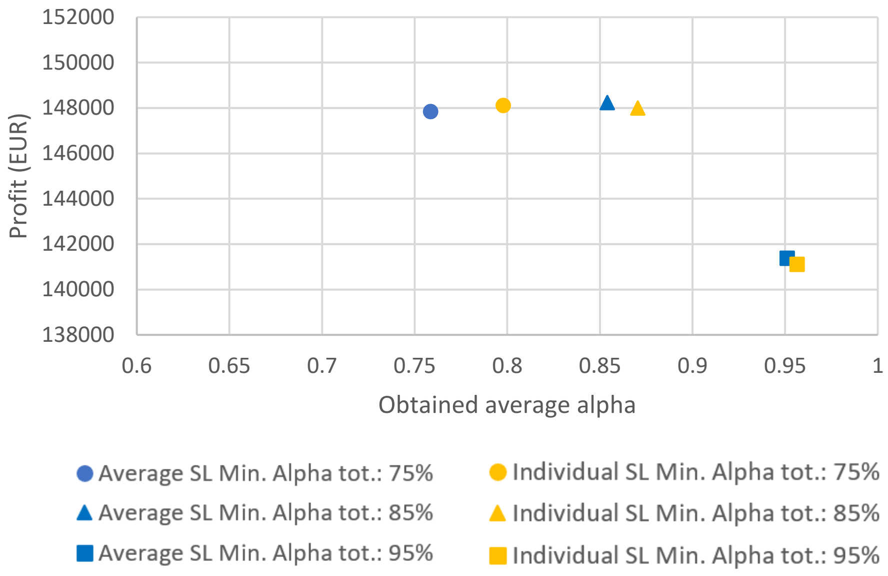

Figure 3: Average obtained alpha versus the obtained profit summed over all products

Raising the minimum average and individual service level to 0.95 results in a steep increase in waste percentage and a steep decrease in profit.

4.3.2 Profit maximisation

The second model aims to maximise profit, whilst keeping the waste under a given percentage. First, the maximum waste percentage was set at 4%. For the highest minimum service level of 0.85 in the second setting (i.e. individual service levels of minimum 0.85) no solution could be found. Which means that no outcome could be generated in which the profit was greater than zero, all individual service levels were higher than 0.85 and the waste levels were less than 4%.

No clear relation was observed when comparing the obtained average alpha with the obtained cumulative profit. All values are in a similar range, showing no increase or decrease when the obtained average alpha increases, as can be seen in Figure 4.

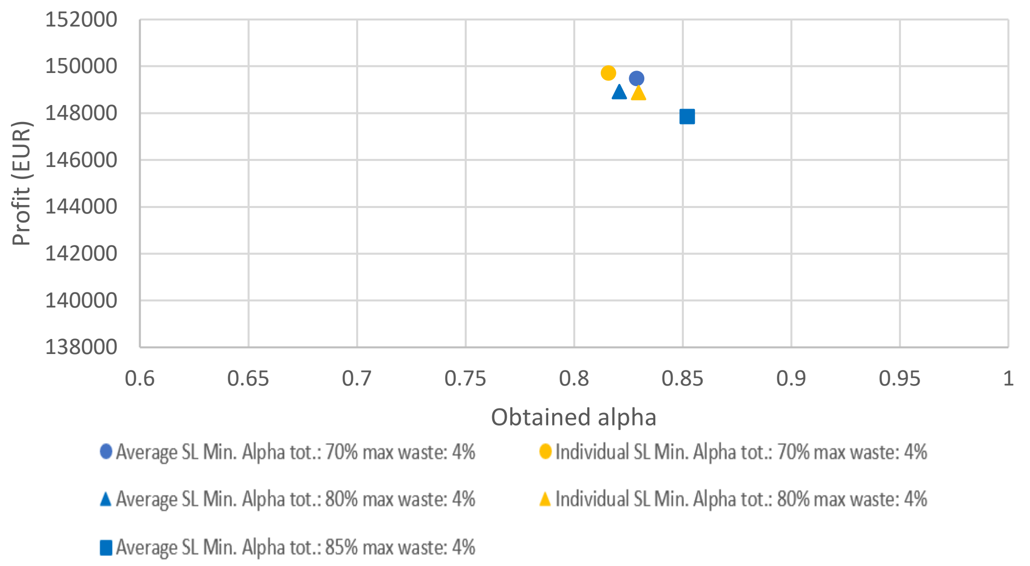

Figure 4: Average obtained alpha versus the obtained profit summed over all products

The obtained average alpha values are in the range of 0.81-0.86, even when a minimum is set at 0.70. This indicates that it is more profitable to have a service level higher than 0.80 when waste can be maximum 4%.

The waste that is produced using an average service level is comparable to the waste produced using individual service levels. As can be seen in Figure 5, both experiments with an average service level and experiments with individual service levels follow the same trend in which a higher obtained service level will result in a higher waste level.

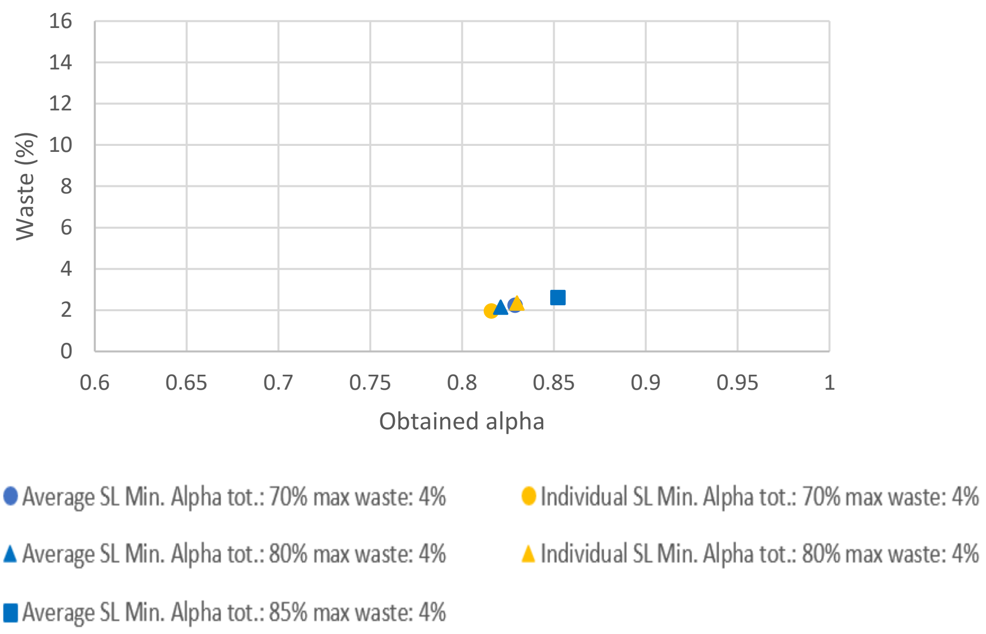

Figure 5: Average obtained alpha versus the obtained waste level

Lastly, the maximum waste constraint was lifted. In this setting, for all minimal values of alpha solutions could be found, since the profit was not limited by a waste constraint. Again, similar values for the obtained alpha were found compared to the experiments that were constrained by a maximum waste value. The solutions obtained with a minimum alpha of 0.95 showed a higher increase in waste levels and a steeper decrease in profit. Again, this effect is in line with the effect the safety factor has on the obtained service level. For a high obtained service level the increase in safety factor is larger, meaning that a larger increase in inventory is needed to provide the higher service levels, explaining the higher waste levels. Lifting the waste constraint did not lead to a steep increase in profit or a decrease in waste, indicating that a high waste level is not profitable in this model.

4.4 Sensitivity analysis

4.4.1 Scenario 1: demand (50, 50, 50)

In the sensitivity analysis the effect of the demand on the obtained alpha, profit and waste are investigated. The first analysis simulated a demand of 50 units per product per period. Since waste values are relative to the amount of units that is ordered, waste values can be compared between the base scenario and the scenario in which is increased to 50 units per product per period.

Waste minimisation

When minimising waste, obtained values for waste are much lower compared to the base scenario in which the demand was five times lower. Even at the highest obtained service levels, product waste is around 3% (Figure 6). The obtained safety factor was lower for each experiment as compared to the base scenario (see Appendix B, Table B1).

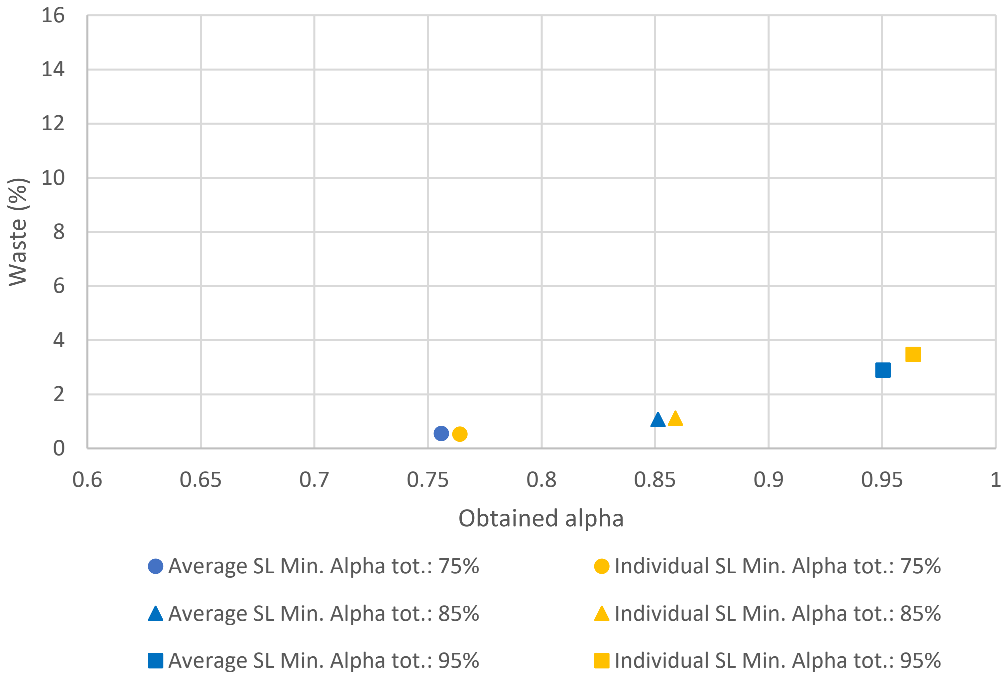

Figure 6: Average obtained alpha versus the obtained waste level

Similar to the experiments done in the base scenario, increasing the minimum alpha from 0.85 to 0.95 leads to a steeper increase in product waste than the increase from 0.75 to 0.85.

Profit obtained in the waste minimisation experiment with higher demand may not be directly compared to the base scenario, since the overall demand is higher and more profit is to be made. However, it should be noted that in this experiment, the same trend is visible (Figure 7). When increasing the minimum alpha to 0.95, profits heavily decrease. Increasing minimum alpha from 0.75 to 0.85 allows for a slight increase in profit.

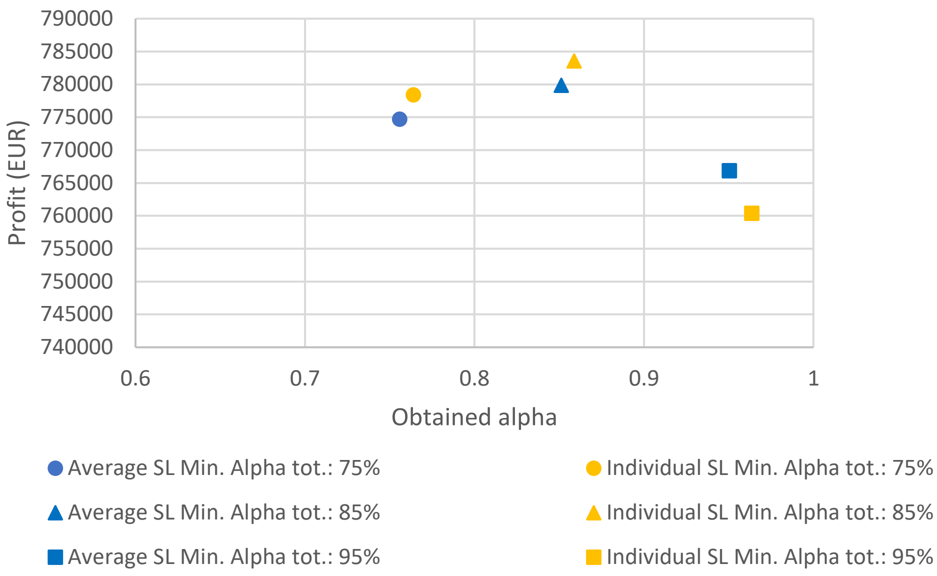

Figure 7: Average obtained alpha versus the obtained profit summed over all products

No clear difference when using average versus individual service levels was observed, neither in waste minimisation or in profit maximisation. (See Appendix B, Table B1)

Profit maximalisation

In the second model profit was maximised, the first experiment set a maximum waste level of 4%. The profits obtained in this experiment showed a similar trend as observed with waste minimisation in the base scenario; A steep decrease in profit is observed when the obtained alpha increases to 0.95 (Figure 8).

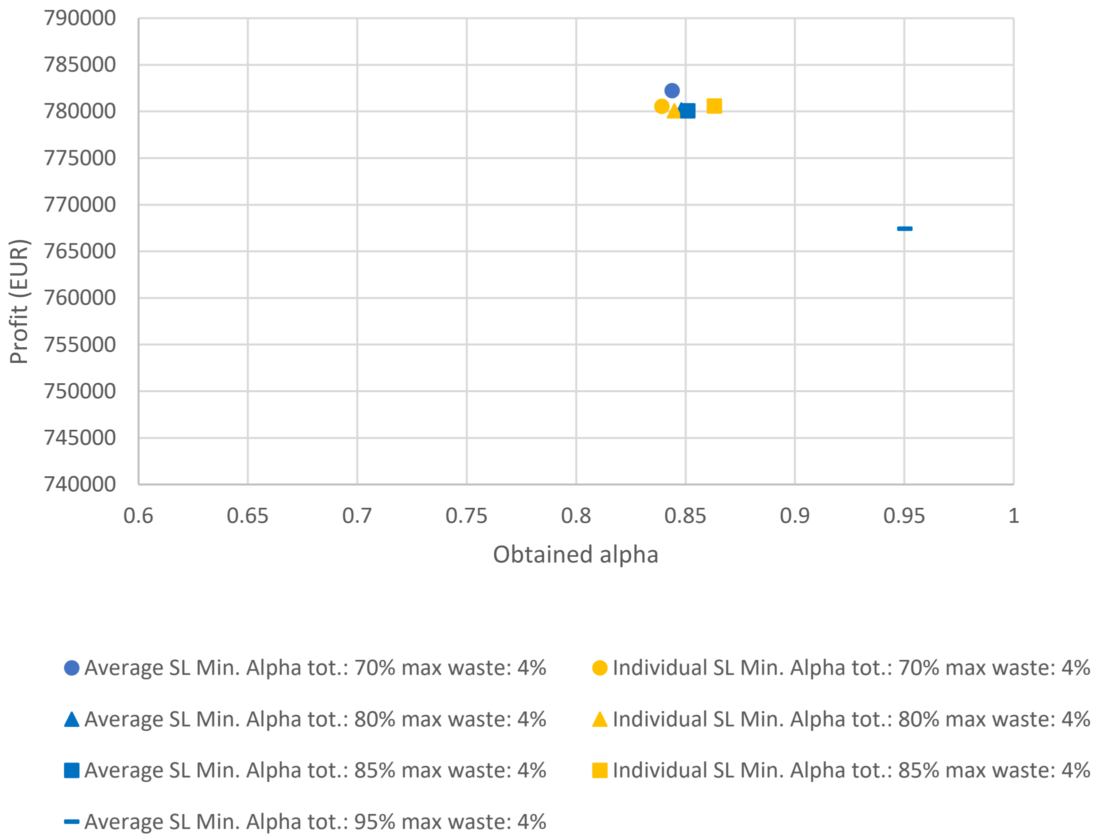

Figure 8: Average obtained alpha versus the obtained profit summed over all products

Increasing values for the obtained alpha resulted in an increasing waste value. The values obtained for the minimum alpha of 0.95 showed a steeper increase in waste values. The values for obtained average alpha with a minimum in the range of 0.70 – 0.85 were all in the range of 0.84-0.88 (Figure 9). This shows that it is most profitable to have a service level in the range of 0.84-0.88 when waste can be maximum 4%. It should be noted that this range of obtained alpha is higher than the range observed in the base scenario for profit maximisation.

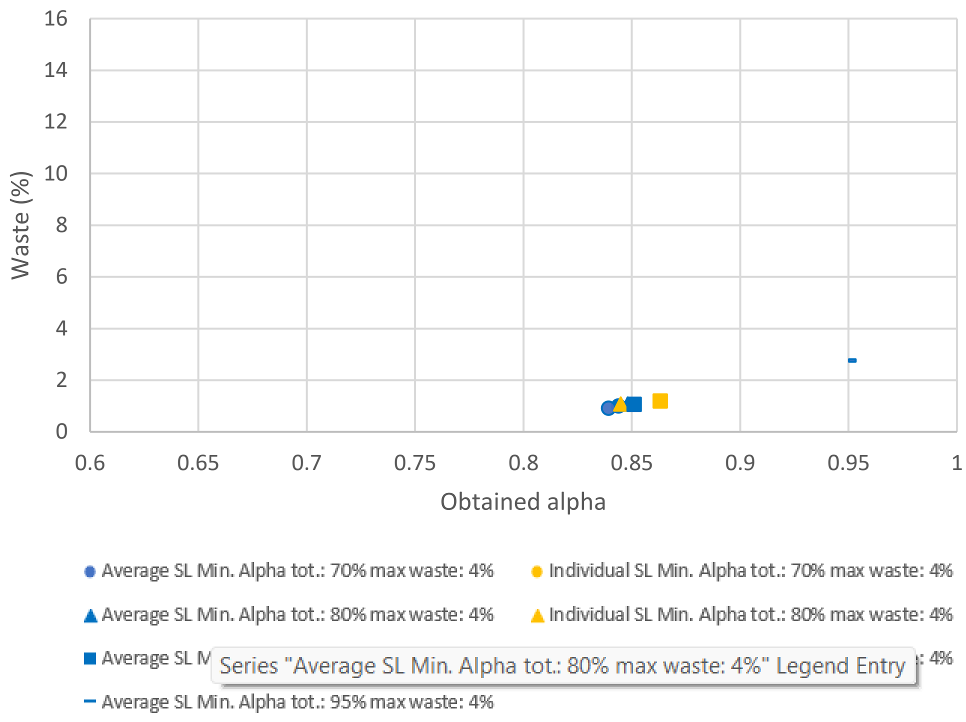

Figure 9: Average obtained alpha versus the obtained waste level

4.4.2 Scenario 2: demand (6, 18, 6)

Secondly, the demand for each of the product was changed into 6, 18 and 6 for products 1,2, and 3 respectively. In these experiments, the total safety factor versus the obtained waste levels and profits was compared.

Waste minimisation

When using differentiated demand, total waste levels are similar compared to the base scenario for all experiments. The individual waste level for the product with the highest demand (i.e. product 2) was the lowest in all experiments.

In this experiment, the obtained profits followed the same trend as observed in other experiments. The profit steeply decreases when the minimum alpha is increased to 0.95. The obtained profits for minimum service levels at 0.75 and 0.85 are higher than the profits obtained in the base scenario.

Although this scenario has the same total demand (and therefore the same total relative standard deviation) as the base scenario, individual demand and individual relative standard deviations differ compared to the base scenario. When using an individual service level, the obtained safety factor of the product with the highest demand (i.e. product 2) was the lowest (see Appendix C, Table C1). When an average service level was used, the safety factors did not show a particular trend. The individual service levels showed no particular trend in both experiments with an average and individual service level. (see Appendix C, Table C1)

Profit maximalisation

The maximum waste level was again set at 4%. No solution could be found for minimum alpha 0.85 when individual service levels were used. This is in line with what was observed in the waste minimisation experiments; The waste levels of these demand settings are higher and therefore don't allow for a solution when the minimum alpha is above 0.85 in an individual service level setting. The obtained profits were higher compared to the base scenario. The waste levels were similar to the waste levels obtained in the base scenario. The individual waste level for product 2 was lowest in all experiments (see Appendix C, Table C2).

5. Discussion and Conclusion

5.1 Base scenario

This research investigated the application of an average service level which allows differentiated individual service levels on the product waste. The waste levels are compared to a situation in which each product has the same individual service level.

5.1.1 Average service levels versus individual service levels

When comparing the outcome of the scenario in which an average service levels is used with the scenario in which individual service levels are used, no evident reduction in waste levels was observed when using an average service level. The small increase in waste that was observed when individual service levels were used is more likely to be the result of the small increase in obtained service level, since this increase fits in the trend in the data that was observed.

This is not in line with the results found by Van Donselaar et al., (2021), since their research showed a decrease in inventory levels up to 28.7% when a differentiated individual service level was applied. However, instead of an average service level, the research done by Van Donselaar et al., (2021) used an aggregated service level. This allows for lower inventory levels than the use of an average service level and can therefore result in lower waste levels.

As was observed in this research, profit heavily decreases when the minimum service level is increased to 0.95. Along with the decrease in profit, the waste values increased heavily. Highest profits were obtained at values for alpha in the range of 0.80-0.85. This indicates that the higher waste that is generated at high service levels is reduces profitability.

5.1.2 Waste minimisation versus profit maximisation

Comparing the obtained average alpha from waste minimisation experiments with those obtained from the profit maximisation experiments, it is observed that values below 0.80 are only optimal when minimising waste and not when maximising profit.

Both experiments show that the profit steeply decreases when a minimal service level of 0.95 is required. Another trend that is observed in both experiments is that the waste levels show a steeper increase when the minimum service level is increased from 0.85 to 0.95. This indicates that in both cases the increase to an alpha of minimal 0.95 is less profitable and yields higher waste levels.

When comparing the waste levels obtained in waste minimisation experiments with waste levels obtained in profit maximisation experiments, it should be noted that these levels are similar, for similar values of obtained average alpha. Likewise, profits obtained for similar values of the obtained alpha in both experiments also fall in the same range.

In all settings, performance of the three products in terms of obtained alpha and waste levels showed similar result. Even though products differ in absolute gross profit, the outcome of the models do not show any distinct preference for one of these products in terms of higher obtained service levels.

5.2 Sensitivity analysis

5.2.1 Increased total demand

The sensitivity analysis showed that the a five times increase of the total demand does not affect the trend observed in waste levels. The same relations between obtained alpha and waste and between obtained alpha and profit were found. Again, no clear distinction in waste levels could be made between the average service level and the individual service levels.

When the total demand is increased five times, less relative waste was obtained as compared to the base scenario. This was in line with expectations, since a larger demand would result in a lower relative standard deviation and therefore less uncertainty. A lower uncertainty allows for lower inventory levels to make sure enough demand is met from stock to attain the service level. This could then in turn lead to lower waste levels.

5.2.2 Different individual demand

As was the case with the increased total demand, similar relations between obtained alpha and waste an between obtained alpha and profit as compared to the base scenario were found. The individual waste levels for the product with the highest demand was the lowest in all experiments, while individual alpha and safety factor were similar to the other products. This indicates that the product with the highest demand can deliver the same service level with lower waste as compared to the product with the lower demands. This is in line with was is expected, since again uncertainty is lower for a higher demand.

Overall, the scenario with differentiated demand performs similar to the base scenario. Indicating that the obtained lower waste value for product two is compensated by the two other products' increased waste level as compared to the base scenario.

5.3 Recommendations

As this research showed that using an average service level did not decrease waste levels, the model that was used can be redesigned to incorporate an aggregated service level. As previous research reported that aggregated service levels decrease inventory levels, it is a promising tool to reduce waste levels.

In addition to the use of an aggregated service level, the model can be improved by assigning a different weight to the each of the products when calculating the obtained alpha. These weights can be based on for instance demand or profits per products. When one of the products is assigned a higher weight, it might induce more differentiation between products in terms of optimal order-up-to levels and resulting waste levels.

Another aspect that could be improved on is the use of the stock-age information. In this research it is only used to determine how much waste is produced. This information could also be used to generate a waste estimate by assigning value to the products in stock according to their age. This waste estimate can then be used to set an order-up-to level that can cover for the anticipated waste.

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Appendix

Appendix A

Table A 1: obtained S-values, alpha values, waste values and profit values for the waste minimisation of the base scenario. 'SF' is the obtained safety factor.

Waste minimisation															
Average SL Min. Alpha tot.: 75%															
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
23	23	23	0.7505	0.7473	0.7574	0.7467	1.2268	1.1999	1.2436	1.2370	147781.84	0.6667	0.6909	0.6974	1.1864
Individual SL Min. Alpha indiv.: 75%															
23	23	24	0.7660	0.7511	0.7514	0.7956	1.4957	1.2721	1.3805	1.8344	147281.50	0.4548	0.4656	0.9083	1.3329
Average SL Min. Alpha tot.: 85%															
25	25	25	0.8511	0.8585	0.8459	0.8489	2.6498	2.5599	2.6462	2.7431	148868.46	1.1220	1.1379	1.1316	1.9581
Individual SL Min. Alpha indiv.: 85%															
25	26	26	0.8717	0.8560	0.8788	0.8802	2.4171	2.8307	3.3385	3.5228	148721.56	1.1356	1.3214	1.3222	2.1822
Average SL Min. Alpha tot.: 95%															
28	30	30	0.9506	0.9335	0.9613	0.9571	7.2792	5.4333	7.5255	7.7259	142415.58	1.7477	2.2060	2.2168	3.5622
Individual SL Min. Alpha indiv.: 95%															
30	30	29	0.9581	0.9648	0.9588	0.9505	7.1781	7.6781	7.7718	6.9393	141162.86	2.1996	2.1973	2.0439	3.7190

Table A 2: obtained S-values, alpha values, waste values and profit values for the profit maximisation of the base scenario. 'SF' is the obtained safety factor.

Profit maximisation															
Average SL Minimal average alpha: 0.70 max waste: 4%															
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
25	25	25	0.8288	0.848077	0.84011	0.837088	2.2406	2.797683	2.648989	2.598858	149493.71	1.1273	1.1146	1.0855	1.9210
Individual SL Minimal individual alpha: 0.70 max waste: 4%															
24	25	24	0.8158	0.8049	0.8415	0.8011	1.9704	1.9069	2.5993	1.8085	149720.00	0.9061	1.1030	0.8623	1.6578
Average SL Minimal average alpha: 0.80 max waste: 4%															
25	25	24	0.8209	0.847527	0.845604	0.804396	2.1559	2.8487	2.5796	2.0106	148924.31	1.1453	1.1151	0.9117	1.8314
Individual SL Minimal individual alpha: 0.80 max waste: 4%															
25	24	25	0.8298	0.8492	0.8058	0.8343	2.3510	2.7542	2.0627	2.6682	148883.00	1.1264	0.9364	1.0834	1.8168
Average SL Minimal average alpha: 0.85 max waste: 4%															
25	25	25	0.8521	0.8464	0.8505	0.8580	2.6141	2.6371	2.7715	2.7755	147861.75	1.1173	1.1654	1.1449	1.9789
Individual SL Minimal individual alpha: 0.85 max waste: 4%															
NO SOLUTION FOUND															
Average SL Min. Alpha tot.: 70% no max waste															
25	25	24	0.8305	0.8429	0.8409	0.8077	2.2856	2.6076	2.7008	1.9670	148431.70	1.0978	1.1553	0.9087	1.8254
Individual SL Min. Alpha tot.: 70% no max waste															
25	24	24	0.8248	0.8473	0.8096	0.8176	2.1350	2.6055	2.0420	2.1877	148097.42	1.1249	0.9378	0.9397	1.7337
Average SL Min. Alpha tot.: 80% no max waste															

25	25	24	0.8278	0.8492	0.8294	0.8047	2.3117	2.8034	2.5847	1.9960	148793.00	1.1353	1.1195	0.8932	1.8174
Individual SL Min. Alpha tot.: 80% no max waste														
25	25	25	0.8321	0.8396	0.8445	0.8121	2.2979	2.7154	2.6905	1.9238	148360.10	1.0948	1.1515	1.1428	1.9566
Average SL Min. Alpha tot.: 85% no max waste														
26	25	25	0.8519	0.8783	0.8404	0.8371	2.7860	3.7544	2.5272	2.6061	149112.00	1.3609	1.1070	1.1041	2.0620
Individual SL Min. Alpha tot.: 85% no max waste														
26	26	26	0.8769	0.8775	0.8769	0.8764	3.2717	3.5619	3.4092	3.4272	149326.52	1.3175	1.3102	1.2961	2.2654
Average SL Min. Alpha tot.: 95% no max waste														
31	28	29	0.9508	0.9681	0.9368	0.9475	6.7197	8.7570	5.6186	6.7237	142224.00	2.4428	1.7987	2.0080	3.6086
Individual SL Min. Alpha tot.: 95% no max waste														
30	30	30	0.9623	0.9643	0.9629	0.9596	7.4386	7.9791	7.7779	7.7505	139992.90	2.2570	2.2238	2.2206	3.8690

Appendix B

Table B 1: obtained S-values, alpha values, waste values and profit values for the waste minimisation of the first scenario in which demand per product is set at 50 units per product per period. 'SF' is the obtained safety factor.

Waste minimisation demand [50,50,50]														
Average SL Minimum average alpha : 0.75														
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
105	105	110	0.7560	0.7223	0.7140	0.8316	0.5493	0.3646	0.3320	0.9512	774730.44	0.5218	0.5026	1.0367	1.1897
Individual SL Minimum individual alpha: 0.75															
107	107	107	0.7641	0.7646	0.7555	0.7723	0.5317	0.5305	0.5096	0.5549	778416.18	0.4629	0.4729	0.6942	1.1905
Average SL Minimum average alpha : 0.85															
111	111	110	0.8514	0.8596	0.8635	0.8310	1.0747	1.1807	1.1114	0.9321	779880.00	1.1145	1.1215	0.9924	1.8638
Individual SL Minimum individual alpha: 0.85															
111	112	111	0.8590	0.8574	0.8662	0.8533	1.1196	1.1599	1.1664	1.0325	783582.24	1.0918	1.1699	1.0615	1.9186
Average SL Minimum average alpha : 0.95															
119	118	121	0.9505	0.9525	0.9418	0.9571	2.8910	2.8637	2.5415	3.2677	766863.20	1.9269	1.7882	2.1013	3.3580
Individual SL Minimum individual alpha: 0.95															
125	119	120	0.9637	0.9766	0.9516	0.9629	3.4739	4.2774	2.9120	3.2323	760425.62	2.5159	1.9305	2.0393	3.7446

Table B 2: obtained S-values, alpha values, waste values and profit values for the profit maximisation of the first scenario in which demand per product is set at 50 units per product per period. 'SF' is the obtained safety factor.

Profit maximisation															
Average SL Minimum average alpha: 70% max waste: 4%															
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
111	111	110	0.8439	0.8577	0.8440	0.8299	1.0061	1.0968	1.0458	0.9418	782258.90	1.1141	1.0723	0.9786	1.8272
Individual SL Minimal individual alpha: 70% max waste: 4%															
110	110	110	0.8393	0.8505	0.8360	0.8313	0.9205	0.9756	0.9589	0.8877	780575.30	0.9982	1.0187	0.9774	1.7287
Average SL Minimum average alpha: 80% max waste: 4%															
111	111	110	0.8482	0.8569	0.8495	0.8382	1.0762	1.2318	1.1190	0.9429	780202.78	1.0931	1.0931	0.9964	1.8374
Individual SL Minimal individual alpha: 80% max waste: 4%															
111	111	110	0.8450	0.8497	0.8478	0.9912	1.0841	1.2356	1.1048	0.9912	780072.00	1.1072	1.1077	0.9982	1.8551
Average SL Minimum average alpha: 85% max waste: 4%															
111	111	110	0.8511	0.8574	0.8596	0.8363	1.0711	1.1676	1.1782	0.9397	780095.80	1.1263	1.1274	0.9789	1.8662
Individual SL Minimal individual alpha: 85% max waste: 4%															
111	112	111	0.8632	0.8610	0.8673	0.8613	1.1917	1.1835	1.2491	1.2251	780604.00	1.1134	1.1769	1.1013	1.9581
Average SL Minimum average alpha: 95% max waste: 4%															
120	119	117	0.9503	0.9582	0.9459	0.9440	2.7629	3.1099	2.7832	2.5518	767443.26	1.9875	1.9007	1.7805	3.2731
Individual SL Minimal individual alpha: 95% max waste: 4%															
NO SOLUTION FOUND															

Appendix C

Table C 1: obtained S-values, alpha values, waste values and profit values for the waste minimisation of the second scenario in which demand per product is set at 6, 18, 6 units per product per period for products 1,2 and 3 respectively. 'SF' is the obtained safety factor.

Waste minimisation (demand [6,18,6])															
Average SL Minimum average alpha : 0.75															
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
15	39	15	0.7534	0.7659	0.7157	0.7786	1.1214	2.0952	0.6111	2.1169	153346.94	0.8554	0.4827	0.8787	1.1489
Individual SL Minimum individual alpha: 0.75															
15	41	15	0.7852	0.7918	0.7882	0.7755	1.5260	2.3581	1.1377	2.3295	154094.00	0.5533	0.5461	0.8571	1.4128
Average SL Minimum average alpha : 0.85															
16	43	16	0.8513	0.8593	0.8602	0.8343	2.5319	3.7515	1.7.9378	6.0507	154143.00	1.1579	1.1895	1.1207	1.9412
Individual SL Minimum individual alpha: 0.85															
17	43	17	0.8786	0.8832	0.8662	0.8863	3.1115	5.0330	2.1559	4.9310	153854.00	1.4717	1.1575	1.4365	2.1963
Average SL Minimum average alpha : 0.95															
245	237	245	1.0000	1.0000	1.0000	1.0000	49.8020	82.9708	58.1169	82.9121	-502870.00	67.2613	33.5458	67.3090	86.1837
Individual SL Minimum individual alpha: 0.95															
NO SOLUTION FOUND															

Table C 2: obtained S-values, alpha values, waste values and profit values for the profit maximisation of the second scenario in which demand per product is set at 6, 18, 6 units per product per period for products 1,2 and 3 respectively. 'SF' is the obtained safety factor.

Profit maximisation (demand [6,18,6])															
Average SL Minimum average alpha: 70% max waste: 4%															
S1	**S2**	**S3**	**Alpha Avg**	**Alpha 1**	**Alpha 2**	**Alpha 3**	**Total waste**	**Waste 1**	**Waste 2**	**Waste 3**	**Profit**	**SF 1**	**SF 2**	**SF 3**	**SF tot**
15	42	15	0.8016	0.7772	0.8379	0.7896	1.8296	2.2953	1.7070	2.4090	153432.76	0.9153	1.0266	0.8684	1.5926
Individual SL Minimal individual alpha: 70% max waste: 4%															
15	42	16	0.8155	0.7816	0.8346	0.8302	1.9945	2.4164	1.6460	3.3151	154933.58	0.9084	0.9911	1.1346	1.6813
Average SL Minimum average alpha: 80% max waste: 4%															
16	42	15	0.8178	0.8321	0.8385	0.7827	2.1161	3.4388	1.8503	2.3019	154316.90	1.1407	1.0174	0.8561	1.6818
Individual SL Minimal individual alpha: 80% max waste: 4%															
16	42	16	0.83993	0.843681	0.833791	0.842308	2.3478	3.611901	1.730061	3.62617	154495.12	1.179882	0.978765	1.1571	1.80218
Average SL Minimum average alpha: 85% max waste: 4%															
16	43	16	0.8525	0.8415	0.8712	0.8448	2.6540	3.4164	2.2865	3.8572	154439.78	1.1797	1.1418	1.1817	1.9390
Individual SL Minimal individual alpha: 85% max waste: 4%															
NO SOLUTION FOUND															