ARTICLE IN PRESS
JID: CAOR [m5G;August 23, 2017;23:40]
Computers and Operations Research 000 (2017) 1–15
Contents lists available at ScienceDirect
Computers and Operations Research
journal homepage: www.elsevier.com/locate/cor

Data-driven assignment of delivery patterns with handling effort considerations in retail

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ARTICLE INFO

Article history:
Received 15 January 2016
Revised 23 March 2017
Accepted 11 August 2017
Available online xxx

Keywords:
Inventory
Handling effort
Joint replenishment
Hierarchical decomposition
Retail

ABSTRACT

We consider a supply chain with one warehouse and multiple stores. At the warehouse, the orders for the stores are picked and in the store, shelves are stacked from the backroom. We include handling costs at the warehouse and stores as these are main drivers for logistics costs. We find delivery patterns and order-up-to levels, both of which shall remain fixed for a certain time. As especially in retail stochastic non-stationary demand structures are prevalent, we extend the classic joint replenishment problem under dynamic demand by a stochastic yet distribution-free optimization approach based on historical data samples. We formulate a mixed integer linear program using the plant-location formulation and develop several hierarchical decomposition approaches and a genetic algorithm. We consider a cyclic approach for orders, which allows an order at the end of the time horizon to fulfill the demand at the beginning of the time horizon. Using this approach, there is no need for initial inventories to be set as an input; they are are optimized within the model. Furthermore, a metacalibration approach is introduced, which allows an automated setting of input parameters for the genetic algorithm. To derive insights into the performance of the models, random instances are solved and then the most promising models are used for a case study with a European retailer. The results for the controlled test instances are analyzed by a meta-modeling approach that provides insights into performance drivers for the investigated model variants. The average logistics cost savings of our model over a deterministic approach with safety stocks amount to 3.02 % for the controlled test instances. In a similar comparison for the case study, average results over different parameter combinations show a 20.60 % logistics costs saving potential.

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1. Introduction

The problem we deal with reflects a common situation at retail chains that face inventory control decisions across many individual stores and a large amount of products, see for example Sternbeck and Kuhn (2014). These companies set fixed delivery patterns for each store and product valid for several weeks, which are revised on a rolling basis. A delivery pattern determines during which periods a delivery from the warehouse to a store is made (e.g. on Monday morning and Wednesday afternoon or only on Thursday morning). Associated with the fixed delivery patterns, order-up-to levels are defined and fixed in the same way. Although this fixed inventory control policy establishes a stable setting for operations, demand in retail is stochastic and clearly non-stationary (Martel et al., 1995).

The model presented in our work includes a data-driven (or robust, distribution-free) approach (see Bertsimas and Thiele (2014)). Historical data points used for the calculation represent multiple samples of the target time horizon (e.g. several weeks). The decisions made in the model are applied to all sample weeks in the same way, e.g. if a delivery on Monday morning with an order-up-to level of 10 is scheduled, a delivery is carried out in all sample weeks where the inventory level is less than 10. This approach has been developed by Iyer and Schrage (1992) to optimize a deterministic (s,S) policy. Bertsimas and Thiele (2006) solve inventory planning problems with a data-driven linear programming formulation and Beutel and Minner (2012) use the approach to determine safety stocks. Other applications include, e.g., the data-driven minimization of emissions in urban areas of Ehmke et al. (2016). If this method is used, parametric distributions do not have to be fitted to sales data. Instead, this data is used as a direct input for optimization. By applying this method, we circumvent the estimation of suitable parameters and choice of theoretical distributions. The approach, therefore, does not need specific knowledge about a suitable parametric distribution (and not even about the

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http://dx.doi.org/10.1016/j.cor.2017.08.004
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Please cite this article as: F. Taube, S. Minner, Data-driven assignment of delivery patterns with handling effort considerations in retail, Computers and Operations Research (2017), http://dx.doi.org/10.1016/j.cor.2017.08.004

moments of the distribution as in, e.g., the distribution-free approach of Braglia et al. (2017)). As inputs are used as-is, the model is easily interpretable for managers. Furthermore, the modeling approach based on a mixed integer linear program (MILP), allows practical constraints, e.g., the addition of capacity constraints to the model. Using the data-driven approach, we rely on demand data as inflated sales, i.e. data that has not been censored by out-of-stock situations. Especially in retail, it has been discussed how to gain this data. For a distribution-free approach, see Sachs and Minner (2014).

Due to the non-stationarity, we get varying utilizations of warehouses and stores from one period to the next. Capacities in terms of available labor at the warehouse and store are scarce as only a limited number of employees is available. Therefore, we incorporate capacity restrictions for the total effort in each period. In doing so, we achieve a smoothing of the load throughout the periods, as, due to the store clerks' shift schedules, store managers only have limited flexibility for coping with high workload peaks. Neglecting this constraint will most likely lead to a high accumulation of delivery patterns right before the weekend, where demand is the highest, which might not be manageable by the workforce in the warehouse. Note that, in a practical setting, these capacity constraints might be soft, which is why managers who use the model should perform a parameter variation on the available capacity to observe the most suitable trade-off between a balanced load and costs. The capacity constraint also serves as an example of how a practical constraint can be included into the MILP formulation.

Given the high percentage of manual labor in a retailer's logistics costs (38% store handling and 28% warehouse handling (Van Zelst et al., 2009)), this important cost factor has to be included in the decision making. The necessity to include handling effort in the decision making of retailers has been shown empirically by Van Zelst et al. (2009) and Reiner et al. (2013). DeHoratius and Ton (2009) conclude that backrooms in stores are often organized poorly and shelf stacking tasks are tedious for store clerks. Van Donselaar et al. (2010) find that order systems neglecting handling efforts are overruled by the store workers anyway. Curşeu et al. (2008) extend the economic order quantity model by adding a handling cost factor and investigate the structure of handling efforts at the store via regression analysis. This analysis supports that there is an additive structure of fixed and variable terms for explaining the handling effort.

Van Woensel et al. (2013) model the problem, including handling efforts as a Markov decision process, and numerically determine the complex long-term cost optimal policy, as well as the performance of structures like (s, S), (s, Q) and a mixture of both. However, orders can be placed during any period, i.e. there is no fixed order (and thus delivery) pattern assigned to the stores and a stationary theoretical demand distribution is assumed. Focusing on the handling effort in a warehouse in a stochastic demand setting, Kiesmüller and Broekmeulen (2010) find that including joint replenishment effects of the warehouse into the decision-making process leads to significant cost savings. They, however, assume that no joint replenishment effects occur at the downstream node (in our case stores).

So far, there has only been a limited number of publications dealing with the handling effort in retail logistics in general and with a quantitative implementation specifically. This is especially true when we are looking at the determination and assignment of delivery patterns for stores with non-stationary demand. The contributions of this paper include an application of the data-driven solution approach for the Joint Replenishment Problem with stochastic non-stationary demand, the introduction and comparison of several hierarchical decomposition methods and a savings heuristic, a cyclical approach for including decisions on the initial inventory into the decision making process and the introduction of a meta-calibration method for a genetic algorithm.

The paper is organized as follows: After a brief literature review in Section 2, the model formulation, and the mathematical program are depicted in Section 3. Hierarchical decomposition and solution methods are covered in Section 4. Benchmark models are introduced in Section 5. A numerical study based on fictitious data is presented and the most promising models are then applied to real data of a European retailer in Section 6. Concluding remarks and ideas for further research are given in Section 7.

2. Literature review

Modeling the deliveries from the warehouse to the stores, along with modeling the shelf stacking in the store are key parts of the problem. This modeling resembles the joint replenishment problem (JRP). The key to the problem is to decide when it is optimal to place a combined order for multiple products, although it might not be optimal for each individual product. For an overview of relevant publications, see Aksoy and Erenguc (1988) and Khouja and Goyal (2008).

In JRP publications that deal with non-stationary stochastic demand, most solutions are based on the three heuristic strategies of static uncertainty, dynamic uncertainty and static-dynamic uncertainty as established in Bookbinder and Tan (1988). The first strategy implements all decisions taken at the start of the planning horizon, whereas the second strategy assumes that decisions are made in each period and the third strategy assumes that decisions are made for the whole horizon, but only implemented for the first period and then updated in a rolling fashion.

Martel et al. (1995) consider a constrained multi-item non-stationary demand setting and develop a stochastic programming formulation for the static-dynamic uncertainty approach, where the replenishment plan of the whole horizon is revised in each period, which results in multiple static demand sub-problems. A stochastic program with simple recourse for the capacitated lot sizing problem with probabilistic time-varying demand is constructed and an equivalent deterministic program is created. Similarly, Hua et al. (2009), again in a static-dynamic approach, re-solve the problem in each period based on updated demand distributions. It is assumed in both papers that decisions can be changed with every revision of the plan, which means that they do not truly represent robust decisions. As our retail setting, however, calls for the decisions to be robust, their approaches are not applicable. Besides, only major setup costs are considered while minor setup costs are neglected.

Tempelmeier and Hilger (2015) apply the static uncertainty approach, which follows the decision-making process in our problem setting more closely. Setup periods as well as lot sizes are defined at the beginning of the planning horizon and not revised later. The authors formulate a MIP model to solve the stochastic multiple-item capacitated lot-sizing problem with β service level constraints and setup carry-overs. They propose a fix & optimize heuristic, where the problem is decomposed into sub-problems with a smaller number of items. At the end, the best solutions of all sub-problems are merged to get a solution for the whole problem. This is similar to our approach of a product and store based decomposition, except that we decompose for all individual products and merge solutions of individual sub-problems by a selection MILP in a second stage.

The determination of delivery schedules and quantities in multiple locations and echelons closely relates to the inventory routing problem (IRP). A given set of customers has to be served by a central warehouse in a multi-period environment, where the decision when to serve each customer, how much inventory to allocate and how to construct best routes for the trucks in each period must

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