# OPTIMIZED MULTI-ECHELON INVENTORY POLICIES IN ROBUST DISTRIBUTION NETWORKS

Dr.-Ing. Katja Klingebiel
Chair of Factory Organization
Technical University of Dortmund
Leonhard-Euler-Str. 5
44227 Dortmund, Germany
katja.klingebiel@tu-dortmund.de

Cong Li
Department of Supply Chain Engineering
Fraunhofer Institute for Material Flow and Logistics
Joseph-von-Fraunhofer Straße 2-4
44227 Dortmund, Germany
cong.li@iml.fraunhofer.de

**KEYWORDS**

Supply Chain Management, Multi-Echelon Distribution Networks, Inventory Policy, Robustness, Optimization, Simulation

**ABSTRACT**

To cope with current turbulent market demands, more robust inventory policies are needed for distribution networks, to lower the inventory cost as well as maintain high responsiveness. This paper analyzes the inventory policies in the context of complex multi-echelon distribution networks and proposes an optimization and simulation integrating approach to robust inventory policies selection for multi-echelon distribution networks. Based on the existing approximation approaches designed primarily for two-echelon inventory model, an analytical multi-echelon inventory model with an efficient optimization algorithm is presented. Through systematic parameter adjustment, "optimal" inventory policies are suggested by this model. In the next step, a simulation model is applied to evaluate the proposed solutions under market dynamics, so that the most favorable ones may be selected. Finally, a case study is conducted and future research directions are suggested.

## 1 INTRODUCTION

As collaboration between different supply chain echelons gains attention, it is imperative to consider inventory policies from a network perspective rather than supposing each stage to be a single isolated player. Moreover, under current market dynamics, the level of customer demand uncertainty itself has significantly increased, which immensely aggravates the difficulty of demand forecasting. And product trends like larger variety and shorter life cycles have intensified uncertainty.

Yet, "optimal" inventory policies obtained through traditional approaches are based on deterministic and stable conditions. They are not capable of delivering the desired results in real situation, or even greatly deteriorate the performance of the entire supply chain, leading to high stock levels or short sales. Thus, to cope with current turbulent market demands, more robust inventory policies are needed for distribution networks, so as to lower the inventory cost as well as maintain high responsiveness. In this paper we propose an optimization and simulation integrating approach to robust multi-echelon inventory policies selection.

The paper is organized as follows: Section 2 reviews the important multi-echelon inventory models and optimization solutions. Section 3 presents our integrated approach, which integrates simulation into the traditional analytical inventory model. The analytical model is presented and discussed in detail in section 4, including model formulation, model calculation and optimization algorithm. The simulation model is described in section 5. The proposed integrated approach is then applied to an industrial case in section 6. Finally, section 7 concludes the current work and provides directions for further research.

## 2 LITERATURE REVIEW

An overview of the fundamental ideas about problem assumptions, model designs and solution approaches of inventory policies for one- or multi- echelon logistic networks has been presented by Zipkin (2000), Axsäter (2006) and Tempelmeier (2006). For the inventory models with stochastic lead time in multi-echelon distribution networks, which is also our research emphasis, Axsäter (2003b) has provided a quite comprehensive review. Starting from the early famous METRIC model presented by Sherbrooke (1968), numerous literatures have been devoted to this research area, among which pioneering research is conducted by Graves (1985), Svoronos and Zipkin (1988), Axsäter (1990, 1993, 1998, 2000) , Kiesmüller and Kok (2005). Apart from the classical multi-echelon model, Dong and Chen (2004) developed a network of inventory-queue models for the performance modeling and analysis of an integrated logistic network. Simchi-Levi and Zhao (2005) derived recursive equations to characterize the dependencies across different stages in the supply chain network. Miranda and Garrido (2009) dealt inventory decisions simultaneously with network design decisions while Kang and Kim (2010) focused on the coordination of inventory and transportation management.

Although great attention has been paid to the analytical model of distribution networks, its application in the optimization field is still strongly restricted because of the modeling complexity and computational

Proceedings 25th European Conference on Modelling and Simulation ©ECMS Tadeusz Burczynski, Joanna Kolodziej Aleksander Byrski, Marco Carvalho (Editors)
ISBN: 978-0-9564944-2-9 / ISBN: 978-0-9564944-3-6 (CD)

requirement in large scale inventory networks. Therefore, various approximation methods and heuristic algorithms have been suggested by researchers for real world applications.

Of note in this context is the work of Cohen et al. (1990), who developed and implemented a system called Optimizer that determined the inventory policies for each part at each location in IBM's complex network with assumptions of deterministic lead time and ample supply. Caglar et al. (2004) developed a base-stock policy for a two-stage, multi-item spare part inventory system and presented a heuristic algorithm based on METRIC approximation and single-depot sub problem to minimize the system-wide inventory cost subject to a response time constraint at each field depot. Al-Rifai and Rossetti (2007) formulated an iterative heuristic optimization algorithm to minimize the total annual inventory investment subject to annual ordering frequency and backorder number constraints. Their approach can be regarded as the further work of Hopp et al. (1997), who utilized $(R, Q)$ policies and presented three heuristic algorithms based on simplified representations of the inventory and service expressions to optimize the same inventory problem in a single stage. Axsäter (2003a) used normal approximations both for the customer demand and retailer demand to solve the general two-stage distribution inventory system. Axsäter (2005) considered a different approach to decompose the two-stage inventory problems. Through providing an artificial unit backorder cost of the warehouse, its optimal inventory policy can be solved first.

From the above analysis, it may be deduced that multi-echelon inventory models have been analyzed extensively in recent years. However, computational scale, integrity and non-convexity make the corresponding optimization problem intractable to exact analysis and up till now no general approach is accepted, which might also explain why two-echelon networks are mostly dealt with. In response to such difficulties, an efficient optimization solution procedure will be presented in this paper, which optimizes inventory policies in a general multi-item, multi-echelon distribution network.

## 3 INTEGRATED APPROACH

It is one task to develop a multi-echelon inventory model for distribution networks and solve mathematically. We will present a model of that kind in section 4. However, even the most delicate model forces abstraction of reality and involves some kinds of simplification or approximation. Besides, as mentioned above, the computational efficiency decreases dramatically with the complexity of the analytical model, so the real world application of these sophisticated models has been greatly limited in the past.

Fortunately, these deficiencies can be compensated to a large extent by simulation models, as they allow to reproduce and to test different decision-making alternatives (e.g. inventory policies) upon several anticipated supply chain scenarios (e.g. forecasted demand development). This allows ascertaining the level of optimality and robustness of a given strategy in advance (Terzi and Cavalieri, 2004). Nevertheless, simulation itself can provide only what-if analysis. Even for a small-sized problem, there exist large numbers of possible alternatives, making exhaustive simulation impossible.

Thus, a simulation model can and should be integrated with analytical models. Through systematic adjustment of input parameters, a limited set of "optimal" alternatives may be derived from the analytical model. After simulating these inventory policies under realistic environment (e.g. dynamic and stochastic volatile customer demand), their performance level (e.g. inventory cost, fill rate) can be evaluated and consulted for decision making. The schematic diagram of such an integrated approach is shown in Figure 1.

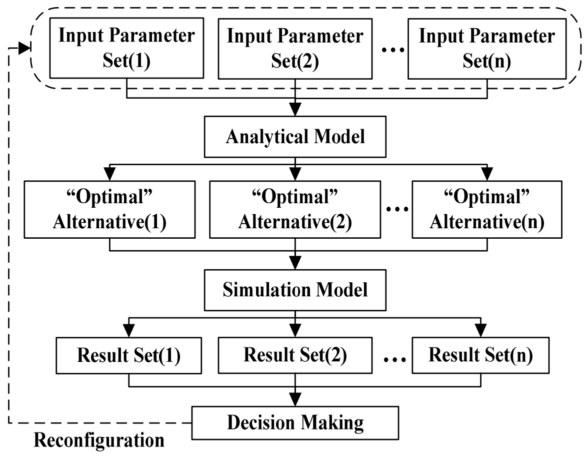


Figure 1: Integrated Approach to Inventory Policy Selection

However, a problem arises when all the suggested alternatives have not fulfilled the desired expectation. One of our answers is to reconfigure the input parameters of the analytical model based on the simulation result (dotted line in Figure 1), and then to restart the optimization process and simulation, so that a closed feedback loop is formed. Such reconfigurations, although feasible, is not quite easy to maintain, because the analytical model is an abstraction of real world. No matter how sophisticated, the "optimal" alternatives obtained from it can act only as a reference or starting point. Thus, it is not wise to look for robust inventory policies merely through analytical optimization. Other approaches, which integrate optimization and simulation more closely, should be introduced to deal with this problem, but are not discussed here.

## 4 ANALYTICAL MODEL

### 4.1 Model Formulation

The distribution network is represented as a multi-echelon inventory model comprising several warehouses in each stage and multiple stock points in each warehouse. Each warehouse is supposed to store the same varieties of items and each stock point corresponds to only one kind of these items. Let $k$ be an arbitrary stock point, $P_k$ be the set of its immediate predecessors and $S_k$ be the set of all its immediate successors. Next, the number of stages in this network is defined as $N$ and the set of stock points at the $n$-th stage as $\mathcal{E}_n$, of which $\mathcal{E}_1$ is the set of stock points facing end customers while $\mathcal{E}_N$ is the set of those supplied directly by the outside supplier. A typical multi-echelon distribution network is illustrated in Figure 2.

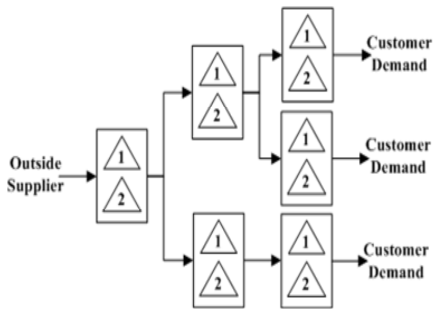


Figure 2: A Typical Multi-echelon Distribution Network

Under such a general multi-echelon network, stock points at the most downstream stage $(k \in \mathcal{E}_1)$ are assumed to face stationary stochastic customer demand which follows a normal distribution; while the demand process for the stock point $k$ at other upstream stages $(k \in \mathcal{E}_n, n = 2, \dots, N)$ is derived as a superposition of the replenishment process from its immediate successors $S_k$. All the stock points are continuously reviewed and implement an $(R_k, Q_k)$ installation inventory policy. This means that when the inventory position, expressed as the physical inventory plus the stock on order minus backorders, is equal to or drops below $R_k$, a replenishment order of size $Q_k$ is placed at its immediate predecessor $j \in P_k$. After placing an order, the actual lead time $L_k$ elapses between placing the order and receiving it. After the arrival of the replenishment order, the outstanding backorders are satisfied according to a FIFO (first in, first out) policy. The outside supplier has infinite capacity and no lateral transshipments are permitted between stock points at the same stage.

The list of notations in this essay is defined as follows:

| | |
|---|---|
| $\mu_k$ | average demand per time unit at stock point $k$ |
| $\sigma_k$ | standard deviation of the demand per time unit at stock point $k$ |
| $\mu_l^k$ | average demand at stock point $k$ from its successor $l \in S_k$ per time unit |
| $\sigma_l^k$ | standard deviation of demand at stock point $k$ from its successor $l \in S_k$ per time unit |
| $Y_l^k$ | number of orders at stock point $k$ from its successor $l \in S_k$ per time unit |
| $I_k$ | stochastic inventory level at stock point $k$ |
| $\varphi(x)$ | probability density function of standard normal distribution |
| $\Phi(x)$ | cumulative distribution function of standard normal distribution |
| $\Phi^1(x)$ | first order standard normal loss function |
| $\Phi^2(x)$ | second order standard normal loss function |
| $h_k$ | inventory holding cost per unit and time unit at stock point $k$ |
| $b_k$ | "artificial" backorder cost per unit and time unit at stock point $k$ |

Notice that $I_k$ here can also take negative values, which interprets backorders as negative inventories; thus, the on-hand inventory is denoted as $[I_k]^+$ while the backorder as $[I_k]^-$, where $[I_k]^+ = max(0, I_k)$ and $[I_k]^- = max(0, -I_k)$.

### 4.2 Model Calculation

To optimize the inventory policy in the distribution network, the exact expression of two critical performance measures, average on-hand inventory level and average backorder level, of each stock point $k$ must be solved. A standard approach for inventory level calculation is given in equation (1) , which describes the relationships among inventory level, lead time demand and inventory position (Zipkin 2000).

$$IN(t + L) = IP(t) - D(t, t + L) \qquad (1)$$

According to Axsäter (1998, 2003a), the inventory position of any stock point $k$ at steady state could be approximated with a uniform distribution over the range of $(R_k, R_k + Q_k]$. Besides, because the exact demand distribution is intractable in this complex network, normal approximation is adopted as Axsäter (2003a). For the stock point at the first stage $(k \in \mathcal{E}_1)$, its average $\mu_k$ and standard deviation $\sigma_k$ is already known, so a normal distribution can be directly fitted. For stock point at other upstream stages, it can be noted that, in the long run, the demand of one stock point will finally be transferred to its predecessor, i.e. $\mu_l^k = \mu_l$. Nevertheless due to the effect of batch-order replenishment, it is not that easy to identify the closed-form expression of its standard deviation. To get this expression, the random number of orders at stock point $k$ from its successor $l$ per time unit $Y_l^k$ has to be analyzed first, the probability of which can be calculated as

$$P(Y_l^k = y) = \frac{\sigma_l}{Q_l}\left[\Phi^1\left(\frac{(y+1)Q_l-\mu_l}{\sigma_l}\right) + \Phi^1\left(\frac{(y-1)Q_l-\mu_l}{\sigma_l}\right) - 2\Phi^1\left(\frac{yQ_l-\mu_l}{\sigma_l}\right)\right] \qquad (2)$$

Thus, the standard deviation of order from its successor $l \in S_k$ is

$$\left(\sigma_l^k\right)^2 = \sum_{y=-\infty}^{\infty} (yQ_l - \mu_l^k)^2 \, P\left(Y_l^k = y\right) \qquad (3)$$

Since the different successors are supposed to be independent, the average and standard deviation of demand at $k$ is the sum of all its successors' order, i.e.

$$\mu_k = \sum_{l \in S_k} \mu_l^k \qquad (4)$$

$${\sigma_k}^2 = \sum_{l \in S_k} \left(\sigma_l^k\right)^2 \qquad (5)$$

After fitting a normal distribution with parameters $\mu_k$ and ${\sigma_k}^2$, the demand distribution at any stock point $k$ is ready for use.

Then, the lead time $L_k$ will be analyzed for each stock point $k$, which is a function of two components, the constant transportation times $L_k^t$ (including ordering, receiving and handling, etc) and the random delay at its predecessor due to out of stock $L_k^s$, i.e.

$$L_k = L_k^t + L_k^s \qquad (6)$$

Due to the assumption of ample supply, the lead time of stock point at the most upstream stage consists of only constant transportation time, i.e. $L_k = L_k^t, \forall k \in \mathcal{E}_N$. For stock point at other downstream stages , however, its lead time is directly influenced by its predecessor $j \in P_k$. The component of lead time due to stock out at its predecessor $j$ has to be determined. Here the famous METRIC approximation (Sherbrooke 1968) is applied which replaces the stochastic lead time by its mean. To achieve this, the backorder level of stock point $j$ is needed, which is

$$E\left([I_j]^-\right) = \frac{L_j {\sigma_j}^2}{Q_j}\left[\Phi^2\left(\frac{R_j - L_j\mu_j}{\sqrt{L_j}\sigma_j}\right) - \Phi^2\left(\frac{R_j + Q_j - L_j\mu_j}{\sqrt{L_j}\sigma_j}\right)\right] \qquad (7)$$

According to the Little's formula (Zipkin, 2000), the average delay due to out of stock at its predecessor $j$ is

$$L_k^s = E\left([I_j]^-\right)/\mu_j \qquad (8)$$

After fitting a normal distribution with parameters $L_k\mu_k$ and $L_k{\sigma_k}^2$ to the lead time demand, the average backorder level is now possible to be solved in analogue with equation (7), i.e.

$$E([I_k]^-) = \frac{L_k {\sigma_k}^2}{Q_k}\left[\Phi^2\left(\frac{R_k - L_k\mu_k}{\sqrt{L_k}\sigma_k}\right) - \Phi^2\left(\frac{R_k + Q_k - L_k\mu_k}{\sqrt{L_k}\sigma_k}\right)\right] \qquad (9)$$

Meanwhile, the average on-hand inventory level is

$$E([I_k]^+) = E(\,I_k) + \mathrm{E}([I_k]^-) = R_k + \frac{Q_k}{2} - L_k\mu_k + E([I_k]^-) \qquad (10)$$

### 4.3 Optimization Algorithm

The target of inventory policy optimization is to find the best reorder points that balance the trade-off between economical consideration (inventory holding cost) and service level (fill rate or inventory backorder cost). Since the decision variables (i.e. reorder points) are not independent, it is impossible to apply blind optimization. Hence, a decomposed concept is introduced so that the inventory policy can be optimized item-by-item and stage-by-stage. The corresponding optimization problem for each stock point is

$$Min\ TC_k(R_k) = h_k E([I_k]^+) + b_k E([I_k]^-) \qquad (11)$$

where $R_k \geq -Q_k$ . Notice that cost function $TC_k$ is convex in decision variable $R_k$. The search procedure presented here is a partial enumeration method that exploits the convexity character, implying that the local minimum is also the global minimum. The outline of the search algorithm is given as below.

Step 0: Initialization
Set $R_k = -Q_k$, $R_k^{min} = R_k$, the lower bound $R_k^{lower} = R_k$ , the upper bound $R_k^{min} = M$ , where $M$ is a sufficiently large integer. The search step $\Delta R_k = \lceil L_k\mu_k \rceil$, where $\lceil x \rceil$ is the smallest integer larger than or equal to $x$.
Step 1: Local search
For $R_k = R_k^{lower}$ to $R_k = R_k^{upper}$, step $\Delta R_k$
 $TC_k^{min} = TC_k(R_k)$
 $R_k = R_k + \Delta R_k$
 If $TC_k(R_k) < TC_k^{min}$
 Set $TC_k^{min} = TC_k(R_k)$, $R_k^{min} = R_k$
 Else: exit the $R_k$ loop
Next $R_k$
Step 2: Intensified search with smaller granularity
While $\Delta R_k > 1$
 Set $R_k^{lower} = R_k - \Delta R_k$ , $R_k^{upper} = R_k + \Delta R_k$
 and $\Delta R_k = \lceil \Delta R_k/2 \rceil$
 Repeat step1
Step 3: Get final result
The optimal reorder point $R_k^{min}$ and the corresponding inventory cost $TC_k^{min}$ have been obtained.

With the above search algorithm for a single stock point, a heuristic optimization procedure is designed to determine inventory policies for the entire distribution network as follows.

1. Set $n = 2$.
2. For each stock point at that stage, i.e.$k \in \mathcal{E}_n$, use the equation (2) and (3) to determine the replenishment process from any one of its successor.
3. Fit a normal distribution for the demand through superposing replenishment from its successors, shown in equation (4) and (5).

4. Set $n = n + 1$ and repeat step 2 and 3 until $n = N$.

After the demand processes are determined upwardly through the distribution network, the inventory policies are optimized stage-by-stage downwardly.

5. Set $n = N$, lead time of stock point $k$ at this stage is $L_k = L_k^t$.
6. Calculate the mean values of backorder level and on-hand inventory level using the equation (9) and (10).
7. Minimize the inventory cost function (11) with the above mentioned search algorithm, so that the optimal inventory reorder point is obtained.
8. Set $n = n - 1$, apply the equation (8) and (6) to determine the lead time of each stock point at this stage, then repeat step 6 and 7 until $n = 1$.

## 5 SIMULATION MODEL

To test the robustness of the "optimal" inventory policies generated from the analytical model, a simulation model is needed to reproduce the real dynamics in the distribution network. For this purpose, the simulation environment OTD-NET, developed by Fraunhofer Institute for Material Flow and Logistics, is applied, which introduces a holistic approach for modeling and simulation of complex production and logistics networks and delivers in-depth insights into information and material flows, stock levels, stability of the network, boundary conditions and restrictions (Wagenitz 2007).

Having implemented a novel, object-oriented methodology of modeling, OTD-NET allows the user to map all relevant network elements as well as many influencing parameters in selectable level of detail. For our problem we are mainly focusing on the network elements of distribution channels, buffers, customers and dealer and parameters like inventory policies and transportation time tables. The discrete-event simulator offers adequate recording and processing of simulation data on this model, which is essential to conduct effective statistical analysis on the simulation results. Thus OTD-NET supports the diversity as well as the complexity of factors inherent in this research problem.

By application of OTD-NET with the presented analytical model, we benefit from the integrated approach as described in section 3. Within the analytical step, the input parameters of unit backorder cost are varied by decision makers according to the trade-off between economical consideration and service level. With these different combinations of parameters, several inventory policies are proposed by the analytical model. Then this limited set of inventory policies is examined by application of an OTD-NET model. The integrated evaluation is focused on two main performance measures (inventory cost and fill rate) here, but may also take other KPI into consideration.

## 6 CASE STUDY

In the following an industrial case is studied to evaluate the effectiveness of the proposed integrated approach. In this distribution network, finished products are manufactured by one single plant and sold in selected 19 European markets. A European distribution center (EDC) and 19 regional distribution center (RDC) are constructed to deliver the products to end customers. The detailed structure of this network is illustrated in Figure 3.

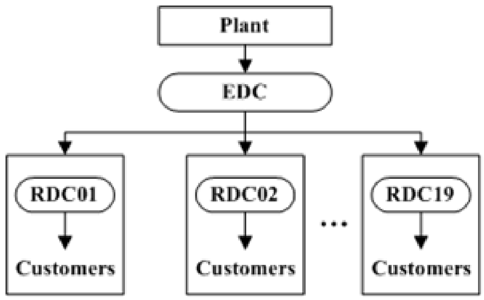


Figure 3: Structure of the Analyzed Distribution Network

The objective is to pursue a high service level while to keep inventory cost as low as possible. Since ordering costs are negligible due to modern communication technologies applied, on-hand inventory cost of different distribution centers are focused for the entire network. Meanwhile, the service level can be quantified by the key figure fill rate, which denotes the proportion of demand that can be fulfilled from the available on-hand stock. The customer demand is derived from several demand forecast scenarios to reflect the volatility, whose average and standard deviation in each regional market is supposed to be known. The order quantity of each distribution center is assumed to be one day's demand. Unit holding cost of EDC is supposed to be 1 monetary unit while that of RDCs to be 2. In this paper results for two RDCs will be presented; One of these is Germany (Code: RDC04), the biggest market, the other is Italy (Code: RDC09) as a counterpart. The basic data of these EDC and RDCs is shown in Table 1.

Table 1: Basic Data of EDC and RDCs

| Code | Ave. Demand | Std. of Demand | Order Quantity |
|---|---|---|---|
| EDC | 11,93 | 22,38 | 12 |
| RDC04 | 6,93 | 17,91 | 18 |
| RDC09 | 0,69 | 1,64 | 2 |

While the unit inventory holding cost is held constant, the "artificial" unit backorder cost can be varied by decision makers in accordance with preferred service levels. Four exemplary combinations of these two kinds of cost are shown in Table 2.

Table 2: Combination of Unit Inventory Cost

| Code | Unit Holding Cost | Unit Backorder Cost | | | |
|---|---|---|---|---|---|
| | | (1) | (2) | (3) | (4) |
| EDC | 1 | 3 | 15 | 100 | 5000 |
| RDC04 | 2 | 15 | 50 | 200 | 10000 |
| RDC09 | 2 | 15 | 50 | 200 | 10000 |

With these data as input parameters of the analytical model, four different "optimal" inventory policies are being calculated. As given in Table 3, each inventory policy (i.e. an alternative) corresponds to one combination of the above presented setting of unit inventory cost.

Table 3: "Optimal" Inventory Policies Generated from Analytical Mode

| Code | "Optimal" Reorder Point | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| EDC | 19 | 36 | 51 | 75 |
| RDC04 | 57 | 73 | 90 | 127 |
| RDC09 | 6 | 8 | 10 | 14 |

After being simulated with OTD-NET under an anticipated demand scenario, the results of average on-hand inventory level and fill rate are documented. The on-hand inventory level in alternative (1) is illustrated in Figure 4. When it touches the x-axis, backorder occurs.

To make a comprehensive comparison of different alternatives, simulation results of all the four alternatives are listed in Table 4. Obviously, alternative (1) leads to lowest inventory cost and worst service level; while the highest cost and best service levels are obtained in alternative (4). With these performance measures, decision makers can select the appropriate inventory policies from these alternatives according to their preferences of economical consideration and service level requirements under different future demand scenarios so that the best trade-off can be acquired.

## 7 CONCLUSIONS

In this paper, an integrated approach is proposed to design robust inventory policies for a complex distribution network. Firstly, a multi-echelon inventory model has been developed to represent such a network. Based on that model an efficient optimization algorithm has been designed to propose optimal inventory policies. To evaluate the robustness of such policies, a simulation model is integrated to reproduce real dynamics under several demand scenarios. The generated alternatives can be assessed by simulation, whose results serve as beneficial references for decision makers to select among the suggested alternatives.

However, we believe that simulation is capable of being more than just an evaluation tool implementing what-if analysis for the presented problem class. As mentioned in Section 3, when all of the suggested alternatives fail to meet the requirements, an intelligent approach should be proposed to enhance the proposed preliminary solutions. Therefore, we are following two paths in our current work: First, we are working on reconfiguration of analytical input parameters based on simulation result. Yet, our results so far have shown that neither the optimality of the solution nor the convergence of this approach is guaranteed due to the abstraction of the analytical model. Second, we are working on integrating the optimization approach within the simulation, so that alternatives evolve automatically. Nevertheless, this implies to propose dynamic inventory policies, i.e. policies that consist of partial policies which are only valid under specific dynamic conditions. This so-called simulation-based optimization approach is our favored approach aimed at robust inventory policies for complex multi-echelon distribution networks.

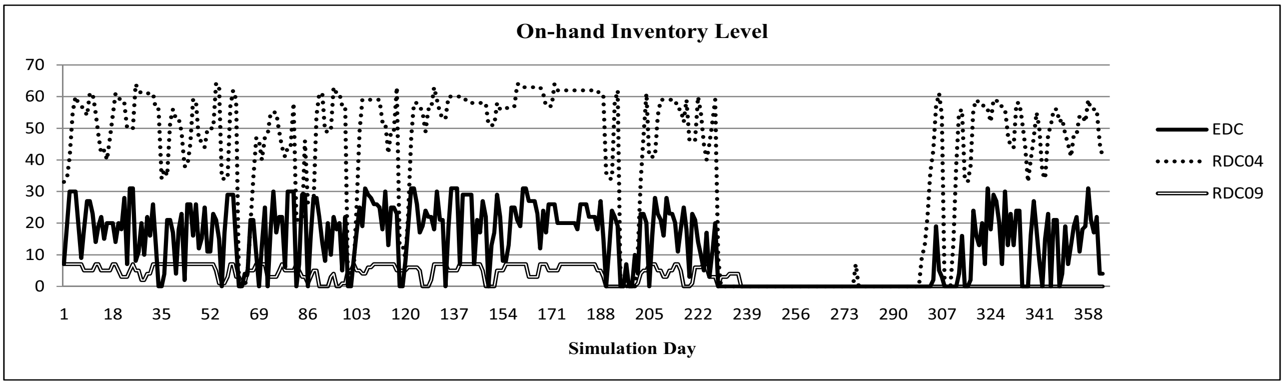


Figure 4: The On-Hand Inventory Level in Alternative (1)

Table 4: Simulation Results of All 4 Alternatives

| Alternative No. | Alternative (1) | Alternative (2) | Alternative (3) | Alternative (4) |
|---|---|---|---|---|

| Code | EDC | RDC04 | RDC09 | EDC | RDC04 | RDC09 | EDC | RDC04 | RDC09 | EDC | RDC04 | RDC09 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ave. On-hand Inventory | 13 | 39 | 3 | 31 | 56 | 6 | 45 | 73 | 8 | 70 | 110 | 12 |
| Ave. Holding Cost | 98 | | | 155 | | | 207 | | | 314 | | |
| Fill Rate | 87, 9% | 66,8% | 54,0% | 93,9% | 75,6% | 92,5% | 95,3% | 82,4% | 98,0% | 95,8% | 93,3% | 100,0% |


## ACKNOWLEDGEMENT

The Authors gratefully acknowledge the DFG project “Modellbasierte Methoden zur echtzeitnahen Adaption und Steuerung von Distributionssystemen” (MMeAS / KU 619/18-1) for their support. This work was also supported by the China Scholarship Council.


## REFERENCES


Al-Rifai, M.H. and Rossetti, M.D. 2007. “An efficient heuristic optimization algorithm for a two-echelon (R, Q) inventory system”. *International Journal of Production Economics*. 109, 195–213.

Axsäter, S. 1990. “Simple solution procedures for a class of two-echelon inventory problems”. *Operations Research*. 38, 64-69.

Axsäter, S. 1993. “Exact and Approximate Evaluation of Batch-Ordering Policies for Two-Level Inventory Systems”. *Operations Research*. 41, 777-815.

Axsäter, S. 1998. “Evaluation of Installation Stock Based (R, Q)-Policies for Two-Level Inventory Systems with Poisson Demand”. *Operations Research*. 46, 135-145.

Axsäter, S. 2000. “Exact Analysis of Continuous Review (R, Q)-Policies in Two-Echelon Inventory Systems with Compound Poisson Demand”. *Operations Research*. 48, 686-696.

Axsäter, S. 2003a. “Approximate optimization of a two-level distribution inventory system”. *International Journal of Production Economics*. 81-82, 545-553.

Axsäter, S. 2003b. “Supply Chain Operation: Serial and Distribution Inventory Systems”. *Handbooks in OR & MS*. 11, 525-559.

Axsäter, S. 2005. “A simple decision rule for decentralized two-echelon inventory control”. *International Journal of Production Economics*. 93/94, 53-59.

Axsäter, S. 2006. *Inventory control,* 2nd ed. International Series in Operations Research & Management Science 90. New York, NY: Springer.

Caglar, D., Li, C.-L. and Simchi-Levi, D. 2004. “Two-echelon spare parts inventory system subject to a service constraint”. *Institute of Industrial Engineers*. 36, 655-666.

Cohen, M.,A., Kamesam, P:V., Kleindorfer, P., Lee, H. and Tekerian A. 1990. “Optimizer: IBM‘s multi-echelon inventory system for managing service logistics”. *Interfaces*. 20, 65–82.

Dong, M. and Chen, F.F. 2005. “Performance modeling and analysis of integrated logistic chains: An analytic framework”. *European Journal of Operational Research* 162 (1), 83–98.

Graves, S. C. 1985. “A multi-echelon inventory model for a repairable item with one-for-one replenishment”. *Management Science*. 31, 1247–1256.

Hopp, W.J., Spearman, M.L. and Zhang, R.Q. 1997. “Easily Implementable Inventory Control Policies”. *Operations Research*. 45, 327-340.

Kang, J.-H. and Kim, Y.-D. 2010. “Coordination of inventory and transportation managements in a two-level supply chain”. *International Journal of Production Economics* 123 (1), 137–145.

Kiesmüller, G.P. and de Kok, A.G. 2005. “A multi-item multi-echelon inventory system with quantity-based order consolidation”. Working Paper, Eindhoven Technical University.

Miranda, P.A. and Garrido, R.A. 2009. “Inventory service-level optimization within distribution network design problem”. *International Journal of Production Economics* 122 (1), 276–285.

Simchi-Levi, D. and Zhao, Y. 2005. “Safety Stock Positioning in Supply Chains with Stochastic Lead Times”. *Manufacturing & Service Operations Management* 7, 295-318.

Sherbrooke, C.C. 1968. “METRIC: a Multi-echelon Technique for Recoverable Item Control”. *Operations Research*. 16, 122-141.

Svoronos, A. and Zipkin, P. 1988. “Estimating the Performance of Multi-Level Inventory Systems”. *Operations Research* 36 (1), 57–72.

Tempelmeier, H. 2006. *Inventory management in supply networks. Problems, models, solutions*. Norderstedt: Books on Demand.

Terzi, S. and Cavalieri, S. 2004. “Simulation in the supply chain context: a survey”. *Computers in Industry*. 1, 3–16.

Wagenitz, A. 2007. *Modellierungsmethode zur Auftragsabwicklung in der Automobilindustrie*. Techn. Univ., Diss.--Dortmund.

Zipkin, P.H. 2000. *Foundations of Inventory Management*. New York. McGraw-Hill.


## AUTHOR BIOGRAPHIES

Katja Klingebiel has studied applied mathematics at the Technical University of Dortmund, Germany. She worked several years in automotive consulting as well as for the Fraunhofer Institute for Material Flow and Logistics, Dortmund, before moving back to university in 2009 after obtaining her PhD. She is now head of the Research Center for Logistics Assistance Systems at the Chair of Factory Organization, Technical University of Dortmund, Germany. Her e-mail address is: katja.klingebiel@tu-dortmund.de.

Cong Li was born in Henan, China and studied industrial engineering in Tsinghua University, Beijing, China, where he obtained Master of Science degree in 2008. After that he has joined the research group of Fraunhofer Institute for Material Flow and Logistics (IML), Dortmund, Germany as a doctoral candidate until now. His research interests include logistic network modeling, inventory policy optimization and simulation modeling. His e-mail address is: cong.li@iml.fraunhofer.de