Logist. Res. (2013) 6:173–185
DOI 10.1007/s12159-012-0097-6

ORIGINAL PAPER

Understanding the robustness of optimal FMCG distribution networks

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Received: 4 September 2012 / Accepted: 26 November 2012 / Published online: 14 December 2012

Abstract Distribution network design is about recommending long-term network structures in an environment where logistic variables like transportation costs or retailer order sizes dynamically change over time. The challenge for management is to recommend an optimal network configuration that will allow for longer term optimal results despite of environmental turbulences. This paper studies the robustness of cost-optimized FMCG (fast-moving consumer goods) distribution networks. It aims at observing the impact of changing variables/conditions on optimized logistic structures in terms of the optimal number and geographical locations of existing distribution centers. Five variables have been identified as relevant to the network structure. A case study approach is applied to study the robustness of an existing, typical, and optimized FMCG network. First, distribution network data of a German manufacturer of FMCG are recorded and analyzed. A quantitative model is set up to reflect the actual cost structure. Second, a cost optimal network configuration is determined as a benchmark for further analysis. Third, the variables investigated are altered to represent changes, both isolated (ceteris paribus) and in combination (scenario analysis). Each one of the variables investigated proves to be fundamentally able to suggest a change of the optimal network structure. However, the scenario analysis indicates that the expected changes will by and large compensate each other, leaving the network in near optimal condition over an extended period of time.

Keywords Distribution logistics · Retailing logistics · Fast-moving consumer goods (FMCG) · Distribution network analysis · Facility location

1 Robust networks in dynamic environments

Manufacturers of fast-moving consumer goods (FMCG) operate networks to distribute finished goods produced in few plants, sold to retailers, and moved to a large number of points of sale. These networks consist of the manufacturing plants, the manufacturer distribution centers (MDC), the retailer distribution centers (RDC), their cross-docks and outlets and finally the transportation fleet, which—in the FMCG industry—is primarily trucks. The network may be completely or in part self-operated or outsourced to logistics service providers. Furthermore, the flows within the network may be organized completely or in part by the manufacturer or by the retailer.

Network design is concerned with the design of the physical network as well as with planning, control, and executive tasks for programing the flow of goods within these networks consisting of transportation, storage, and material handling processes (cf. [15]).

Network design faces a typical but important challenge: It is a long-term decision subject to variables that will change over time. Among others, fuel prices, toll prices, or shipment sizes are some of these variables. Recent surveys prove that these variables will continue to change.[1] Despite

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[1] For an overview of the recent changes and reactions in Germany compare Otto [28].

these changes, manufacturers as well as retailers have to make “firm” decisions on their network structures. The goal is to establish an optimal network structure. This paper is based on a case study, will focus on a manufacturer’s perspective, and addresses the following research question: “Which variables do have a decisive effect on a given, optimal distribution network structure in the German FMCG market?”

“Optimal” is interpreted as “cost minimal” and “decisive” as “changing the optimal number of MDCs” (and consequently also the geographical locations of the MDCs) for a given manufacturer, in our case the manufacturer “Dryco”. We will consider a (cost) optimal distribution network as “robust” if the number and geographical locations of MDCs remain unchanged despite considerable alterations of the variables.[2] It is important to understand the robustness of optimized distribution network structures. They are the result of long-term decisions which cannot be changed easily. For a manufacturer, it is important to understand the relative importance of the variables, because it will help putting management attention on forecasting the development of the important variables as input into optimization routines. If, for example, a manufacturer learns that the structure of his network is primarily driven by the shipment size and the number of plants, he will allocate more time to understand how shipment size and plant number will change over time.

The paper is organized as follows: The literature is reviewed to understand which variables are considered fundamentally relevant to network design. Based on this, we select five variables for further analysis. The analysis is carried out in three steps: (1) The current network of an existing, but disguised FMCG manufacturer is represented in a quantitative network model. (2) The optimal network structure for this manufacturer is identified. (3) The robustness of the optimized network is determined. This is done first per variable and second per scenario, where a scenario is a combination of particular values of the variables. Finally, the results are discussed. The paper concludes with some remarks on how to proceed.

2 Dryco: a typical German FMCG manufacturer

2.1 Network structure and shipment data

Dryco is an existing FMCG manufacturer whose true identity has been disguised for the purpose of this publication. It operates a network of 22 plants that produce 500,000 tons of dry, that is, nonperishable and non-refrigerated FMCG per year split up into 1,200 stock-keeping units (SKUs), for the German market. Dryco supplies all major retailers in Germany both via retailer distribution centers (RDCs; 10 % ship-to locations) and direct store delivery (DSD; 90 % ship-to locations) out of three manufacturer distribution centers (MDCs), which all carry the full SKU range. Shipments from the plants to the MDCs are always done in full truck loads, shipments from the MDCs to the retailers via full truck loads (FTL, above 11 tons), less than truck loads (LTL, 2–11 tons), and Groupage (below 2 tons). The physical logistic operation (warehousing, pick and pack, transportation) has been completely outsourced to several logistics service providers (LSP).

2.2 Cost breakdown

The distribution costs for Dryco consist of

- *Transportation costs*: Costs for shipments from the plants to the MDCs and for shipments from the MDCs to the RDCs or outlets. The transportation costs are completely represented by incoming invoices, since all transportation is outsourced. The logistics service providers apply tariffs that depend on shipment size and distance.
- *Inventory holding costs*: The inventory holding costs of Dryco consist of cycle and safety stock. The stock levels are derived analytically.
- *Handling costs*: The handling costs represent the costs of moving pallets in and out of the MDCs and pick and pack operations.

Table 1 presents the cost breakdown of the current network.

3 The drivers of turbulence in Dryco’s environment

The literature discusses a wide variety of variables that potentially affect the network structure of a manufacturer. These can be organized around internal and external variables. Chopra [6], arguing that distribution systems need to address customer expectations, suggests a list of external, customer-related variables: response time (time between placing and receiving an order), product variety (expected number of stock-keeping units), product availability (probability of stock out), customer experience (ease of placing an order), order visibility (ability to track an order), and returnability (ease of returning merchandises). A second group of external variables originates in the environment and in supplier markets: transportation cost, driver wages, vehicle prices, toll cost, and others. Finally, internal variables, under the control of the manufacturer, affect the

[2] According to Mulvey et al. [27], we will observe the “solution robustness” of the optimal distribution structure.

Table 1 Current network–cost breakdown

Cost	Percentage of total distribution costs
Transportation costs	60.35 %
Transportation costs: MDC inbound	41.35 % in transportation costs
Transportation costs: MDC outbound	58.65 % in transportation costs
Inventory holding costs	14.02 %
Handling costs	25.63 %
Total distribution costs	100.00 %

network structure: the number of plants, the desired service level, the delivery policy (factory gate pricing), the assortment policy (product proliferation), the value (cost of goods sold, COGS) of the products, and the interest rate used to value inventory.

Literature describing the influence of internal and external conditions on the cost optimal network configuration in FMCG distribution is provided by Boutellier and Kobler [4] who describe market trends and derive implications for network configurations. However, their argumentation remains on a qualitative level. Lalwani et al. [21] present a method to identify those factors that the structure of a distribution network is sensitive to. Via case study analysis they find that the optimum distribution design is highly at risk due to uncertainties associated with stock holding costs and delivery frequencies.

Since the number of variables which potentially affect network structure optimality is large, the analysis needs to be reduced to a smaller subset that can be analyzed with more detail. In particular, the analysis should focus on variables that, first, can be argued to have a strong impact and, second, are expected to change over the next years, either driven by external or internal changes. Thus, the need to appreciate certain variables is a reflection of internal and external conditions. Table 2 explains which variables are relevant for Dryco. Especially the internally driven variables, like "COGS" and "number of plants", appear to be highly idiosyncratic. However, we do expect that Dryco, with its trend towards centralization of production (number of plants) and its ongoing record of acquisitions (COGS), resembles the situation of multiple manufacturers in the European FMCG industry to a good extent. The appraisal of the importance of the variables is fundamentally in line with earlier analyses as suggested by Lalwani et al. [21], who studied the relative impact of transport and inventory costs, delivery frequency, and demand volume on network structure in the European automotive aftermarket industry. The authors identified inventory cost to have by far the highest contribution to the number of distribution centers in the network.

4 An approach to analyzing network robustness

4.1 Review of the related literature

Network robustness as a design goal: A distribution network represents a major investment, either for the manufacturer or the logistics service provider, and is supposed to be kept stable for a considerable amount of time. During this time, conditions and parameters may change rendering the actual network configuration suboptimal. Thus, network robustness becomes important (see [24, 31, 34]). Much research has been performed during the last decades to present approaches for designing robust logistic networks (see [31]). In contrast to deterministic facility location problems, for which all input parameters are known or vary deterministically over time, stochastic location problems aim at integrating the uncertain/unknown nature of some variables. Snyder [34] classifies location problems under uncertainty as robust optimization problems that typically attempt to optimize the worst-case performance of the system. The goal is to set up networks that "perform well" for a broad range of parameter settings. Snyder [34] discusses the meaning of the term "robustness" and describes several robustness measures in the context of facility location. Klibi et al. [19] present a review on research concerning the design of robust value-creating supply chain networks. In this paper and according to Mulvey et al. [27], we will observe the "solution robustness" of an optimized distribution network. The aim is not to propose a distribution network that performs well under a number of conditions but to investigate network sensitivity to consider a cost optimal distribution network as "robust" if it remains unchanged despite (considerable) alterations of the input variables. In his review on facility location under uncertainty, Snyder [34] lists suggested applications of stochastic and robust facility location models for various industries and purposes. In this framework, the following case study is destined to present an integral methodology to model FMCG industry specific variable changes and to estimate the sensitivity of an optimized distribution network on altering conditions that might be important in the field of FMCG distribution.

Strategic facility location problems: A comprehensive literature review on facility location (problem formulations, solution procedures, and applications) is provided by Melo et al. [25]. Daskin et al. [9], Klose and Drexl [20], Domschke and Krispin [10], and Aikens [1] present overviews on existing facility location and supply chain design models and exact and heuristic solution approaches. Owen and Daskin [31] review literature on strategic facility location, both for deterministic and stochastic planning problems. Deterministic facility location problems in the FMCG industry have been studied extensively during the

Table 2 Expected changes in Dryco's network and expected impacts

Variable	Expected impact (relevance) on Dryco's network	Expected change
Transportation costs	Transportation costs are known to have a major impact on network structure. Rising transportation costs favor multi-MDC configurations as the global distance to the customers (i.e. outlet or RDC) is shortened [2, 6]	Transportation costs can be expected to rise due to rising fuel costs, rising toll costs, and driving time regulations. In Germany, during the period from 1990 to 2009, fuel prices more than doubled.[a] Furthermore, the digital tachometer will enforce the strict adherence to driving time regulations[b]
Cost of goods sold (COGS) of distributed goods	The COGS of the finished goods influence the cost of holding inventory. Rising COGS favor fewer MDCs [6]	Dryco, like many European FMCG manufacturers, has a long record of acquisitions and expects to acquire additional FMCG producers over the next years. If the respective distribution volumes become integrated, the value (COGS) of the distributed products will change.[c] On top, a change in the product portfolio (increase product group A, drop group B, …) will also affect the average COGS
Number of plants	Changes in the number of plants will affect the network structure since it does affect the distances from the source to the customer (retailer)	Currently, Dryco is served by 22 European plants. Centralization is expected to happen over the next years
Shipment size	Larger average shipment sizes favor fewer MDCs. To an extreme, only full truck loads are shipped. In this case, one central MDC becomes ceteris paribus more attractive	The shipment size is the result of the ordering behavior of Dryco's retailers. Various trends are relevant: First, FMCG retailers in Germany seek to increase the share of products received via RDCs pushing back the DSD share (see below), which will increase the shipment size. Second and contrary to this, the retailers seek to increase the frequency of restocking the RDCs to allow reducing the inventory levels. Thus, the resulting trend is unclear. However, a manufacturer needs to understand the impact of changing shipment sizes on the optimal network, since he can offer incentives to the retailer to alter the shipment size
DSD share[d]	The DSD share will affect the network structure since DSD shipments are smaller than shipments to RDCs. Thus, a rising DSD share leads to reduced shipment sizes	Due to multiple reasons, Dryco has an interest in shipping directly to retailing stores and bypassing RDCs (direct Store delivery, DSD).[e] However, over the last years DSD lost importance. According to Thonemann et al. [38], the share of DSD deliveries (not volume!) reached 81 % in 1985 and came down to 23 % in 2005

[a] Average price per liter diesel fuel: 0.4079 Euro per liter in 1990, 0.8528 Euro per liter in 2009 [35]

[b] Rodrigues et al. [32] present a general, systematic review on literature dealing with causes being able to affect transport operations and cost

[c] Think, for example, of a salty snack producer with light and low-value products to acquire a chewing gum producer with heavy and high-value products

[d] DSD (Direct Store Delivery) share: share of the total of distributed tonnage that is directly transported from MDCs to the outlets, bypassing retailer distribution centers

[e] Otto et al. [29], Müller and Klaus [26], and Otto and Shariatmadari [30] give more insight into the concept of DSD and its implication for retailing logistics

last decades: Wouda et al. [41] present a mixed-integer linear programing model that was used in a real life case to identify the optimal supply network for a Hungarian FMCG manufacturer, to determine the optimal number of plants, the respective locations, and the allocation of the product portfolio to these plants, when minimizing the sum of production, warehousing, and transportation costs. Levén and Segerstedt [22] present a capacity analysis model applied to a FMCG manufacturer. For the investigated case, the authors propose to locate additional storage capacity in the vicinity of existing production facilities and to concentrate production capacities. Another facility location case study in the field of food distribution is provided by Tüshaus and Wittmann [39].

Methodological approaches to model transportation and inventory costs in supply chains: Higginson [17] reviews how transport costs can be modeled for physical distribution analysis. More insight into how to model transportation costs for nonlinear cost functions in the framework of a facility location problem is given by Stolletz and Stolletz [36]. Fleischmann [15] presents a concrete approach for a distribution planning model. In this model, the nonlinear character of transportation costs regarding shipment size and transport distance is respected. Eppen [13], Schwarz [33], and Wanke and Saliby [40] present research to understand the effect of centralization of stocks on overall supply chain inventory in a multilocation distribution system. An overview on planning and managing inventories in supply chains is given by Chopra and Meindl [7].

Estimating network sensitivity: Bottani and Montanari [3] present a simulation model to quantitatively assess the effects of different supply configurations on the resulting total costs of a FMCG supply chain. Several supply chain configurations are examined, based on the combination of several design parameters: number of echelons, reorder and inventory management policies, demand information sharing (absence vs. presence of information-sharing mechanisms), demand value (absence vs. presence of demand peak), and responsiveness of supply chain players. In that study, it is shown that all supply chain parameters examined affect total logistics cost but to different extents: In particular, the number of supply chain echelons and the inventory management policy has major influence on total cost. More research on modeling and estimating sensitivities in distribution networks has been performed by Lalwani et al. [21]. The authors find that the optimum configuration is most at risk due to the uncertainties associated with stock holding costs and delivery frequencies, rather than customer demand volume changes and transport tariffs. Manzini and Gebennini [23] present different mixed-integer linear models applied to the dynamic facility location–allocation problem and describe the application of the proposed models to a case study. The authors evaluate the robustness of the optimal solution and find that the optimal configuration of the logistic network is always composed of the same warehouses for different (simulated) increments/decrements of demand. With focus on the ecological sensitivity of distribution networks, Kellner and Igl [18] identify three network design related leverages to affect greenhouse gas emissions of a FMCG distribution network, namely changing the number of distribution centers, engaging a more efficient logistics service provider, and adjusting shipment structure. Gross et al. [16] present research on the impact of the oil price on the optimal degree of centralization of logistics networks and evaluate the impact of the degree of centralization (in terms of the number of warehouses) on greenhouse gas emissions of transportation. Overall costs vary with the degree of centralization in the network and the value of traded goods. The authors find that dependency on the oil price increases for high-value goods compared to low-value goods. Furthermore, carbon dioxide emissions diminish with a lower degree of centralization, as an effect of lower total transport distance.

4.2 A three-step analysis

We suggest studying the impact of the identified variables on the optimal network structure in the following procedure: (1) Represent an existing FMCG distribution network (number and locations of plants and MDCs, shipment data, cost structure) in a quantitative model. Accept cost differences between the model and reality as an indicator of modeling quality. (2) Optimize the network in terms of number and geographical locations of MDCs. Use the optimized network as a reference to study the impact of the identified variables on the network. (3) Change the shipment data to simulate changes in the identified variables and determine the new optimal network. These steps are explained in more detail in the remainder of this chapter.

4.2.1 Step 1: Modeling Dryco's network

Estimating transportation costs: Dryco mandates logistics service providers. The respective tariffs depend on distance and shipment size (measured in tons). However, the tariffs have not been transferred into the optimization model but have been represented by transport cost functions. The parameters of the functions were estimated using regression analysis based on Dryco's shipment and tariff data.[3]

Production flows (*PF*) Shipments from plants to MDCs are always full truck loads. The costs only depend on the distance:

$$\text{Total shipment cost } \mathrm{PF}_{ij} = \sum_{f} \big(a + b * \mathrm{km}_{fj} * \mathrm{demand}_i * \mathrm{fq}_{fi}/\mathrm{AvgTons}\big) \quad (1)$$

PF_{ij} corresponds to the costs for all shipments supplying MDC j with the demand of customer i. a and b are regression coefficients and have been estimated as $a = 87$ and $b = 1.13$. km_{fj} is the distance between plant f and MDC j. We use distances proposed by EWS ("Entfernungswerk Straße") that serves as basis of computation for tariffs in German truck freight traffic. fq_{fi} is the "factory quota" of plant f related to customer i and represents the percentage of demand_i that is produced in and shipped from plant f. Finally, to compute the number of shipments, the average shipment size is calculated and represented by AvgTons. This step is necessary, since Dryco's data did not reveal the number of shipments from the plants to the MDCs.

Delivery shipments–DS-FTL The costs of larger shipments (>11 tons) from MDCs to RDCs or to outlets are also calculated as full truck loads, that is, depending on distance. a and b are regression coefficients and have been

[3] A similar approach to represent transportation costs and their dependence on distance and tonnage can be found in Tempelmeier [37].

estimated as $a = 153$ and $b = 0.85$. km_{ij} is the distance between MDC j and customer i. nb_shpmt_{ic} is the total number of DS-FTL shipments that was done to deliver the demand (in tons) of customer i in this shipment class c during the observed period.

$$\text{Shipment cost DS-FTL}_{ij} = \left(a + b * \text{km}_{ij}\right) * nb\_\text{shpmt}_{ic} \quad (2)$$

Delivery shipments–DS-LTL The costs of medium-sized shipments (2–11 tons) from MDCs to customers are calculated as less than truck load shipments, that is, depending on distance and tonnage. a, b, c are regression coefficients: $a = 2.86$, $b = 0.336$, and $c = 0.34$. nb_shpmt_{ic} now is the total number of DS-LTL shipments that was done to deliver the demand to_{ic} of customer i during the observed period in this shipment class.

$$\text{Shipment cost DS-LTL}_{ij} = \left(a * \text{km}_{ij}^{b} * (\text{to}_{ic}/\text{nb\_shpmt}_{ic})^{c}\right) * \text{nb\_shpmt}_{ic} \quad (3)$$

Delivery shipments–DS-Grp The costs of small shipments (<2 tons) from MDCs to customers are calculated as Groupage shipments, that is, depending on distance and tonnage. a, b, c are again regression coefficients. However, they differ from the parameters used for LTL shipments: $a = 3.21$, $b = 0.24$, and $c = 0.71$.

$$\text{Shipment cost DS-Grp}_{ij} = \left(a * \text{km}_{ij}^{b} * (\text{to}_{ic}/\text{nb\_shpmt}_{ic})^{c}\right) * \text{nb\_shpmt}_{ic} \quad (4)$$

Estimating inventory holding costs: Inventory holding costs consist of cycle and safety stock. Dryco's order sizes per article are represented by the EOQ (economic order quantity) model. Thus, we are able to derive cycle stocks:

$$\text{Cycle stock}_{jp} = \text{sqr}\left(2 * F * \text{demand}_{jp}/c_p\right)/2 \quad (5)$$

Cycle stock at MDC j for product p depends on the fixed cost per order (F), the demand for product p of all customers allocated to MDC j, and on the value of product p that influences the stock holding costs c_p. Safety stock for product p at MDC j is determined by a safety factor k that implies a fixed probability of stock out per replenishment cycle, the standard deviation of demand for product p for all customers that are allocated to warehouse j, and the replenishment cycle time RC.[4]

$$\text{Safety stock}_{jp} = k * \sigma_{jp} * \text{sqr}(\text{RC}) \quad (6)$$

Dryco calculates its inventory holding costs at a fixed percentage of the stock value held.

[4] Theoretical background to the EOQ model and to the safety stock policy that is applied by Dryco is presented, for instance, in Chopra and Meindl [7].

Estimating handling costs: Handling costs are calculated by the number of pallets per MDC. This number is calculated by the aggregated demand of all customers allocated to the MDC per article and the number of articles per pallet. Inbound pallets (plant-MDC) are homogeneous and lead to a larger number of products per pallet than the heterogeneous outbound pallets (MDC-customer). The load losses are calculated based on Dryco's historical data. All handling costs within the MDCs are proportional to the number of pallets with no differences between the MDCs. This represents Dryco's experience of being able to negotiate identical rates between locations. For each MDC, Dryco estimates overhead costs that correspond to one man-year.

Model quality: Costs estimated as explained above do represent the real data to a good extent (see Table 3). The total distribution costs sum up to 99.92 % of the real cost as reported by Dryco. Their reports are based on inbound invoices. The same high level of fit has been achieved also for single shipments and inventory estimations per product. Regression analysis for the transport cost functions determined an R^2 between 85 and 94 %.

4.2.2 Step 2: Optimizing the current network

Dryco's current network represents the status quo (number and locations of MDCs). However, as it turned out, this network was not cost minimal. In order to study the impact of the variables on network robustness, the network needs to be optimized first. The following two subheadings explain the optimization.

Solution approach: The solution approach for identifying the cost optimal distribution network configuration corresponds to a p-median problem formulation:

$$\text{Minimize} \sum_{ij} (c_{ij} * x_{ij}) \quad (7)$$

$$\text{subject to} \sum_{j} x_{ij} = 1 \quad \forall i \quad (8)$$

$$\sum_{j} y_j = p \quad (= \text{number of MDCs}) \quad (9)$$

$$x_{ij} \le y_j \quad \forall i, j \quad (10)$$

Table 3 Model quality

Cost component	Real data (initial configuration) (%)	Cost estimation (%)
Total distribution costs	100	99.92
Transportation costs	100	99.34
Inventory holding costs	100	99.73
Handling costs	100	102.10

x_{ij} takes the value 1 if customer i is allocated to warehouse j, 0 otherwise (11)

y_j takes the value 1 if a warehouse is installed on site j, 0 otherwise (12)

The model allocates each customer i (i, out of M customers) to a warehouse j (j, out of N sites), thereby minimizing the sum of the customer-warehouse allocation costs (7). Equation (8) ensures that each customer is served by exactly one MDC, which also resembles Dryco's current practice. Equation (9) fixes the number of MDCs to a predefined value. This will allow later on to observe how costs develop for different MDC configurations (in terms of the number) when the influencing variables will change. Equation (10) guarantees that a customer can only be allocated to a site where a MDC is opened. Capacity restrictions concerning the MDCs do not exist, as sufficient capacities are assumed for all N preselected sites. This is based on Dryco's policy to outsource all physical logistic operations to logistics service providers. Dryco does not own any warehousing or transportation assets. Experience shows that, over a planning time frame of 1–2 years, Dryco has always been able to secure sufficient warehousing and transportation capacity. c_{ij} captures the total costs for allocating customer i to MDC j. These costs consist of the transportation costs between plant and MDC that occur for supplying MDC j with the demand of customer i plus the transportation costs that occur for delivering the demand of customer i from MDC j to customer i (customer: RDC or outlet; made up of FTL, LTL, and Groupage shipments). This allows integrating the nonlinear nature of the transport cost functions (see above) into the optimization model.

Costs for holding inventory as well as handling costs are not integrated into the optimization model but are subsequently derived for the identified solution. As the MDC cycle and safety stock are determined by the demand (variations) of the customers that are allocated to the MDC, inventory holding cost must be integrated into the model in order to guarantee optimality. As for the safety stock, Dryco computes the safety stock per product by the standard deviation of the demand during the lead time σ and a fixed safety factor k. For a particular MDC j, it is determined by σ_{jp}, the standard deviation of demand per product p that depends on the allocation of all customers (x_{ij}). The effect of the customer-MDC allocation on inventory becomes important if the demand variations of the different customers are correlated:

$$\sigma_{jp} = \mathrm{sqr}\left(\sum_{a} \sigma_{ap}{}^{2} + 2 * \sum_{a,b=a+1} \sigma_{ap} * \sigma_{bp} * \rho_{abp}\right) \qquad (13)$$

where $\rho_{abp} \in [-1;1]$ is the correlation coefficient of demand of customer a and b (that are allocated to site j) regarding product p (see [5, 13]). In order to estimate the effect of different customer-MDC allocations on inventory holding costs—and the importance of integrating these costs into the optimization model—a pre-analysis has been performed. Within this pre-analysis, we allocated Dryco's customers several times to given numbers of MDCs in a random way.

Total inventory holding costs varied for given numbers of MDCs and different customer-MDC allocations at a low degree as it is shown in Table 4. The maximum deviation from the average total inventory holding costs is about 1.5 % for each sample. We observed coefficients of variation of about 1 %. Regarding to the apparently low influence of customer-MDC allocation on total inventory holding costs and the minor importance of inventory holding costs on overall distribution costs (see Table 1), inventory holding costs do not need to be integrated into the optimization model but can be derived for the transport cost optimal solution found. We might say that the deviation of the optimum exclusively based on transportation costs from the overall optimal solution, integrating transportation, inventory, and handling cost should be marginal.[5]

Lagrangian relaxation: Within the presented analysis, several thousand customer destinations were allocated to a given number of warehouses out of a set of several hundred potential sites. To cope with the huge amount of data and the fact that only integer/binary variables enter the model, the problem was reformulated resorting to a Lagrangian relaxation: Based on the p-median problem given above, the single-sourcing constraints (8) are relaxed. When these constraints are multiplied by Lagrange multipliers, we obtain the following model formulation:

$$\text{Maximize}(\lambda)\text{Minimize}(x,y)\text{OF} = \sum_{ij} (c_{ij} * x_{ij}) + \sum_{i} \lambda_i * \left(1 - \sum_{j} x_{ij}\right)$$

subject to (9), (10), (11), (12) (14)

Based on an iterative solution procedure, the objective function OF (14) is maximized with respect to λ_i and minimized with respect to the original decision variables to

[5] An approach, as proposed by Croxton and Zinn [8], to integrate inventory holding costs into the above presented network optimization model is to estimate the holding costs related to a certain network configuration by using the Square Root Law: in case that the demand variance for a product is the same at all customer locations and that the demands for a product at all customer locations are uncorrelated, savings due to centralization of inventory are proportional to the square root of the ratio of the new number of stocking locations over the original number of stocking locations [13]. As we did not suppose the two conditions to meet perfectly the situation of Dryco, we derive inventory holding costs for given network configurations analytically as presented above.

Table 4 Inventory holding costs for given numbers of MDCs: statistical results

Simulation runs…	… for 2 MDCs (%)	… for 3 MDCs (%)	… for 4 MDCs (%)
Total inventory holding costs: coefficient of variation	0.73	0.73	1.10
Total inventory holding costs: maximum deviation from average	1.30	1.50	1.50

Table 5 Distribution costs for given numbers of cost-optimized networks

Aggregated cost drivers	Initial situation (%)	Config.: 1 MDC opt (%)	Config.: 2 MDCs opt (%)	Config.: 3 MDCs opt (%)	Config.: 4 MDCs opt (%)	Config.: 5 MDCs opt (%)	Config.: 6 MDCs opt (%)
Total costs	100	96.68	**96.47**	97.56	99.09	101.08	102.90
Transportation costs	100	106.14	99.59	95.97	94.45	93.39	92.46
Inventory holding costs	100	51.58	77.41	99.91	116.57	134.48	150.57
Handling costs	100	99.07	99.53	100.00	100.47	100.93	101.40

obtain a lower bound for the original problem, that is, the largest value of OF overall iterations. In case that lower and upper bounds converge, we can identify optimal solutions for the original problem. Before starting the iterative procedure, the values for the Lagrangian multipliers $\lambda_i \geq 0$ have to be set. The upper bound UB is initialized to ∞, the lower bound LB to 0. The number of iterations the procedure needs to converge depends on the pre-initialized values as well as on the strategy to update the Lagrangian multipliers (see step *c*). Within each iteration *t*, we…

(a) Solve the simplified problem: We determine matrix $\mathrm{L}_t = \mathrm{l}_{tij} = \min\ (0;\ c_{ij}\ \in\ \mathrm{C} - \lambda_{it})$ and compute $\mathrm{l}_{jt} = \sum_i \mathrm{l}_{\mathrm{tij}}$. We set $\mathrm{y}_{jt} = 1$ for all sites where $\mathrm{l}_{jt} \leq$ the p smallest value of all l_{jt}, 0 otherwise. For matrix X_t^* we set $x_{ijt}^* = 1$ where $\mathrm{y}_{jt} = 1$ and $c_{ij} < \lambda_{it}$, and 0 otherwise.

(b) Update LB and UB: We calculate the lower bound $\mathrm{LB}_t = \sum_j \mathrm{l}_{jt} + \sum_i \lambda_i$ where $\mathrm{y}_{jt} = 1$, as well as the upper bound $\mathrm{UB}_t = \sum_{ij} (c_{ij} * x_{ijt}^{\mathrm{u}})$ where $x_{ijt}^{\mathrm{u}} = 1$, if $\mathrm{y}_{jt} = 1$ and $c_{ij} = \min_{\in \mathrm{y(jt)}\,=\,1} (c_{ij})$, and 0 otherwise. Set LB: = max (LB; LB_t) and UB: = min (UB; UB_t).

(c) Modify the Lagrange multipliers: If LB = UB the optimal solution for the original problem has been found. Otherwise, we modify the Lagrange multipliers:

$$\lambda_{i,t+1} := \max\left(0; \lambda_{it} - (\alpha_t * (\mathrm{UB} - \mathrm{LB}))/\left(\sum_i \left(\sum_j x_{ijt}{}^* - 1\right)^2\right) * \left(\sum_j x_{ijt}{}^* - 1\right)\right) \tag{15}$$

α_t determines the step size at iteration t to modify the Lagrangian multipliers and decreases during the procedure. After updating the multipliers, we return to step a and repeat steps a to c until (a) a certain number of iterations has been done or (b) LB = UB and $\sum_i (\sum_j x_{ijt} * - 1)^2 = 0$.[6]

In our case, the solution approach converges within a couple of minutes (about 900 iterations), and optimal solutions are identified.

A more pragmatic approach that reduces the data entering the optimization model would be to aggregate customers to clusters and to allocate these clusters (e.g. German districts) to MDCs. In Germany, MDCs are often allocated to postal regions, that is, 2-digit postal code areas. This was also current practice for Dryco as it reduces the complexity significantly since only 99 remaining postal code areas have to be allocated. However, we found that this procedure leads to an increase in total transportation costs of 0.15 %. Thus, all results presented in this article rest on more exact 5-digit postal code assignments.

Determining the cost minimal network: As a starting point for the subsequent robustness analysis, the cost minimal network for the given (real) data was determined using the approach explained above. Setting the cost components of the current network to 100 %, a configuration with 2 MDCs (as opposed to 3 MDCs in the current network) is optimal and reduces the costs down to 96.47 % (bold value in Table 5), an improvement of 3.53 % (see Table 5).

Figure 1 displays the development of the cost components for given numbers of warehouses. As expected, transportation costs decrease with the number of MDCs whereas inventory holding and handling costs increase resulting in a parabolic shape for the total cost curve.

[6] For a more comprehensive overview of the solution procedure we refer to Drezner and Hamacher [11] and Eiselt and Sandblom [12]. An introduction to the Lagrangian relaxation method for solving integer programming problems is given by Fisher [14].

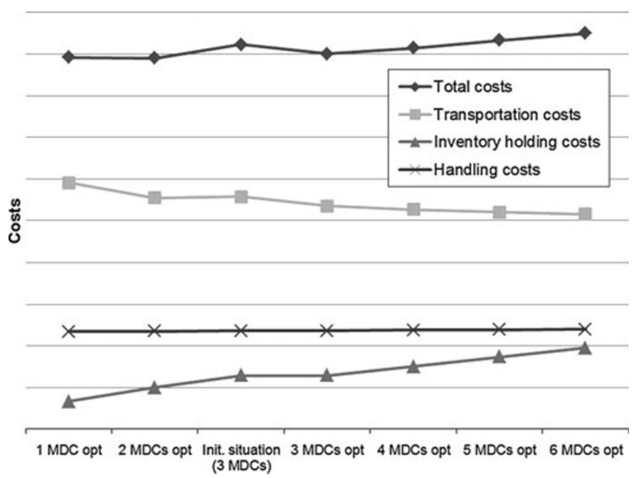

Fig. 1 Distribution costs for given numbers of cost-optimized networks

4.2.3 Step 3: Manipulating selected input variables

To understand the impact of the described variables on the network configuration, the input data have been manipulated in order to simulate the changes in the variables introduced above.

Transportation costs: The manipulation of the transportation costs has been done by altering the transportation costs (as estimated by the cost functions and as driven by the regression factors) by a multiplier. A multiplier below/above 1 represents a decrease/increase in transportation costs. Note that the multiplier affects all components of the transportation costs, like fuel prices, driving time regulations, tolls, etc.

COGS of finished goods: The manipulation of the COGS of the finished goods is done by changing the COGS values in the respective product master data file.

Number of plants: In the initial situation, 6 out of 22 European plants were serving about 70 % of the total demand of the German market. These were located in Germany, the Netherlands, and Belgium. By "closing down" one or several plants (i.e. output equals zero), the total number of plants is altered and the output of the single plants that is destined for the German market is changed (between 0 and 50 %).[7] When closing down one plant, the plant-customer supply quotas fq_{fi} given in the initial situation are respected, that is, the other plants adapt their output in such a way that all customer demands remain satisfied and that the relative contribution of each factory to satisfy the individual customer demands respects the contribution in the initial situation.

Shipment size: As per definition, a manipulation of the shipment size will change the relative share of FTL, LTL, and Groupage shipments and vice versa. Table 6 displays the initial situation.

When manipulating data and thereby moving tonnage from one shipment class to another, it is important to maintain the initial situation as far as possible in order to create realistic scenarios. To fix the tonnage to_{ic} transported to a certain customer i within shipment class c, we use the following approach:

(a) The sum of tonnage that is transported in a certain shipment class c must correspond to its relative share RS_c within the delivery shipments:

$$\sum_i to_{ic} = RS_c * \sum_{ic} to_{ic} \forall c \tag{16}$$

(b) Each customer i must be satisfied:

$$\sum_c to_{ic} = demand_i \forall i \tag{17}$$

(c) The tonnages per customer and shipment class generated shall be as near as possible to the tonnages transported in the initial situation to^I_{ic}. For each loading class, we determine a factor a_c that corresponds to the minimum increase/decrease in tonnage transported in a shipment class and that adapts the new transported tonnage to that of the initial situation:

$$to_{ic} \geq a_c * to_{ic}{}^I \quad \forall i, c \tag{18}$$

$$to_{ic} \leq (1/a_c) * to_{ic}{}^I \quad \forall i, c \tag{19}$$

$$\text{Maximize} \sum_c a_c \text{ Objective function} \tag{20}$$

DSD share: Redirecting the flow of goods from DSD destinations towards RDC and vice versa will change the average shipment size and the total number of shipments since DSD deliveries are smaller than RDC deliveries. In the initial situation, the average delivered tonnage per DSD shipment is about 1.6 and 8.1 tons for RDC deliveries (see Table 7). Within the simulation, we respect individual customer demands (to_{ic}) as well as order sizes (to_{ic}/nb_shpmt_{ic}), separately for each shipment class c.

5 The sensitivity of FMCG distribution networks: findings from the analysis

5.1 Single variable changes

Table 8 reports the results of the threshold value analysis, that is, for isolated, single variable changes. All reported

[7] The output is measured in tons. As factories are specialized in the production of different segments of consumer goods, one or two factories cannot produce 100% of the total distributed tonnage.

Table 6 Relative importance of FTL, LTL, and Groupage shipments in the initial situation

Shipment class	Delivered tonnage	Number of shipments	Avg. tonnage per shipment
FTL shipments	61 %	11 %	18.7 tons/shipment
LTL shipments	33 %	37 %	2.9 tons/shipment
Groupage shipments	6 %	52 %	0.4 tons/shipment
Sum	500,000 tons	145,000 shipments	3.3 tons/shipment

Table 7 Relative importance of RDC and DSD shipments in the initial situation

Destination type	Delivered tonnage (%)	Number of shipments (%)	Avg. tonnage per shipment
DSD destinations	35	73	1.6 tons/shipment
RDC destinations	65	27	8.1 tons/shipment

results are ceteris paribus. The table lists the threshold values that change the cost optimal distribution network configuration, from currently 2 MDCs to either 1 or 3 MDCs (Fig. 2).[8]

Transportation costs: An increase of transportation costs of 1 % will increase the total distribution costs by 0.6 %. If the transportation costs increase by 50 %, the optimal network will need to have 3 MDCs. If the transportation costs will decrease by 10 % or more, a 1-MDC network becomes cost minimal.

COGS: The effect of an increase of COGS of 1 % increases the total distribution costs by 0.1 %. A 1-MDC network will become optimal if the COGS increase by 10 %. Three MDCs become optimal once the COGS fall by 50 % or more.

Shipment size: Larger shipments call for fewer MDCs. However, a 1-MDC network only becomes optimal if, for example, the Groupage share is reduced to 2 % and the FTL share is increased to 70 %. In this case, the average tonnage per shipment (over all 145,000 shipments) would rise from 3.3 tons per shipment in the initial situation to 4.8 tons per shipment. On the other hand, only if, for example, FTL shipments go down to 38 % and Groupage shipments increase to 25 %, a 3-MDC network becomes optimal. These percentages are associated with an average tonnage per shipment of 1.2.

DSD share: An alteration of the DSD share changes the FTL-, LTL- and Groupage-shares (compare values in brackets in Table 8). Only if the DSD share increases to 70 %, a switch to a 3-MDC configuration becomes necessary. On the other hand, if the DSD share goes down to 27 %, a 1-MDC configuration becomes optimal.

5.2 Joint variable changes—scenarios

In order to study how current developments in the German FMCG market may affect the structure of the distribution network over the next years, sets of variables have been composed into scenarios. Scenario 1, called “Steady Change”, expects an ongoing trend, that is, moderate increases in transportation costs, constant COGS, an ongoing concentration of production which results in fewer plants serving the German market, smaller shipments sizes, and a decreasing DSD share (which in part compensates for the decreasing shipment sizes). Scenario 2, “Fast Change”, assumes changes for all variables in the same direction but with higher amplitude. Scenario 3, “Reverse Change”, assumes that the current trends are stopped or reverted, that is, constant transportation costs, COGS, and number of plants complemented by increasing shipment sizes and increasing DSD shares (Table 9).

Table 10 presents the estimated development of distribution costs per scenario and compared to the optimized 2-MDC configuration. For each scenario, the optimal and the second best configuration is displayed.

It turns out that, for each scenario, a 2-MDC configuration proves to be optimal (bold values in Table 10). The geographical locations of the MDCs either do not change significantly (max. ±90 km) or not at all. Whereas we observe for the initial situation as well as for Scenario 3 a single MDC as second best solution, this is not the case for the Scenarios 1 and 2 where the optimal configuration “tends” to a 3-MDC configuration.

6 Discussion and implications

6.1 Single variable changes

(1) Transportation cost: As expected, increasing transportation costs will favor additional MDCs. However, already an increase by 50 % (based on 2007 price level!) will leave the current 2-MDC network suboptimal. (2) COGS: On the other hand, already a slight increase by 10 % in the COGS of the stored products requires a move to a 1-MDC network. Such a change may be a result of manufacturing cost fluctuations. But it may as

[8] Certainly, larger changes per variable lead to optimal networks consisting of 4 or more MDCs, but these threshold values are not reported in this analysis.

Table 8 Threshold values changing the cost optimal distribution network configuration (values are rounded)

Variable	1 MDC is optimal if…	Initial values of current optimal network (2 MDCs)	3 MDCs are optimal if…
Transportation costs	90 %	100 %	150 %
COGS	110 %	100 %	50 %
Shipment size			
FTL–LTL–Grp shipments	70–28–2 %	61–33–6 %	38–37–25 %
Avg. tonnage per shipment	4.8 tons/shipment	3.3 tons/shipment	1.2 tons/shipment
DSD share (DSD–RDC)	27–73 %	35–65 %	70–30 %
(FTL–LTL–Grp shipments)	(65–30–5 %)	(61–33–6 %)	(43–46–11 %)

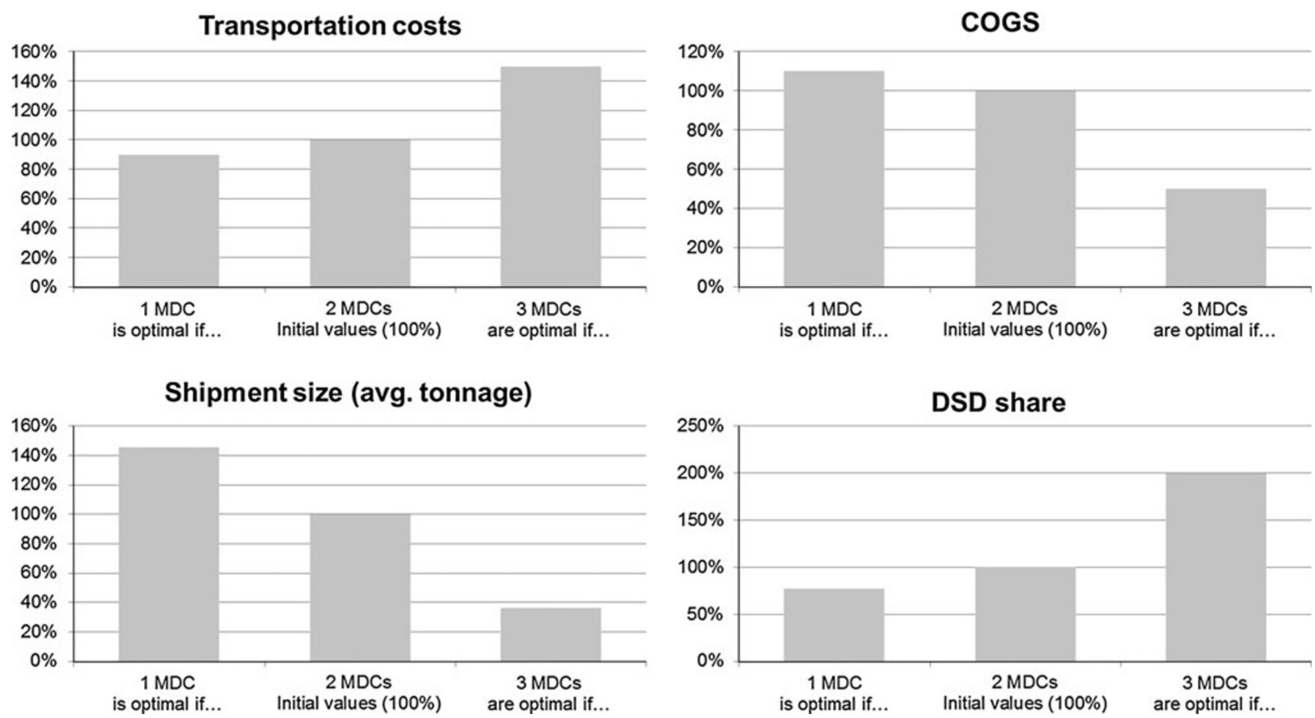

Fig. 2 Threshold values (ceteris paribus) changing the cost optimal distribution network configuration

well be driven by changes in the assortment due to takeovers. For example, think of a FMCG manufacturer with a low-value assortment that takes over a manufacturer with higher value products which will be distributed via the same network. (3) Shipment size and DSD share: The strategy of retailers to reduce inventory levels will lead to smaller shipment sizes and more frequent replenishment of the RDCs by the manufacturer. However, this will be compensated in part by the strategy of retailers to reduce the DSD share which will increase the product volume that is shipped to the RDCs. As the analysis reveals, the optimal network configuration is robust to changes in shipment size. Only if the average shipment size is reduced to 1.2 tons, a 3-MDC configuration becomes optimal.

6.2 Scenarios

Due to complex interdependencies, the effect of several variable changes on the optimal number of MDCs is not obvious. In this context, the presented scenarios give insights into how a cost-optimized distribution network actually reacts to changing conditions. On the basis of the scenarios analyzed, it is not possible to derive a general strategy in terms of the optimal number of MDCs ("one more or one less"). A central insight is that the current optimized 2-MDC configuration is quite robust. No scenario recommends a change of the current network structure. However, as the single variable analysis reveals, the high level of robustness is the result of compensating developments (transportation costs versus shipment size).

Table 9 Scenarios

Variable	Initial situation	Scenario 1: Steady change	Scenario 2: Fast change	Scenario 3: Reverse change
Transportation costs	100 %	Increase (130 %)	Strong increase (150 %)	Constant (100 %)
COGS	100 %	Constant (100 %)	Moderately decreasing (97 %)	Constant (100 %)
Number of plants	22	Decrease (16)	Strong decrease (10)	Constant (22)
		(6 small volume out of 22 plants closed down)	(12 small volume out of 22 plants closed down)	
Shipment size				
FTL–LTL–Grp shpts (in %)	61–33–6	Decrease	Strong decrease	Increase
Avg. tonnage per shipment	3.3 to/shpt.	(60–32–8)	(59–32–9)	(63–33–4)
		(3.0 to/shpt.)	(2.7 to/shpt.)	(3.8 to/shpt.)
DSD share	35 %	Decrease (31 %)	Strong decrease (28 %)	Increase (38 %)

Table 10 Results of the scenario analysis (values in %)

Scenario analysis	Initial situation			Scenario 1: Steady change		Scenario 2: Fast change		Scenario 3: Reverse change	
Network configuration	1 MDC	**2 MDCs**	3 MDCs	**2 MDCs**	3 MDCs	**2 MDCs**	3 MDCs	1 MDC	**2 MDCs**
Total costs	100.2	**100**	101.1	**120.8**	121.7	**131.3**	132.2	99.5	**99.3**
Transportation costs	106.6	100	96.4	133.2	129.4	150.3	146.7	105.4	98.8
Inventory holding costs	66.6	100	129.1	100.8	128.9	99.1	126.9	66.8	100
Handling costs	99.5	100	100.5	100.1	100.5	100.1	100.6	99.5	99.9

So, the most likely trends offset each other and leave the networks "in good shape".

7 On the generalizability of the findings and need for further research

The generalizability of the findings presented above is subject to a set of restrictions: (1) All results presented in this paper are obtained by modeling the distribution system of Dryco, an existing but disguised German FMCG manufacturer. Dryco certainly does not represent all German FMCG manufacturers. They may differ in terms of shipment structure (size, ship-to addresses), number of plants supplying the MDCs, and COGS. Other modeled data may resemble industry averages more closely, like the estimated tariffs of the logistics service providers for transportation, inventory storing, and handling. (2) Service levels were no concern during the analysis. It is assumed that all network configurations in the relevant realm (1–5 MDCs) will allow to meet the replenishment cycle time as requested by the retailers (72 h). However, this may not hold true for fresh/perishable products (which Dryco does not offer) where cycle times are shorter and tend to become "much shorter". However, once cycle times become a concern, the analysis becomes far more complex, since the configurations need to be checked for resulting cycle times and cycle time violations need to be quantified by cost.

Further research may be directed at least into three directions: (1) First, the scenarios may be formulated in a joint effort between retailer and manufacturer to compose a "most likely" scenario. Despite joint efforts, this may only make sense for particular segments of the FMCG market. (2) By recognizing that cooperative distribution becomes more important to cope with the future developments, cooperation partners may use the proposed approach to feed their joint distribution volumes into the model and study the effect of cooperation on the optimal network, that is, understand which and how many MDCs will be needed in a cooperative, joint network. (3) Finally, manufacturers will feel a need to complement cost-based optimization by pollution-based optimization. As this always encounters massive valuation problems, it should be started by determining a pollution minimal network which may differ in number and locations of MDCs.

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