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Simulation-based Optimization for a Supply Chain with Load Bundling Opportunity

Simulationsbasierte Optimierung in Liefernetzwerken mit gebündeltem Gütertransport

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Abstract: For a multi-stage, multi-item supply chain the optimal inventory management parameters reorder point and lot size are investigated using a simulation based optimization approach. The optimization approach consists of a simulation model and a metaheuristic search procedure, which is a subclass of evolutionary algorithm. For the evaluation of the load bundling opportunity in different demand structures, the Pareto frontiers of the multi-criterial objective function, i.e. service level and inventory costs, are discussed. The paper shows that the load bundling opportunity has significant cost and environmental benefits compared to the situation without this opportunity. This potential increases with the number of products. Finally, results show that for a service level value of $\eta = 0.95$ the ABC clustered demand scenario leads to 34.1 % lower supply chain costs than the constant demand scenario.

1 Introduction

According to Chopra und Meindl (2007) and Pazhani et al. (2016) inventory, transportation and sourcing are the main cost drivers in a supply chain. Therefore, minimizing transportation costs in supply chain management is an important issue. Transportation related costs are either directly caused, by transportation and material handling or indirectly caused, by inventory holding. Also from an environmental perspective green supply chain management yields to reduce CO_2 emission by efficient transportation strategies. Nevertheless, according to Sarraj et al. (2013) the way physical objects are moved, stored, realized, supplied and used is still economically, environmentally and socially inefficient and unsustainable. Quantitative results confirm their former statement, illustrating that the average of weight-volume capacity is only 60 %, and 25 % of trucks travel empty. Load bundling, which means that different items are loaded on the same truck, is a transportation strategy with the aim of high truck utilization and one-step to efficient transportation.

Available inventory management literature shows that supply chain optimization usually focusses on optimal lot sizes and re-order policies assuming stochastic demand and static order costs (Shah 2009; Tamjidzad und Mirmohammadi 2015; Kouki et al. 2015; Stadtler 2015). However, using an efficient transportation mode, where different items are transported on the same truck (i.e. load bundling), order costs per item are no more fix and, therefore, classical integrated inventory and supply chain optimization models need to be extended. In a recent paper, Peirleitner et al. (2016) present a simulation framework to optimize the lot size and reorder points of a three stage supply chain applying an integrated metaheuristic and simulation-based solution approach. The framework presented in Peirleitner et al. (2016) also enables the discussion of real world transportation effects and shows first results concerning the load bundling opportunity. The former paper gives first insights that the bundling of items for transportation can lead to significant cost reductions. However, an in depth analysis of the item and demand structure effects within the supply chain is left for further research and is still a research gap.

In the proposed paper, the recently published framework of Peirleitner et al. (2016) is extended to study the effect of different demand scenarios on the effectiveness of load bundling in supply chain transportation. Whereas the discussion of different demand scenarios is neglected in the former work in the new numerical study, two demand parameters, i.e. the number of items and the demand distribution are varied. In detail, two different empirical demand distributions are tested: (1) each item has the same order rate; (2) a ABC clustered order rate, where 20 % of items, i.e. cluster A, lead to 7 5% of overall order rate, 20 % of items, i.e. cluster B, lead to 20 % order rate and 60 % of items, i.e. cluster C, lead to 10 % order rate. Additional to the above-mentioned order demand distributions also the number of products is varied and analysed.

In this paper, the following three research questions are addressed using the simulation based optimization approach.

- RQ1: What is the impact of load bundling on the overall carbon emission (CO_2) generated by transportation in a multi-stage supply chain?
- RQ2: How does the number of items effect the cost benefit of load bundling in a multi-stage supply chain?
- RQ3: How is the load bundling benefit related to the two specific demand distributions?

The remainder of the paper is organized as follows. In Section 2, the investigated supply chain is presented and the model / problem specifications are discussed for each supply chain member. Additionally, the simulation and optimization framework is introduced in this section. In Section 3, the experimental design and the numerical study are presented. The results for integrated supply chain management and inventory management with load bundling are discussed in Section 4. Finally, in Section 5, the paper contribution is summarized and some perspectives for future research are mentioned.

2 Problem description

Figure 1 shows the multi-stage and multi-item supply chain. The investigated supply chain structure and the reorder logic of the supply chain members is modelled using the simulation software AnyLogic©. The supply chain consists of a manufacturer *m*, a distribution centre *d* and several retailers *r* with the opportunity of load bundling between each supply chain member. The objective is to minimize inventory and order costs while maximizing service level η for retailers, which leads to a bi-objective optimization problem. Note that in the model no backorder costs are calculated within the cost function. Therefore, service level η is considered as key performance indicator for the supply performance and is integrated in the bi-objective optimization problem. For the calculation of overall costs *C* cost components are summarized over all supply chain members, whereas the service level η, i.e. item availability to the customer, is only evaluated for retailers that deliver their goods to customers.

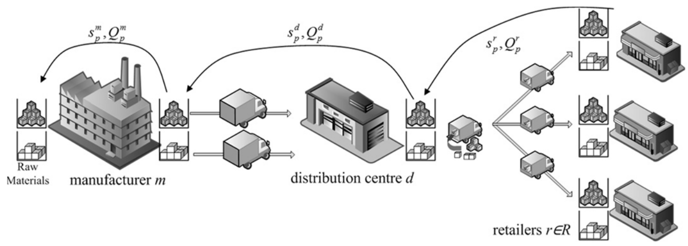

Figure 1: *Multi-item, multi-stage supply chain*

The applied inventory management system for each of $p \in P$ product of all supply chain members is the (*s*, *Q*)-policy. The critical decisions variables for this inventory system are reorder point *s* and lot size *Q* for each product *p* at each supply chain member. According to basic literature (Axsäter 2015) the influence of reorder point *s* and lot size *Q* on inventory and service performance for streamlined systems is known. A high reorder point *s* reduces tardiness and simultaneously increases service level η, but also increases inventory costs. An increase of the lot size *Q* leads to fewer orders and order costs, but increase inventory costs too.

The retailers $r \in R$ sale *P* different products to the anonymous customers, which require immediate delivery. If product *p* is not available for the customer at the retailer, the order is backlogged and service level is zero for this specific order. Once the echelon stock, i.e. the physical on hand inventory plus the orders in progress minus the backlog, drops below the reorder point s_p^r, the retailer orders lot size Q_p^r from the distribution centre *d*. When lot size Q_p^r is larger than the maximum truck load, it is split into $\lceil Q_p^r / maximum\text{-}truckload \rceil$ trucks. The same reorder logic is applied between distribution centre and manufacturer.

When the inventory falls below the replenishment point s_p^r we assume a static one day order processing time between retailer and distribution centre. After this time, the order of lot size Q_p^r for the specific product is packed requiring a stochastic packing time b^d at the distribution centre and transported with random distance depended delivery time t_t^r to the Retailer r. The product independent expected replenishment lead time L^r is defined as the sum of the static order processing time, the expected packing time b^d as well as the expected transportation time t^r. Note that for distances between retailers r and the distribution centre we use different values. This leads to different expected values $E[t^r]$ for the delivery times. The order costs for retailers r and the distribution centre d, i.e. c_s^r and c_s^d respectively, are the sum of transportation costs and packing costs. The replenishment lead time for the orders of the distribution centre L^d is the sum of the random packing time at the manufacturer b^m and a random transportation time to the distribution centre t^d. For the manufacturer m, cleaning costs c_s^m occur whenever two orders of lot size Q are produced after each other. The production system of the manufacturer m has one machine, where all the products p are produced. Additionally, we assume that raw materials are always available. The replenishment lead time at the Manufacturer L^m consists of processing and waiting time of the single-stage manufacturing system.

The load bundling opportunity offers the chance that different products are transported simultaneously in the same truck. In detail, the load bundling for the transport between retailer and distribution centre as well as between distribution centre and manufacturer is modelled as follows: If the lot size of the retailer Q_p^r does not utilize the truck to 100 %, the truck waits up to a specific truck waiting time t_w to be filled with further orders for the same retailer. The truck waiting time t_w is also an optimization parameter within our studies.

3 Numerical Study

The studied supply chain consists of one manufacturer m, one distribution centre d and six retailers r. Each retailer r offers P different products with overall order arrival rate λ^r=100 pcs/day, i.e. the sum of all product order rates. The inter-arrival times of each product p follow an exponential distribution. After the simulation run all customer orders that cannot be fulfilled reduce the overall service level η. The distances between the retailer and the distribution centre d are 30 km for retailers$r \in \{1,2,3\}$, 60 km for retailers $r \in \{4,5\}$, and 120 km for retailer $r \in \{6\}$. The distance between manufacturer m and distribution centre d is 50 km. The packing time at the distribution centre b^d and for the manufacturer b^m are triangular distributed with min, max and mode of {1, 3, 5} hours respectively. Before we start with the packing at distribution centre or manufacturer we assume a static order processing time of one day. The random transportation times t=$\alpha+T$ are the sum of a fix $\{\alpha^d,\alpha^r\}$ value, i.e. the minimum time it takes without any disturbances, and an exponential distributed random part $\{T^d, T^r\}$ implementing the possible disturbances in the transportation process. Note that all transportation times are distance dependent. For the transportation time t^d from manufacturer to the distribution centre α^d = 0.125 days and $E[T^d]$ = 0.03125 days. The transportation time t^r of the nearest retailers with distance of 30 km, i.e. $r \in \{1,2,3\}$, have α^r = 0.075 and $E[T^r]$ = 0.19 days. The next 2 retailers, i.e. $r \in \{4,5\}$, with medium distance of 60 km have a constant transportation time of α^r = 0.15 days and an exponential part $E[T^r]$ = 0.0375 days. Finally, retailer r=6 which has the longest distance of 120 km has a transportation time of α^r = 0.3 and $E[T^r]$ = 0.075 days. For the transportation, we assume an average truck speed of 50 km/h and two different truck types. The first truck type, which is responsible for the transportation between distribution centre and retailers, has a maximum truckload of 18 pallets and a maximum truck weight of 12 tons. The second truck type, which drives between manufacturer and retailer, has maximum truckload of 34 pallets and a maximum truck weight of 22.66 tons. For the calculation of the CO_2 emissions we refer to Sarraj et al. (2013) and use their weight dependent equation. For the calculation of the transportation costs, we use the unit cost of truck transportation, which is 1.385 currency units per km (CU/km).

The inventory costs are c_h^m = 0.05 CU/day, c_h^d = 0.1 CU/day, and c_h^r = 0.2 CU/day (equal for all retailers r). Packing costs c_s^r for the retailers r and the distribution centre d, i.e. c_s^d, are 20 CU per order. Cleaning cost at the manufacturer are c_s^m = 100 CU per order. The setup times per lot at the machine are 0.49 hours and processing time per piece is 0.012 hours leading to a planned utilization of 97.5 % with an optimal lot size Q_p^m calculated according to the EOQ equation. For the simulation studies a simulation time of 1250 days is used, whereby 250 days are used as warm up time. Each iteration is evaluated within the simulation model using 20 replications.

Table 1: *Parameter independent of scenario*

Description	Value
Overall order arrival rate λ^r per retailer r	100 pcs/day
Transportation time t^r from distribution center to retailer r	$t^r = \alpha^r + T^r$ hours
Transportation time t^d from manufacturer to distribution center	$t^d = \alpha^d + T^d$ hour
Min, max and mode for the triangular distributed packing time at the distribution centre b^d and the manufacturer b^m	{1,5,3} hours
Weight dependent carbon emission per km	(0.772+(truck weight)*0.013) kg CO_2/km*
Order processing time	1 day
Holding costs for retailer c_h^r, distribution centre c_h^d, and manufacturer c_h^m	{0.2, 0.1, 0.05} CU/day
Unit cost of truck transport	1.385 CU/km*
Maximum truckload for distribution center and manufacturer	18 / 34 pallets
Maximum truck weight for distribution center and manufacturer	12 / 22.66 tons
Packing costs of retailer c_s^r and distribution centre c_s^d	20 CU per order
Cleaning costs c_s^m at the manufacturer	100 CU per order

*Parameter values rely on Sarraj et al. (2013).

To answer the research questions stated in the introduction, Table 2 shows the scenario depend parameter values that are varied in this simulation study. In this paper, we differ between scenarios, with and without load bundling of products. For the constant demand distribution, the order rate per retailer and product is defined with $\lambda_p^r = \frac{\lambda^r}{P}$. For a scenario where the number of products P is 10 applying the overall arrival rate $\lambda^r = 100$ *pcs/day* leads to the arrival rate $\lambda_p^r = 10$ *pcs/day* for all products. For the ABC clustered demand distribution the tuple τ ={(20 %, 75 %), (20 %, 15 %), (60 %, 10 %)} is introduced. The tuple describes the combination of the relative number of products and the respective relative demand. According to τ the investigated ABC clustered demand distribution, i.e. 20 % of products lead to 75 % of demand, the next 20 % of products lead to 15 % of demand and finally the last 60 % of products lead to 10 % of demand is defined. Assuming a scenario where the number of products P is 10 and applying the overall arrival rate $\lambda^r = 100$ *pcs/day* the arrival rate λ_p^r for products $p\epsilon\{1, 2\}$ is 37.5 *pcs/day*, the arrival rate for products $p\epsilon\{3,4\}$ is 7.5 *pcs/day* and the arrival rate for products $p\epsilon\{5,6,7,8,9,10\}$ is 7.5 *pcs/day*.

Table 2: *Scenario specific parameter*

Description	Value
Transportation mode	no load bundling, load bundling
Number of products P	{5,10,20}
Demand distribution	constant, ABC clustered order rate

For the optimization procedure, the simulation model is connected to the (meta-) heuristic optimization framework HeursticLab, which is a tool where different metaheuristic search concepts, such as evolutionary algorithms, are implemented. The tools can be connected with a simulation software by the use of an external evaluation problem (Beham et al. 2012). In this study the problem is bi-objective, therefore a Nondominated Sorting Genetic Algorithm II (NSGA-II) is used. The chosen algorithm creates the parameter set and sends them to the simulation model for evaluation. The simulation model returns the performance measures, i.e. overall costs *C* and service level η to HeuristicLab. In some preliminary studies we identify the following parameterization of the NSGA-II: population size is 100, selected parents are 400, crossover probability is 90 %, and a mutation probability is 5 % (Peirleitner et al. 2016). For the crossover operator MultiRealVectorCrossover is used which randomly selects different crossover methods applicable for solutions encoded as real vectors. Additionally, a MultiRealVectorManipulator is used for the mutation of the solution parameter vectors.

4 Results

In this section, the research questions stated in the introduction are addressed as follows. Subsection 4.1 discusses the cost improvement effect of load bundling and its impact on CO_2 emissions, i.e. RQ1. Subsection 4.2 evaluates how the cost benefit generated due to load bundling is effected by the number of products and therefore investigates RQ2. The influence of ABC clustered item demand on the cost benefit of load bundling is addresses in subsection 4.3, which provides insights on RQ3.

4.1 Load Bundling Effect on Costs and CO_2 Emissions

To identify the potential of load bundling, firstly, a basic benchmark scenario is analysed without the load bundling opportunity. For scenarios with and without load bundling the number of products *P = 10* and the demand distribution is constant, which lead to an order rate of $\lambda_p^r = 10$ *pcs/day*. Note that also for the scenario without load bundling the replenishment parameters lot size Q and reorder point s are optimized. Figure 2 shows the results of this basic scenario in comparison to the results when load bundling is allowed. Note that for the load bundling scenario, we also identify the optimal truck waiting time.

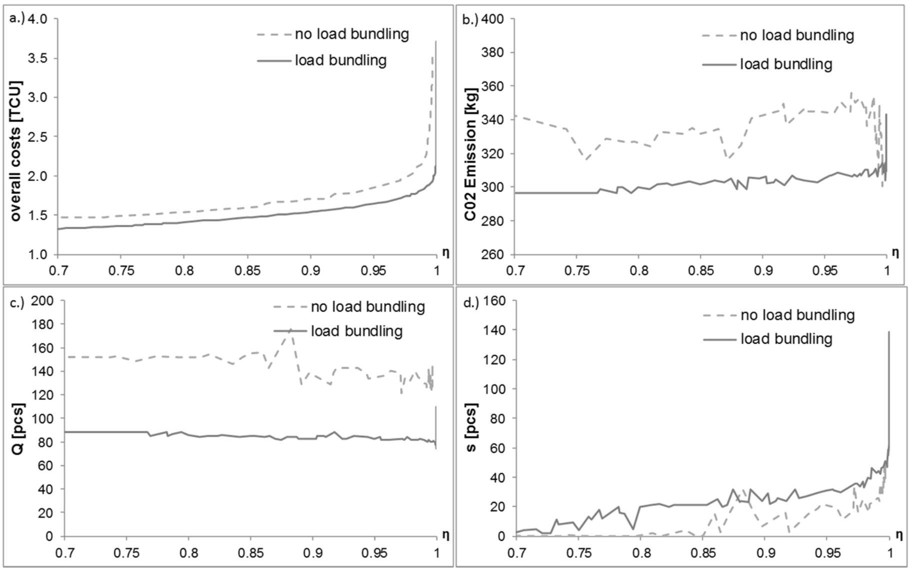

Figure 2: *Basic scenario improvement potential with load bundling*

Figure 2a shows the Pareto frontier of the performance measures service level and overall cost. The minimal overall costs on the y-axis are depicted for the respective service level value $(0.75 \leq \eta \leq 1)$ on the x-axis. The chart shows that the load bundling opportunity leads to significantly lower costs. For a common service level target value of $\eta = 0.95$ the overall costs of the supply chain can be decreased by 12.8 %. Addressing the CO_2 emissions from transportation in the studied supply chain, Figure 2b (where the overall CO_2 emission per day is visualized) shows that the load bundling strategy leads to an average CO_2 decrease of approximately 10 %. An interesting finding is that despite CO_2 reduction also the lot sizes Q can be nearly bisected (see Figure 2c for the optimal lot sizes at the retailer $r = 6$). Intuitively the lot size reduction would lead to more truck tours. Nevertheless, the study shows that the bundling of products outweighs the higher number of orders. The reorder point s increases with the load bundling opportunity see Figure 2d showing the reorder point at the retailer $r = 6$). The reason for this is that due to the implemented truck waiting time the mean replenishment lead time increases with load bundling. Therefore, the demand within replenishment also increases and more inventory is needed to deliver in time.

4.2 Investigation of the Number of Products on the Load Bundling Effect

In this scenario, we vary the number of products $P \in \{5,10,20\}$ and analyse how the number of products effects the cost improvement with load bundling. For the charts with $P = 10$ we refer to Figure 2a (overall costs with respect to service level) and 2c (lot size w.r.t. service level).

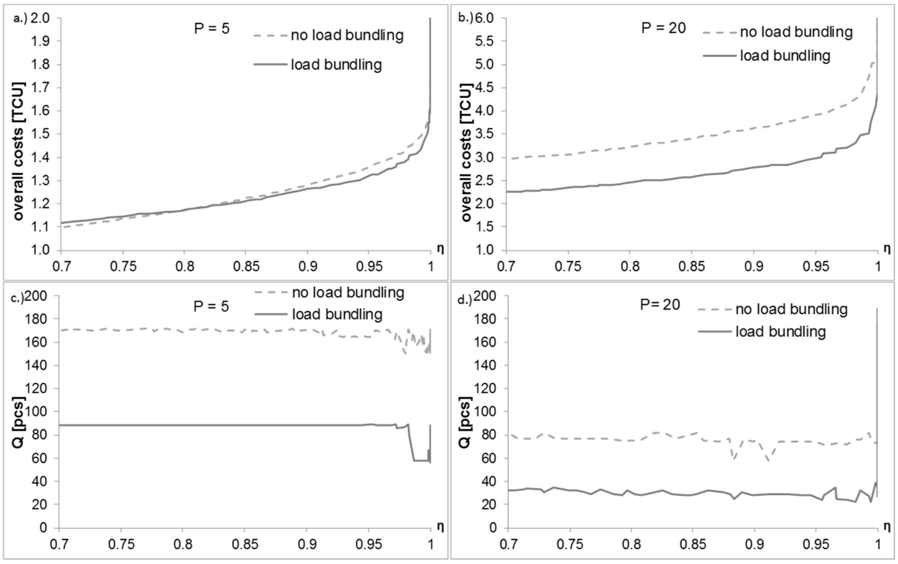

Figure 3: *Optimal costs and lot size with respect to the number of products*

Figure 3a and Figure 3c show the benefit of load bundling with respect to the number of products *P*. Analysing a service level value of $\eta = 0.95$, the study shows for *p=5* only marginal changes (2 %) in overall costs. An increase of the number of products to *p=10 / p=20* identifies an overall supply chain costs benefit of 12.8 % and 22.9 %, respectively. The higher number of products leads to a higher number of smaller orders and a lower truck load utilization for the basic scenario without load bundling. Therefore, the benefit of load bundling increases with respect to the number of products. Figure 3c, 2c and 3d shows that in all scenarios load bundling leads to smaller lot sizes (shown for retailer $r = 6$). We find that a fourfold increase of the number of products (compare Figure 3c with 3d), which lead to a quarter in demand per product λ_p^r, lead to approximate halved lot sizes. This finding is in line with literature (Axsäter 2015) where the optimal EOQ lot size decreases with respect to the square root of the demand rate.

4.3 Influence of the two different demand distributions

In this scenario, the influence of the two proposed demand distributions is investigated again related to the number of products (i.e. $p \in \{5, 10, 20\}$). Figure 4 shows the Pareto frontier of cost and service level with constant and ABC clustered demand for different number of products. The results of Figure 4a and Figure 4b show that for a low number of products the demand distribution has no ($P = 5$) or only very low ($P = 10$) effect on the overall costs and leads to very similar Pareto frontiers. However, for a higher number of products (i.e. $P = 20$) a significant cost effect can be observed. The ABC clustered demand scenario leads to significantly lower costs which is an interesting managerial insight. For a service level value of $\eta = 0.95$, the overall costs for the ABC clustered demand are 34.1 % below the costs of the constant demand. The specific simulation results (which are not reported here) indicate that in the ABC clustered demand situation, the A products are delivered in full or half truck load, while the B and C products apply a lot size optimization which seems to be independent of the truck load. Specifically, the C product behaviour can be interpreted as using the remaining truck load capacities for transportation. We assume that real supply chain settings usually consist of a lot more products, which often have demand distributions similar to the ABC clustered demand in this study. Therefore, the results indicate a very high cost reduction potential due to load bundling in real world load applications.

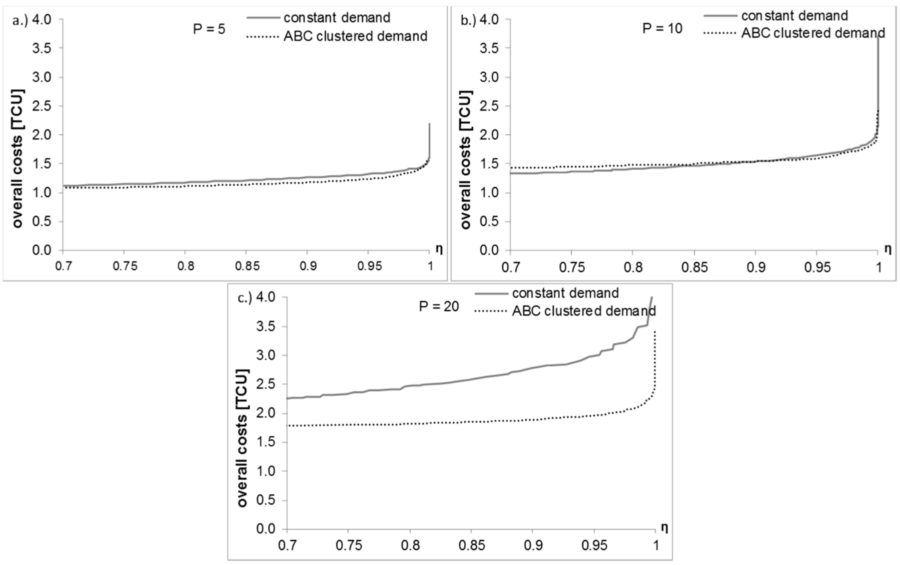

Figure 4: *Overall costs and service level for constant and ABC clustered demand*

5 Conclusion

In this paper a multi-stage, multi-item supply chain is investigated. For the supply chain partners, i.e. a manufacturer, a distribution center and 6 retailers, the optimal reorder parameters for lot size Q and reorder point s are identified analysing two different demand distributions. We found that the load bundling opportunity leads to significant cost improvements. The study shows that for a service level value of 95 % costs are 12 % lower with the load bundling opportunity in a setting with 10 products. Additionally, despite a reduction of lot sizes, the CO_2 emissions can be reduced by 10 % when load bundling is applied. Furthermore, an increase of the cost reduction potential with higher number of products is identified. For the comparison of different demand distributions, we found that the ABC clustered demand leads to significantly lower costs for the scenario with a high number of products.

For further research, other supply chain structures, real size problem instances and further replenishment policies could be studied. Additionally, the green supply chain objective of reducing CO_2 emissions could be included in the parameter optimization and the effect of taxes on CO_2 emissions on the optimal replenishment policies could be identified.

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