International Journal of Operations Research

International Journal of Operations Research Vol. 8, No. 1, 3–22 (2011)

Myopic and Anticipated Planning in Stochastic Swap Container Management

Thomas Huth[1], Dirk C. Mattfeld[1,*]

[1] Decision Support Group, Carl-Friedrich Gauss Department, University of Braunschweig, D-38106 Braunschweig, Germany

Received June 2010; Revised November 2010; Accepted December 2010

Abstract — We introduce a dynamic and stochastic transportation problem consisting of two subproblems. For parcel transportation in hub-and-spoke networks, swap containers are used to carry out hub-to-hub shipments. This constitutes a pickup and delivery problem on the operational level. On the tactical level, empty swap containers are balanced over the hub-network in order to match the stochastic demand of empty swap containers in future periods. This two-level problem is referred to as Stochastic Swap Container Problem. In this paper, mathematical models and integrated solution strategies considering stochastic arrival patterns for shipments are developed. We present a comprehensive computational study comparing myopic and anticipating planning approaches.

Keywords — Allocation, dynamic stochastic transportation problem, routing, general pickup and delivery problem, model integration.

1. PROBLEM DESCRIPTION

Large hub-and-spoke networks are backbones for parcel service providers (Gruenert and Sebastian, 2000). Parcels are collected at spokes before they are consolidated within sending hubs. After shipment to destination hubs, parcels are decollated and delivered to their final customer destinations at spokes. In the following, we focus on hub-to-hub shipments, which are typically performed by 3rd party carriers paid on the basis of traveled distances.

In Europe, for hub-to-hub transportation typically trailer trucks designed for swap containers are used. Swap containers are self-contained transportation units with a standardized size of 24.5 foot length, 8.2 foot width and a maximal gross weight of 16 tons. Swap containers can be deposited without any extra equipment by pulling out the foldable put-down feet. A trailer truck can transport at most two swap containers.

The problem under consideration encounters the allocation and routing of swap containers. On the tactical level, swap containers have to be balanced over the hub-network in order to match the stochastic demand of empty swap containers in future periods. The routing of empty as well as full containers constitutes a pickup and delivery problem on the operational level of planning. This two-level problem is referred to as Stochastic Swap Container Problem (SSCP), compare Huth and Mattfeld (2009) for its deterministic counterpart.

In the following, we discuss the SSCP in more detail and propose two concepts in order to solve the problem. The main issue of Section 2 is the development of transportation models to solve the allocation subproblem by considering stochastics explicitly. In Section 3, the routing subproblem is discussed and a mathematical model as well as a meta-heuristic is sketched. In Section 4, we introduce four strategies, which implement the concepts using the optimization models developed in Sections 2 and 3. In Section 5, the strategies are investigated by means of a computational study before important findings are discussed. Section 6 summarizes the paper.

1.1 The Stochastic Swap Container Problem

The main task of the considered problem is the transport of swap containers between every pair of hubs. Every swap container represents one *transportation request* (TR). The construction of distance minimal routes visiting several hubs allows for combining TR on trailer trucks. This constitutes a general pickup and delivery problem whit a truck

* Corresponding author's email: d.mattfeld@tu-bs.de

capacity of two units. A secondary, either important task is the supply of empty swap containers (empties) in order to satisfy the demand of swap containers in future periods. Whenever a lack of empties occurs due to imbalances of containers in the network, an *allocation request* (AR) for an empty swap container is generated. The selection of appropriate supply nodes for empties can be formulated as a transportation problem.

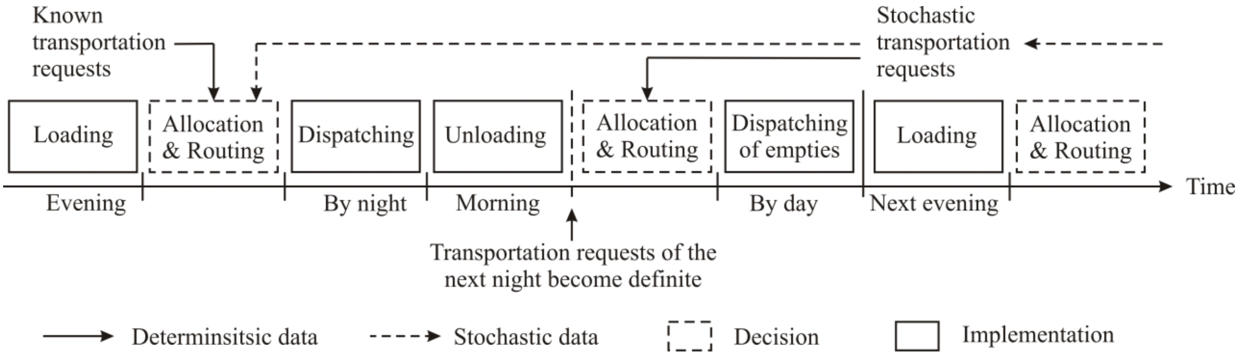

Figure 1. The SSCP in the course of time

Figure 1 depicts the tasks to be performed over the course of time. First, swap containers are loaded in sending hubs. Afterwards, the allocation of AR is planned. For this task, the currently known and the anticipated future TR are considered. Both types of requests, TR and AR are routed in an integrated way. During nighttime, the requests are dispatched followed by the unloading of swap containers in the receiving hub in the morning. At this time, TR to be handled in the next night become definite. If the assumption about demanded empties is shaped up as wrong, i.e. a need for empties becomes obvious, some repair action of the former plan is needed. To this end additional AR are generated and carried out during daytime. This entire procedure is repeated day by day.

1.2 Decision levels

On the strategical level, infrastructure decisions are made for a planning horizon exceeding one year. Tactical planning bases on the strategic decisions and varies in the planning horizon considered. Periodically executed routes and resource allocations are mid-term decisions subject to frequency service network design. In particular we focus on dynamic service network design, where adaptations of mid-term plans become necessary due to unforeseen demand fluctuations. Beneath the tactical decision level, operational decisions include the routing and scheduling of trucks and other resources on a daily basis. Figure 2 depicts relevant decision levels as described by Crainic (2003).

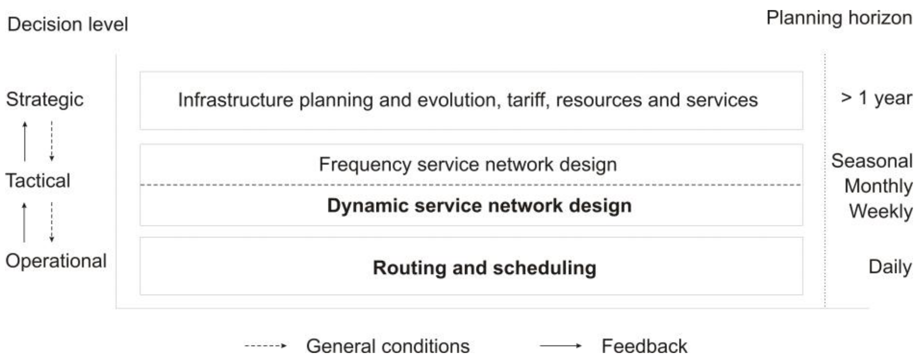

Figure 2. Decision levels in logistics and particular in the SSCP

Wieberneit (2008) states that the costs for the services occur on the operational planning level. Considering this, the operational planning level has to be incorporated into the tactical planning problem. This conclusion may be important for the SSCP, because we have two subproblems on hand. The allocation problem implements the tactical level of the dynamic service network design by considering demand information about future periods. The routing of TR and AR is a purely operational issue. Analogous to Wieberneit we can state, that the anticipation of future demand on the level of the dynamic service network design may gain savings with respect to routing.

Huth and Mattfeld: *Myopic and Anticipated Planning in Stochastic Swap Container Management*
IJOR Vol. 8, No. 1, 3−22 (2011)

We see three ways of supporting operations on the tactical level. First, the reach of allocation planning may be extended by means of dynamic, multi-period models. Second, the demand variation may be covered by means of dynamic and stochastic models. Third, synergies with respect to routing may be gained by integration of TR and AR on the same truck. In the following, possible benefits are demonstrated by example. First, the impact of a dynamic allocation on the tactical level is illustrated. Second, an example for an integrated routing of several transportation requests is presented.

1.2.1 Dynamic allocation

The time-space network in Figure 3 shows nodes of a network with the supply and demand situation in each period. A solution of a one-period transportation model supplies the demand of Node 1 in Period 2 by providing an empty container from Node 2. A further demand of Node 2 in Period 3 is supplied by Node 3. Two shipments are necessary in this example. To the contrary, the solution of a dynamic, multi-period model shown in Figure 3b overcomes this weakness by satisfying the demand of Node 1 in Period 2 with the provision of an empty container from Node 3. This way the shipment for satisfying the demand of Node 2 in Period 3 is saved already on the tactical level. The stochastic demand of future periods may be even better supported by extending the dynamic transportation model to a dynamic and stochastic one.

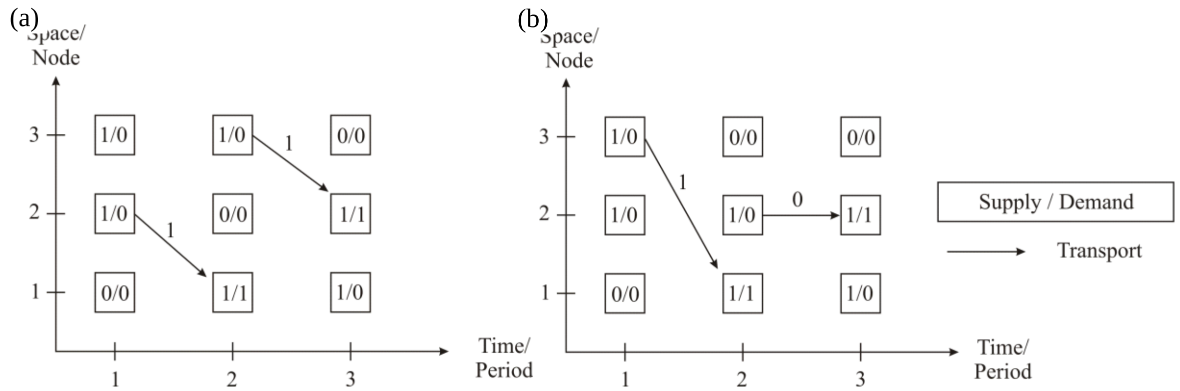

Figure 3. Two solutions for a dynamic transportation problem
(a) Myopic solution (b) Anticipating solution

1.2.2 Integrated routing

Figure 4 shows the inferiority that arises from implementing the solution of the transportation model on an operational level. Suppose a demand of two empties in Node 4 and a possible supply of one empty swap container in each of the remaining nodes of the example (c.f. Figure 4a). The edge weights express distances between nodes. The task of the transportation problem is to select two of the supply nodes. Because of the shorter direct distances, the solution given in Figure 4b applies: Node 1 and Node 2 supply Node 4 with a total distance of 11 units. By considering a truck trailer with the capacity of two units, routing features entrainment by supplying one empty from Node 2, bypassing Node 3 and picking up the second demanded empty swap container. The resulting distance is 10 units, c.f. Figure 4c. This feature, referred to as *entrainment and detouring* in the following, benefits from a larger number of routing requests because of the bigger potential for entrainments.

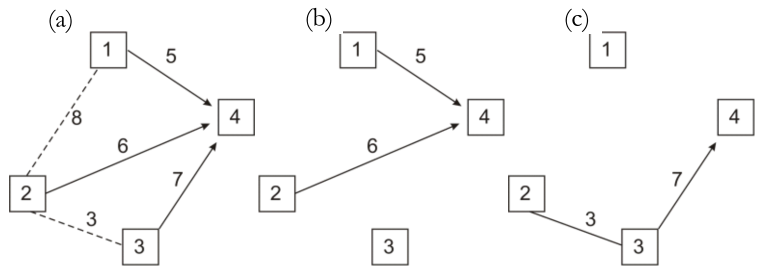

Figure 4. Allocation problem and the according solution of the routing problem
(a) Example (b) Solution 1 (c) Solution 2

As we have seen, not every detail being subject to the routing model can be covered on the tactical level already. Thus, tactical planning may generate inferior solutions with respect to options offered by the routing model. Furthermore, the variation in demand may render dynamic planning useless. In order to assess possible benefits of stochastic and dynamic planning in the case of the SSCP, we are going to compare *myopic planning* (MP) with *anticipating planning* (AP).

1.3 Concepts of planning

In the following, a myopic approach and its anticipating counterpart are developed on a conceptual level.

1.3.1 Myopic planning

MP confines to a one-period transportation model and makes the decisions for each period of the planning horizon independently of future periods. Figure 5 depicts its conceptual model. The TR for the current period are routed at night leading to a certain pre-allocation configuration of the network (Arrow a). Thereby, the demand of empties for the next period becomes known (Arrow b) and a transportation problem is formulated (Arrow c). The output of this model is flows of empties from supply to demand nodes that are interpreted as AR (Arrow d). These AR are input to routing (Arrow e). Since TR have been dispatched by night already, the routing of AR has to be performed independently of TR during daytime, c.f. Figure 1.

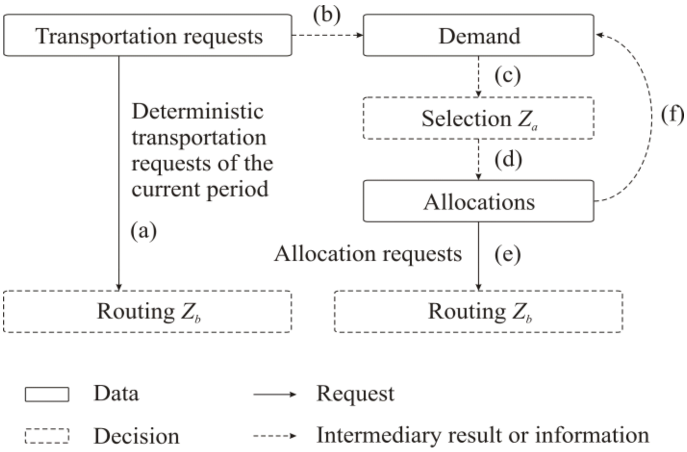

Figure 5. Myopic planning process

The operational routing considers objective Z_b for TR and for AR in the same way. A typical goal is the minimization of the overall distance driven in a single period. Things are becoming slightly more difficult for the objective Z_a of the transportation model. Arrow f in Figure 5 indicates that an allocation at least partially determines the demand of swap containers for the next period. Therefore objective Z_a should be formulated with respect to this dynamic property and may contradict the short term oriented objective Z_b. A dynamic transportation model as proposed in the example of Figure 3b supports reasonable allocations over time.

1.3.2 Anticipated planning

Since the future is uncertain, a dynamic model introduces the need to incorporate stochastics. Since TR is now considered as stochastic data, also the derived demand of swap containers is stochastic. Figure 6 depicts the scheme for the modified anticipating planning process.

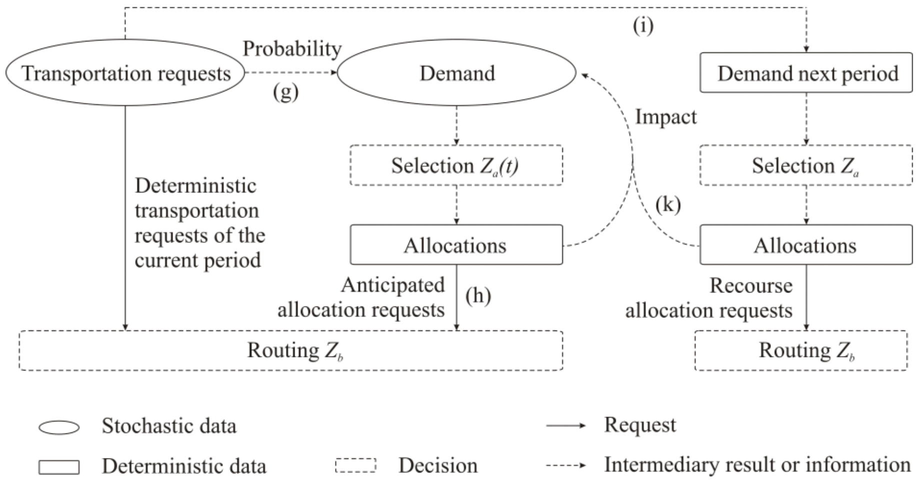

Figure 6. Anticipating planning process

The probability of TR impacts the future demand (Arrow g). A dynamic stochastic allocation anticipates this demand and selection decision considering objective $Z_a(t)$ results in *anticipated allocation requests* (AAR) (Arrow h). Different to MP where AR had to be routed separately, in AP anticipation allows an integrated routing of AAR and TR, which may exploit synergies with respect to integrated routing. However, AAR may not exactly meet the demand observed in the forthcoming periods. Therefore a short termed allocation with respect to the actual demand observed becomes necessary (Arrow i). These *repair allocation requests* (RAR) are regarded as the non-anticipating counterpart of AR as shown for MP. Finally, the resulting AAR as well as RAR impact the future demand (Arrow k).

For the SSCP, we have discussed MP and AP on a conceptual level. The following questions remain to be answered:

1. AP incorporates stochastic future demand. Does dynamic stochastic planning outperform its deterministic counterpart?
2. Routing partially distorts the results of allocation. Is anticipation worth the effort in the SSCP case?
3. Different hub networks and demand distributions may require different ways of planning. Is there just one preferred strategy available?

In order to answer the above questions, the necessary transportation and routing models and methods are described in the following two sections, before the developed optimization models are integrated into the aforementioned concepts resulting in strategies. These strategies are investigated in the sequel of this paper.

2. THE ALLOCATION OF EMPTY RESOURCES

The allocation of resources belongs to the class of network problems (Ford and Fulkerson, 1962; Wagner, 1969; Powell, 1988; Hillier and Liebermann, 2005). Various models have been developed focusing on different particular problems under consideration (Klein, 1967; White and Bomberault, 1969; Ahuja et al., 1993; Chen and Chen, 1993; Crainic et al., 1993; Klein et al., 1995). We describe and develop multiple mathematical models required for the implementation of the conceptual models introduced. Starting point is the model of Hitchcock-Koopmans followed by the consideration of dynamics. Third, a mathematical model for the dynamic stochastic model with recourse is introduced.

2.1 The Stochastic Swap Container Problem

The simplest form of a transportation problem is the classical Hitchcock-Koopman Transportation Problem (Hitchcock, 1941). Assuming network supply and demand nodes, this problem seeks the cost-minimal flows of goods from the supply to the demand nodes. The following mathematical model TP depicts this problem.

$$(Model - TP) \quad min \sum_{i \in M} \sum_{j \in N} c_{ij} w_{ij} \tag{1}$$

Subject to:

$$\sum_{j \in N} w_{ij} = a_i \qquad \forall i \in M \tag{2}$$

$$\sum_{i \in M} w_{ij} = b_j \qquad \forall j \in N \tag{3}$$

$$w_{ij} \geq 0 \qquad \forall i \in M, j \in N \tag{4}$$

The decision concerning flows from node *i* to node *j* is represented by the variable w_{ij}. The objective is to minimize the overall costs c_{ij} transporting all the goods from node *i* to node *j* (1). Constraints (2) and (3) assure the satisfaction of the demand b_j of node *j* by flows from supply nodes i with a supply of a_i. The flows must be non-negative (4). MP and the RAR applying in AP required a one-period transportation model similar to TP. Two adaptations are made:

1. The supply exceeds the demand of empty swap containers. Therefore an artificial node has to be introduced taking up all the unnecessary empties.
2. Swap containers are not divisible. So the decision variable w_{ij} is restricted to integer values.

Powerful solution methods are available for this kind of static transportation problem. We confine to the implementation provided in CPLEX 11.0 in order to solve this problem.

2.2 Multi-stage Transportation Model

The consideration of dynamics in the transportation model requires three major adaptations. First, a third index *t* for the time dimension is introduced to the decision variable leading to the notation w_{ij}^t. Second, the demand becomes an auxiliary variable allowing for updates of the number of empties residing at a node at a certain point in time. The respective empties are stored at this node with no charge for this period and show up again in the next period. Third, a dynamic balancing constraint ensures that empties are either stored or allocated in the next period. The notation of the dynamic transportation problem is adapted to the new features as depicted in Figure 7.

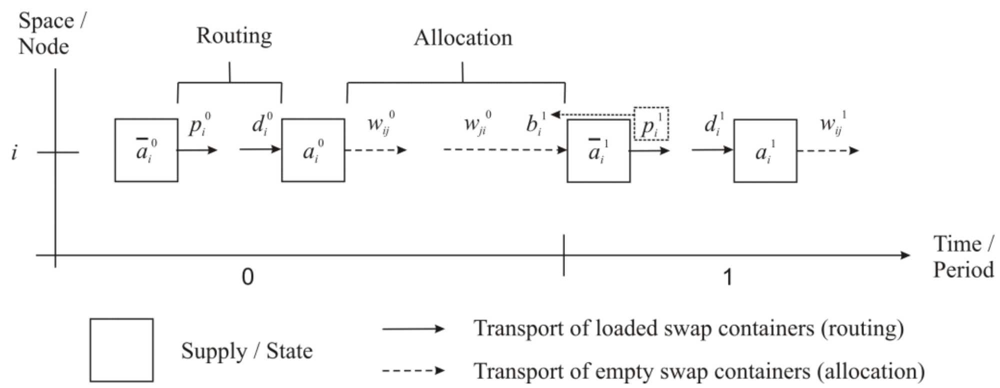

Figure 7. The notation of the dynamic transportation problem

The initial configuration of the network is given in state $\bar{a}_i^0$. The routing of the TR reduces the swap containers in node *i* by the number of pickups p_i^0 and increases the number of swap containers by the deliveries d_i^0. This leads to the initial state for the allocation decision a_i^0. The state $\bar{a}_i^1$ before the next routing takes place depends on the allocations w_{ij}^t and w_{ji}^t performed from node *i* to *j* and to node *j* from *i*. Its balance is due to the number of empties b_i^t demanded in the next period. Note that b_i^1 is determined by the pickups p_i^1 of the forthcoming periods. Model DTP considers these dependencies.

$$(Model - DTP)\ min \sum_{t \in T} \sum_{i \in N} \sum_{j \in N} c_{ij} w_{ij}^t \tag{5}$$

Subject to:

$$\bar{a}_i^{t+1} = \sum_{j \in N} w_{ji}^t \qquad \forall i \in N, t \in T \tag{6}$$

$$a_i^t = \sum_{j \in N} w_{ij}^t \qquad \forall i \in N, t \in T \tag{7}$$

$$a_i^t \geq p_i^t \qquad \forall i \in N, t \in T \tag{8}$$

$$a_i^t, \bar{a}_i^t, w_{ij}^t \in \mathbb{N} \qquad \forall i, j \in N, t \in T \tag{9}$$

The objectives are cost minimal flows satisfying the demand occurring at some nodes from the possible supply at other nodes over time. Balancing constraints determine the outgoing and incoming flows of nodes. In more detail, Constraints (6) ensure that all incoming flows w_{ji}^t are equal to the number of empties in the next period $\bar{a}_i^{t+1}$. Constraints (7) ensure that all empties a_i^t leave node *i*. A floww_{ij}^t with *i* = *j* represents a storage of a swap container from period t to $t + 1$. The supply of all nodes must exceed the demand (8) and the integer requirements are provided by (9).

Tailored methods have been developed for dynamic transportation models (Ford and Fulkerson, 1958; Ford and Fulkerson 1962; Bellmore et al., 1969; Assad, 1987; Aronson, 1989; Ahuja et al., 1993). Since SSCP instances of reasonable size can be solved with CPLEX, we confine ourselves to standard software.

2.3 Dynamic Stochastic Transportation Model

Various methods dealing with uncertain demand in transportation problems have been developed (Wets, 1982; Ermoliev, 1983; Birge and Wets, 1986; Ermoliev, 1988; Powell, 1988; Holmberg, 1995; Powell et al., 1995; Frantzeskakis and Powell, 1990; Chong, 1991; Vladimirou, 1991; Cheung and Powell, 1996; Powell, 2007). Among others, Stochastic Programming can be applied. According to (Wagner, 1969; Kall and Walace, 1994; Holmberg, 1995) we propose a stochastic model with recourse applied on a rolling planning horizon.

2.3.1 Representation

In principle, the notation of the dynamic stochastic model corresponds to Model DTP. However, the demand b_i^t becomes stochastic because of uncertain TR. The uncertainty in period t influences the demand of empties β_i^t and the respective number of empties available in the future. In detail, the unknown number of pickups determines the quantity of empties before routing $\bar{a}_i^t$ and the uncertain pickups and deliveries determine the inventory of empties before allocation a_i^t. The notation is summarized in Figure 8.

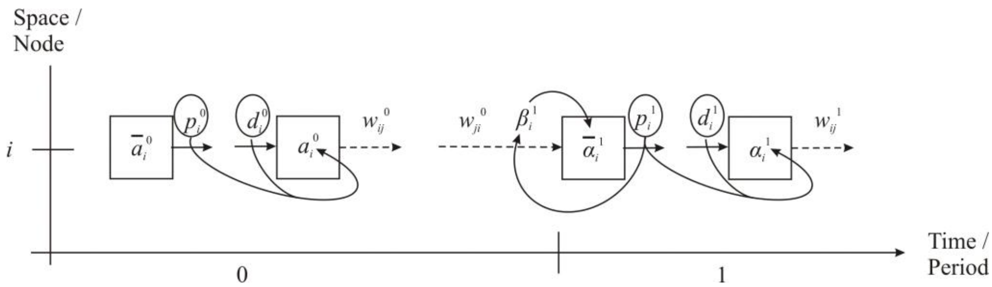

Figure 8. The notation of the dynamic stochastic transportation problem

The key-feature of this model is the concept of scenario trees. Assuming two realizations $s = 1$ and $s = 2$ in every period t of the stochastic variable β_i lead to the example of the scenario tree in Figure 9. The stochastic demand β_i is represented by the deterministic values b_{is}^t whereas the probability π_{is}^t of the appearance of b_{is}^t is given by $\sum_{s \in S} \pi_{is}^t = 1 \; \forall i \in N, t \in T$.

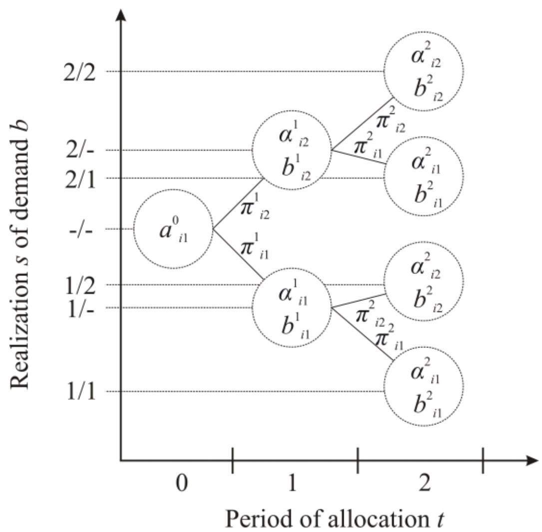

Figure 9. Scenario generation in stochastic programming

In period zero, a given initial configuration supplies a_{i1}^{0} empties at node *i*. The demand of the next period *t* = 1 is stochastic and may become b_{i1}^{1} with probability π_{i1}^{1} or b_{i2}^{1} with probability π_{i2}^{1}. Depending on the TR observed and the decision to be made in this period, again we differentiate between two possible realizations for the next period. Now four possible states can be observed for period two. Every directed path between root and leaf represents one possible scenario with an overall probability resulting from the multiplied individual probabilities along the edges of the path. The size of the scenario tree is determined by the number of periods *T* and the considered number of realizations leading to $|S|^{T-1}$ final states in general and $2^2 = 4$ final states in this example.

Figure 10 explains the way of successively updating the current system state of the SSCP in accordance to Wagner (1969). Note that stochastic variables are represented by Greek letters. Consider the determination of a first solution given in the bottom row of Figure 10. The supply a_i^1 is given and the demand β_i^1 can have several realizations. Because a solution of the dynamic stochastic transportation problem is determined for all periods, the supply and demand of Period 2 and Period 3 become stochastic variables (α_i^2, α_i^3 and β_i^2, β_i^3) as well. After implementing the solution w_{ij}^t determined in Period 1, the system state is updated according to the observed demand of empties. In this way, a deterministic supply a_i^2 is considered for the next stage.

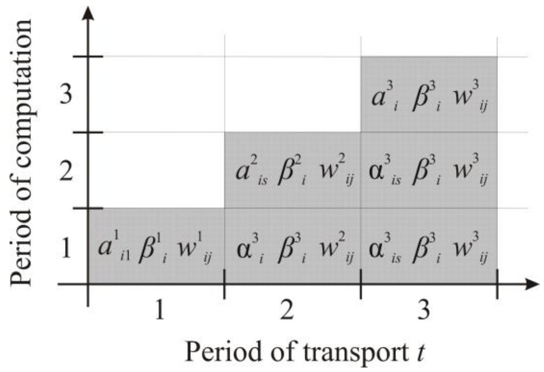

Figure 10. Multi-stage stochastic modeling with successive system state updates

2.3.2 Model

In the anticipating concept AP, we differentiate between anticipated allocation requests (AAR) and repair allocation requests (RAR), c.f. Figure 6. In the stochastic model, AAR is just an estimate of the overall allocation requests to be performed. Overemphasizing the anticipation will lead to a small number of necessary RAR only, but may generate superfluous AAR at the same time. Vice versa, a relatively smaller number of AAR will lead to a larger number of RAR as repair action with hindsight. The flows induced by RAR are referred to as recourse flows v_{ijs}^t from node *i* to node *j* with observed realization *s* in period *t*.

In practice, the balance of AAR against RAR should be subject to transport tariffs for both kinds of allocation requests. However, the actual costs with respect to routing are not known in advance. In the best case, a request can be entrained on a trailer truck without any extra costs. In the worst case, an additional tour with an empty container as the only load has to be carried out. For sure, there is a tendency of smaller transportation costs for AAR compared to RAR. Since AAR are routed integrated with TR, the number of synergies due to entrainment will be larger than the much smaller number of RAR to be carried out. In order to assess the impact of potential transport tariffs, a recourse factor R is introduced to the objective function in order to balance AAR against RAR in the stochastic and dynamic transportation model with recourse.

$$(Model - DSTP)\ min \sum_{t\in T}\sum_{i\in N}\sum_{j\in N} c_{ij}w_{ij}^t + \sum_{s\in S}\sum_{t\in T}\sum_{i\in N}\sum_{j\in N} Rc_{ij}v_{ijs}^t\pi_{is}^t \tag{10}$$

Subject to:

$$\bar{a}_{is}^{t+1} = \sum_{j\in N}\left(w_{ji}^t + v_{jis}^t\right) \qquad \forall i \in N, s \in S, t \in T \tag{11}$$

$$a_{is}^{t} = \sum_{j\in N}\left(w_{ji}^t + v_{jis}^t\right) \qquad \forall i \in N, s \in S, t \in T \tag{12}$$

$$a_{is}^t \geq p_{is}^t \qquad \forall i \in N, s \in S, t \in T \qquad (13)$$
$$a_{is}^t, w_{ij}^t, v_{ijs}^t \in \mathbb{N} \qquad \forall i, j \in N, s \in S, t \in T \qquad (14)$$

Consequently, model DSTP features a second term in the objective function (10) to represent deferred flows v_{ijs}^t and weights them with recourse factor R and the probability π_{is}^t. The balancing and quantity constraints (11), (12) and (13) correspond to Model DTP and the new decision variables v_{ijs}^t are restricted to integer values (14).

3. ROUTING OF FULL AND EMPTY RESOURCES

A General Pickup and Delivery Problem (GPDP) serves as the routing model used in order to dispatch full as well as empty swap containers. See Parragh et al. (2008a) and Parragh et al. (2008b) for a recent review on pickup and delivery models. Because of a) multiple pickups and/or deliveries per node, b) identical coordinates of request locations, and c) depot locations with multiple trucks per depot, we adapt the model of Savelsbergh and Sol (1995) to the needs of the SSCP.

The GPDP is defined on a graph containing nodes N and edges E. Hubs are defined as nodes in N. A transportation request $tr \in TR$ features an origin hub and a destination hub, which are referred to as pickup and delivery nodes (r_{tr}^+, r_{tr}^-). The set of pickup and delivery nodes is determined by the pickup and delivery nodes of all requests $R^+ := \bigcup_{tr \in TR} r_{tr}^+$ and $R^- := \bigcup_{tr \in TR} r_{tr}^-$. $R = R^+ \cup R^-$ and $R \subseteq N$. The trucks $k \epsilon K$ have an origin depot k^+ and a destination depot k^- with $D^+ := \{k^+ | k \in K\}$ and $D^- := \{k^- | k \in K\}$. $D = D^+ \cup D^-$ and $D \subseteq N$.

The readability of the model is improved by a multi-digraph representation for the set of edges. To this end, the set of all feasible edges E^k is considered. A truck *k* can travel the set of edges coming from node i ($O(i,k)$) and going into node i ($I(i,k)$). These sets described in detail in Huth (2009) strengthen the model by avoiding big-M notations.

The capacity required for a swap container equals one unit. A pickup decreases the truck capacity by one and visiting a delivery node increases the available capacity. So $q_{tr} = q_{r_{tr}^+} = -q_{r_{tr}^-} = 1 \; \forall tr \in TR$. The sequence decision variable x_{ij}^k holds if truck k travels from node i to node j. The assignment decision variable z_{tr}^k holds if request tr is assigned to truck k. The model is formulated as follows.

$$(Model - GPDP)\; min \sum_{i \in R \cup D} \sum_{j \in R \cup D} \sum_{k \in K} x_{ij}^k c_{ij} \qquad (15)$$

Subject to:

$$\sum_{k \in K} z_{tr}^k = 1 \qquad \forall tr \in TR \qquad (16)$$
$$\sum_{j \in O(k^+,k)} x_{k+j}^k = 1 \qquad \forall k \in K \qquad (17)$$
$$\sum_{i \in I(k^-,k)} x_{ik^-}^k = 1 \qquad \forall k \in K \qquad (18)$$
$$\sum_{j \in O(r_tr^+,k)} x_{r_tr^+ j}^k = \sum_{i \in I(r_tr^+,k)} x_{ir_tr^+}^k = z_{tr}^k \qquad \forall tr \in TR, k \in K \qquad (19)$$
$$\sum_{j \in O(r_tr^-,k)} x_{r_tr^- j}^k = \sum_{i \in I(r_tr^-,k)} x_{ir_tr^-}^k = z_{tr}^k \qquad \forall tr \in TR, k \in K \qquad (20)$$
$$d_{r_tr^+} + t_{r_tr^+ r_tr^-} \leq d_{r_tr^-} \qquad \forall tr \in TR \qquad (21)$$
$$d_i + t_{ij} - d_j \leq \left(1 - x_{ij}^k\right)\left(\hat{d} + t_{ij}\right) \qquad \forall k \in K, (i,j) \in A^k \qquad (22)$$
$$d_{k^+} = 0 \qquad \forall k^+ \in D^+ \qquad (23)$$
$$d_i \geq 0 \qquad \forall i \in R \cup D \qquad (24)$$
$$d_{k^-} \leq \hat{d} \qquad \forall k^- \in D^- \qquad (25)$$
$$(l_i + q_i) x_{ij}^k = l_i x_{ij}^k \qquad \forall i, j \in R \cup D, k \in K \qquad (26)$$
$$0 \leq l_i \leq 2 \qquad \forall i \in R \cup D \qquad (27)$$
$$x_{ij}^k \in \{0,1\} \qquad \forall i, j \in R \cup D, k \in K \qquad (28)$$
$$z_{tr}^k \in \{0,1\} \qquad \forall tr \in TR, k \in K \qquad (29)$$

The objective function minimizes the total traveled distance (15) that is independent of the load utilization of the truck. A transportation move with two swap containers is as costly as the transportation of two swap containers. A request tr is assigned to exactly one truck *k* (16) whose route starts and ends with the associated origin and destination depots (17, 18). Furthermore, (19, 20) bind the two decision variables so that a truck k leaves or enters a node only if a request exists (z_{tr}^{k} holds). The time constraints (21) to (25) lead to a feasible temporal structure of a route and the load constraints (26, 27) ensure a feasible utilization of the trucks. All decision variables are binary (28, 29).

The GPDP is a complex optimization problem for which powerful metaheuristics has been developed. We follow recent literature and implement Large Neighborhood Search (LNS) proposed by Ropke and Pisinger (2006). This is a Simulated Annealing based neighborhood search heuristic with varying removal and insertion strategies to improve existing solutions, i.e. routing plans. Some adaptations to the needs of the SSCP make the LNS a reasonable solution method for the GPDP. The predecessor-successor pair insertion algorithm of Nanry and Barnes (2000) yields initial solutions. Moreover, promising parameters are evaluated and proposed for GPDP, e.g. for the Shaw removal operator and the Regret-k insertion heuristic. We apply these settings and refer to Ropke and Pisinger (2006) and Huth and Mattfeld (2009) for details.

4. STRATEGIES

The purpose of this section is to provide strategies derived from the concepts developed in Section 1.3. To this end, different transportation models are combined to four strategies as summarized in Table 1. In the computational investigation the performance of the strategies will provide answers whether anticipation is worth the effort spent in the case of the SSCP. In the sequel of this section a detailed, pseudo-code oriented outline of the defined strategies is given.

Table 1. Conceptual models, derived strategies and its underlying transportation problems

Concept	Strategy	Anticipated allocation	Repair allocation
MP		-	TP
AP	deterministic	DTP	-
AP	expected	DTP	TP
AP	stochastic	DSTP	TP

4.1 MP

This strategy does not use anticipation, thus any anticipating strategy should clearly outperform MP. In MP all stochastic information about future system states is neglected. This leads to the straightforward implementation shown in Algorithm 1. Line 1 sets the initial configuration of the network: First, the demand of empties for the TR of the first period is calculated; secondly model TP generates the required AR accordingly. Third, AR are routed using GPDP, so that the swap containers (SC) are distributed in a way which avoids a shortage of empties already in the first period. This initial configuration is in line with all other planning approaches.

Algorithm 1 *MP*

```
1: Set initial configuration
2: for all period do
3:     Input TR to GPDP and generate routes
4:     Update SC demand according to routes
5:     Input SC demand to TP and generate AR
6:     Input AR to GPDP and generate routes
7:     Update SC distribution according to routes
8: end for
```

For each period, the following steps apply (Lines 2 to 8). After computing initial routes using the predecessor-successor pair insertion algorithm, LNS determines the best obtainable routes subject to model GPDP. The dispatching of routes is simulated by updating the swap container demand for the next period (Lines 3 and 4).

Model TP is solved with CPLEX in Line 5 and generates AR considering the current system state. Note that at this point in time the demand of the next period is known and the TR of the next period enter model TP. This results in flows of empty swap containers that are transformed into AR. The remainder of the algorithm routes AR similar to the routing of TR (Lines 6 and 7).

4.2 AP-deterministic

In AP-deterministic, stochastic variables are assumed to be known with certainty. This assumption is made to compare the stochastic approaches with its deterministic counterpart. Literature refers to such a benchmark as competitive analysis (Krumke, 2001; Jaillet and Wagner, 2004; Jaillet and Wagner, 2006; Angelelli et al., 2007; Jaillet and Wagner, 2008). For this strategy the dynamic transportation problem (DTP) is used (c.f. Section 2.2). Since the demand is known, no repair actions with respect to RAR are needed. This strategy can make use of perfect information and therefore poses a lower bound on the overall distance of routes.

In Line 2 of Algorithm 2 the dynamic transportation model is solved with deterministic known demand of empties. The solution of the DTP contains flows of empties for the entire planning horizon considered. Within the for-loop (Lines 3 to 6), the AAR are successively fetched from this solution in order to build the set of requests from the known TR and the AAR of the respective period. Afterwards, the integrated routing of TR and AAR is implemented by LNS (Line 4) and the position of the swap containers are updated according to the results obtained (Line 5).

Algorithm 2 *AP-deterministic*

```
1: Set initial configuration
2: Input demand to DTP and generate AAR
3: for all period do
4:     Input TR and respective AAR to GPDP and generate routes
5:     Update SC demand according to routes
6: end for
```

4.3 AP-expected

AP-expected uses expected values of the probability distribution of demanded empties. Hence the DTP can be used without modification. Because anticipation by DTP may fail, required empties have to be balanced at short notice as RAR. For the determination of RAR a one-period transportation problem is solved when the demand of the current period becomes known with certainty. Since in update of information occurs in every period, DTP is executed on a per-period basis. AP-expected applies non-stochastic models to a stochastic problem. It should be outperformed by a model that considers stochastics explicitly. However, under the assumption that anticipation is beneficial, it should do better than MP.

Algorithm 3 *AP-expected*

```
1: Set initial configuration
2: for all period do
3:     Input demand to DTP and generate AAR
4:     Input TR and AAR to GPDP and generate routes
5:     Update SC demand according to routes
6:     Input demand to TP and generate RAR
7:     Input RAR to GPDP and generate routes
8:     Update SC distribution according to routes
9: end for
```

Algorithm 3 shows the steps to perform. The observed demand realization may need some additional allocations. Hence the determination of AR has to apply twice and in each period (Lines 2 to 9): Anticipation by performing model DTP for the rest of the periods (Line 3) and repairing of this solution by model TP (Line 6). According to the temporarily distribution of the considered requests, routing of TR, AAR and RAR by LNS has to be applied twice as well (Lines 4, 5 and 7, 8).

4.4 AP-stochastic

AP-stochastic anticipates possible future demand realizations derived from a probability distribution. Therefore the allocation problem is formulated as a D*ynamic Stochastic Transportation Model* (DSTP), (c.f. Section 2.3). This strategy considers stochastics explicitly and is supposed to produce superior solutions.

Algorithm 4 *AP-stochastic*

```
1: Set initial configuration
2: for all period do
3:     Input demand to DSTP and generate AAR
4:     Input TR and AR to GPDP and generate routes
5:     Update SC demand according to routes
6:     Input demand to TP and generate RAR
7:     Input RAR to GPDP and generate routes
8:     Update SC distribution according to routes
9: end for
```

In AP-stochastic, the dynamic transportation model with recourse (as equivalent to a dynamic stochastic transportation problem) takes into account discrete probabilities concerning the realization of demand of empties. This is implemented in Algorithm 4 where model DTP is replaced by model DSTP in Line 3. This way, the repair action is anticipated by considering the cost of RAR in the transportation problem. Besides, Algorithm 4 is identical to Algorithm 3.

5. COMPUTATIONAL STUDY

The computational study is performed in order to assess the effectiveness of the above defined strategies. We are going to clarify whether the consideration of dynamic and stochastic models is worthwhile the effort spent in the face of the options and restrictions routing obeys to. Statements are to be derived for varying application scenarios. Simultaneously efficiency is considered in terms of computation times.

In the following, application scenarios are defined by generating hub networks and request distributions for those networks. Next, a reasonable setting of parameters for the AP-stochastic strategy is determined. Finally, the four strategies defined are compared with respect to the results yield for the applications scenarios under consideration.

5.1 Design of application scenarios

We vary the geographical structure of the network by considering different distributions of hub locations. Solomons VRP-benchmark instances introduced for vehicle routing problems with time windows are adopted to the requirements of the SSCP (Solomon, 1987). Each network consists of 25 nodes that are distributed randomly (instance R101), clustered (instance C101), and randomly clustered (instance RC101).

Transport requests are defined by pickup and delivery hubs. Heterogeneously distributed pickup and delivery hubs can model regions of different economic viability. Regions of different economic prosperity lead to unbalanced flows of goods and eventually to an unbalanced number of empties at hubs. A request structure may be one of the following:

- Uniform distribution *(uniform)*: Pickup and delivery locations of requests are uniformly distributed over the network. Only few imbalances are expected and allocations are easy to deal with.
- Normal distribution *(normal)*: Some hubs are characterized by a large number of pickups whereas other hubs show a larger number of deliveries. This can be found e.g. in networks with decentralized distribution centers. Obviously this leads to an imbalance of empties in the course of time. However, a demand of swap containers at hubs characterized by many pickups may be satisfied from adjacent hubs with predominant delivery activity.
- Normal distribution with clustered pickups and deliveries *(clustered)*: Pickup and delivery locations of normal distributed requests are clustered in geographical different regions of the network. The farthest north-west hub features the most pickups. The number of pickups at hubs decreases in south-east direction. Analogously, the farthest south-east hub features most deliveries in the network. This scenario may stand proxy for distant container seaports and hinterland cities, where local balancing of swap containers is not an option.

Unbalanced swap container fleets as induced by normal and clustered distributed request structures are rather norm than exception from a practical point of view. Thus, conclusions drawn from these experiments are considered more important.

Crainic et al. (1993) and Choong et al. (2003) discuss the relevance of choosing the appropriate number of periods to consider for dynamic problems. They state that 10 to 15 periods are necessary to warrant an adequate settling time for the system and to eliminate end of horizon effects. We consider 20 periods with an initial inventory of three swap containers per hub. We consider one, two or three transportation requests with an identical probability of occurrence to be transported between a pickup and a delivery node.

Since service times and time windows are not considered, the maximum tour length is to be defined in an explicit way. We set the maximum tour length to three times the maximum distance between any two hubs in the network. The larger the maximum tour length of a vehicle is set, the fewer vehicles are needed. More or less independent subtours are combined by repositioning moves of vehicles.

The LNS is implemented in Java 1.6 and the transportation models in CLPEX 11.0. LNS carries out a fixed number of 250 neighborhood moves regardless of the neighborhood size and improvement. The experiments are performed on a 3 GHz Intel PC with 1 GB RAM running Windows Vista.

5.2 Analysis of AP-stochastic

In order to incorporate DSTP into strategy AP-stochastic two parameters have to be set. We derive reasonable settings by means of experiments and discuss impacts on the different modes of swap container transports performed.

1. *Planning Horizon*: Psaraftis (1988) and Psaraftis (1995) propose that events in the near future shall receive more attention than events in the distant future. Following this line of argumentation, we limit the planning horizon to at most 5 periods. Anticipating a smaller time horizon decreases the exponent in the number of possible final states $|S|^{T-1}$. This way the decision tree can be shrunken dramatically.
2. *Recourse factor* R: An increasing recourse factor R favors the anticipation of allocations whereas a decreasing R leads to a potential larger number of repair action allocations to be performed. In the following R is varied between 0.0 assuming that RAR are performed without costs and 2.0 assuming that RAR are performed at twice the costs of AAR.

Table 2 summarizes the parameters used in the experiment. Network structure, distribution, planning horizon and recourse factor are varied and for every variation ten independent problem instances are generated. In order to investigate the impact of the recourse factor and the planning horizon on the overall distances driven by truck, averages obtained from the ten instances of each variation of parameters are considered.

Table 2. Experiment to determine recourse factor and planning horizon for DSTP

Parameter	Characteristic	Count
Network	R101; C101; RC101	3
Distribution	uniform; normal; clustered	3
Planning horizon *ph*	1; 2; 3; 4; 5	5
Recourse factor *R*	0.0; 0.2; … ; 2.0	11
Strategy	AP-stochastic	1
Instances		10
Number of runs		4,950

5.2.1 Planning horizon and recourse factor

In order to derive a generally applicable setting for the two parameters, a further aggregation over the three application scenarios is done. Therefore Figure 11 shows aggregates over 30 problem instances, i.e. ten instances for each of the three application scenarios.

Unfortunately, different magnitudes of distances are obtained for the problem instances of the proposed application scenarios. Therefore a normalization of distances between zero and one is performed as follows: Mean values (*dmean*) for 30 instances are calculated. Then, the minimum and maximum values (*dmin*, *dmax*) are calculated leading to *dnorm* = (*dmean* – *dmin*) / (*dmax* – *dmin*). Smaller values represent smaller overall distances obtained by AP-stochastic.

The Planning Horizon determines the number of anticipated periods varied between one and five periods. Obviously, an anticipation of multiple periods ahead does not lead to significantly better results. Indeed, Figure 11 advices to choose a planning horizon of two periods because of the shortest normalized distance observed.

The recourse factor controls the tendency of performing allocation requests. If a planning horizon of just one period is considered, the value of the recourse factor is irrelevant. This is depicted in the topmost curve of Figure 11. For all other settings of the planning horizon considered, $R > 1$ favors anticipated allocations yielding smaller overall distances. For $R > 1.2$, distances slightly increase again because of allocations anticipated mistakenly. Hence, we choose a recourse factor of 1.2 for the following experiments.

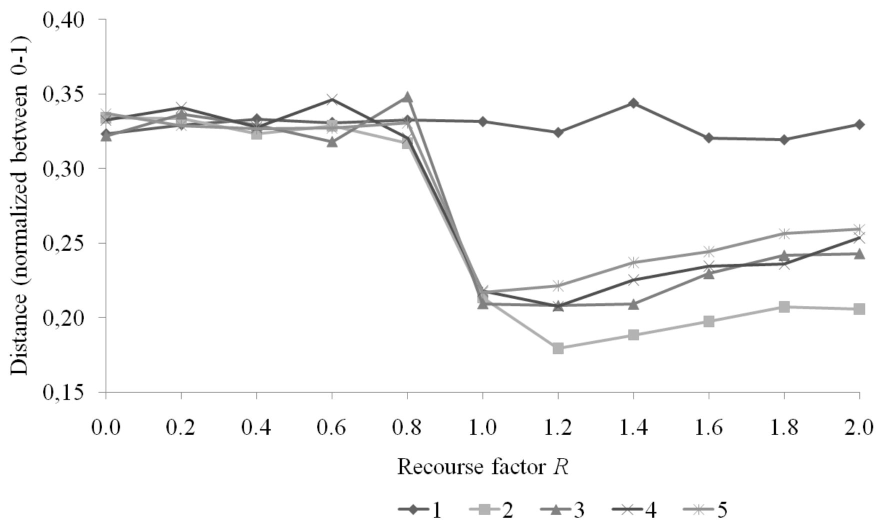

Figure 11. Analysis of variation of recourse factor and planning horizon

5.2.2 Analysis of transports

In the following, the structure of the itineraries of trucks is investigated for the three application scenarios independently. For this purpose, we differentiate possible types of truck utilization. Table 3 summarizes the variety of how a truck can travel an edge.

Table 3. Utilization of trucks and definition of the types of legs

Slot of truck	Slot of trailer	Types of leg
TR	TR	Transport
TR	-	
AAR	AAR	Anticipated allocation
AAR	-	
RAR	RAR	Repair allocation
RAR	-	
-	-	Repositioning
TR	AAR	Entrainment

A swap container can be transported on the truck as well as on the trailer. Depending on the type of request, the swap container is utilized by TR, AAR and RAR. Whenever only TR are involved, we call such legs transports. Other types of legs are referred to for genuine allocation moves. If an RAR as a result of repair action is performed, this leg is called repair allocation; else an anticipated allocation is carried out. If the truck moves without swap containers, a so called repositioning move takes place. This includes moves from the depot to the first pickup node, moves from the final delivery node to the depot and moves from the delivery node of the last container to a further pickup node. Whenever TR and AAR are considered jointly, an entrainment of empties is carried out.

Figure 12 depicts the absolute mean distances observed for the ten problem instances of an application scenario with respect to different types of legs (c.f. Table 3). A planning horizon of 2 periods is used, the recourse factor is varied between 0.0 and 2.0 in steps of 0.2. For all application scenarios we observe a structural change of legs between $0.8 \leq R \leq 1.4$ such that AAR increase and RAR decrease. The reason is that RAR become costlier and the model tends to pre-draw swap container allocations whenever possible. These allocations show up as AAR in the integrated routing plans. However, the most improbable demands are still deferred to later periods. A minor effect is the slight increase of entrainments with increasing *R* which is due to the fact that only AAR can be entrained by routing.

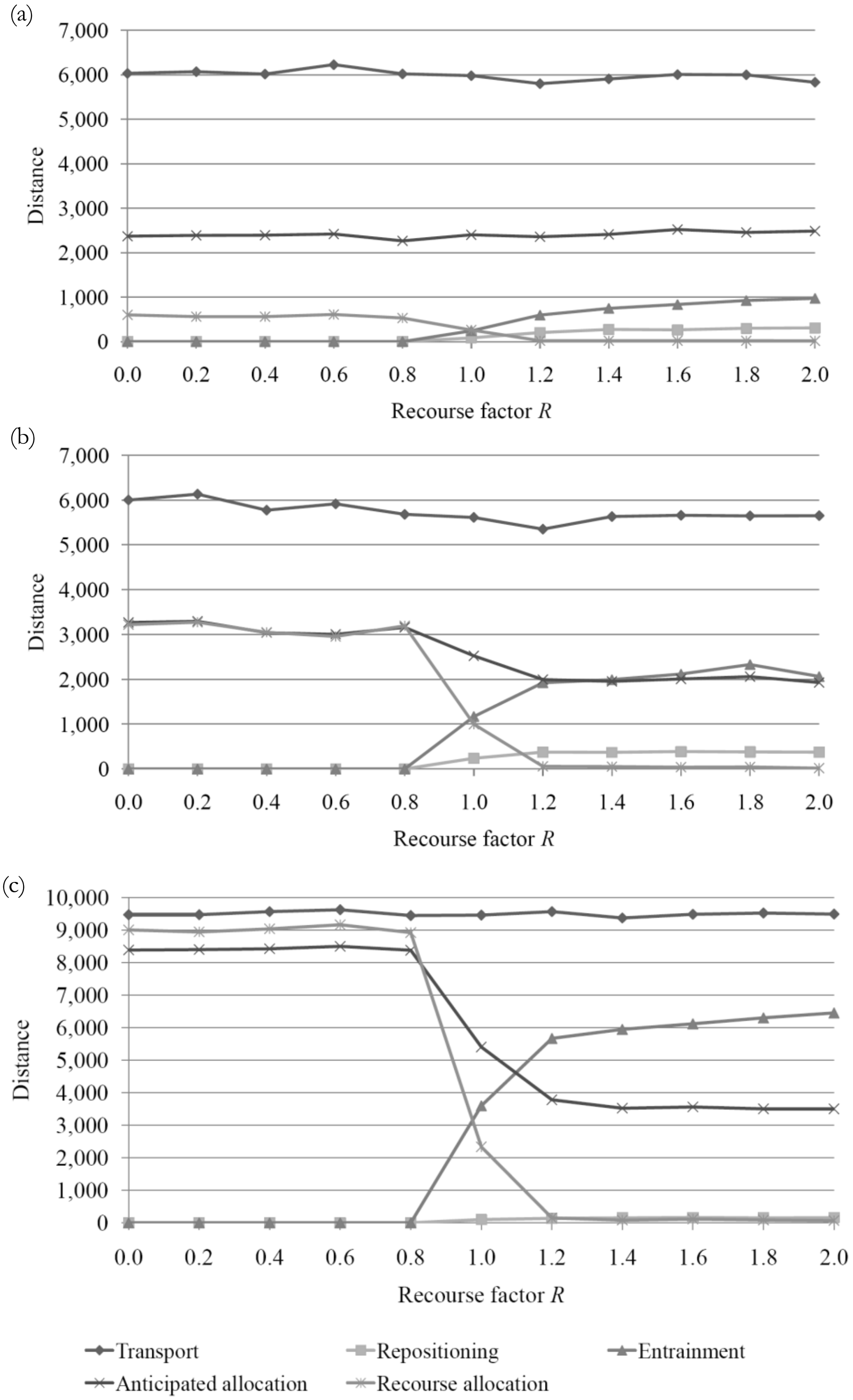

Figure 12. Structure of routes for AP-stochastic, a planning horizon of two periods and varying recourse factors (a) Uniform distribution (b) Normal distribution (c) Clustered distribution

A major effect can be observed with regard to repositioning legs. The distance driven without load tends to decrease whenever the routing model can exploit synergies of integration resulting in two swap containers per truck and traveled edge. With an increasing R more AAR are generated, which can a) be planned in a multi-period way and b) benefit from integrated routing. AAR replace RAR which typically cause costly repositioning moves. These observations hold for all application scenarios considered, the effects however become more explicit with an increasing imbalance imposed by the problem instance.

5.2.3 Analysis of runtimes

The runtimes of AP-stochastic heavily depend on the recourse factor and the planning horizon. Because the planning horizon has a direct impact on the size of the scenario tree within model DSTP, CPLEX runtimes increase strongly with an increasing planning horizon. The second driver of the size of the scenario tree is the number of realizations, which is fixed to three in the experiments. The mean runtimes observed are depicted in Table 4. The fraction of the runtime used by CPLEX (DSTP) is given in brackets. Generally, a planning horizon of up to three periods does not result in a notable runtime of CPLEX due to a relatively small scenario tree leading to a small model size. The last two rows of Table 4 depict the number of constraints and variables of the transportation model DSTP. The model size growths rapidly with the number of periods of anticipation considered.

Table 4. Average runtimes over all network structures, request distributions and independent runs in seconds (CPLEX)

Recourse factor *R*	**Planning horizon**				
	1	**2**	**3**	**4**	**5**
0.0	10 (0)	12 (0)	20 (0)	58 (40)	166 (146)
0.2	10 (0)	12 (0)	20 (0)	47 (28)	159 (138)
0.4	10 (0)	13 (0)	20 (0)	48 (28)	161 (140)
0.6	10 (0)	13 (0)	21 (0)	47 (29)	169 (148)
0.8	10 (0)	13 (0)	19 (0)	49 (30)	175 (155)
1.0	10 (0)	28 (0)	44 (0)	76 (31)	200 (155)
1.2	10 (0)	48 (0)	64 (0)	96 (31)	220 (161)
1.4	10 (0)	53 (0)	69 (0)	100 (31)	228 (159)
1.6	11 (0)	54 (0)	72 (0)	101 (31)	238 (167)
1.8	11 (0)	58 (0)	74 (0)	104 (31)	240 (163)
2.0	11 (0)	60 (0)	74 (0)	105 (31)	242 (167)
Constraints	-	160	550	1,700	9,700
Variables	-	1,480	5,350	15,500	84,800

The impact of the recourse factor on the runtime depends on the tendency of deferring allocations to future periods. With increasing R, RAR are replaced by AAR to be routed together with TR in GPDP. Although LNS performs a fixed number of 250 exchange moves in every case, with increasing R the metaheuristic evaluates a more complex neighborhood that is more time consuming. We can conclude that anticipation by means of AP-stochastic works in general, but has to be paid by some extra computational effort.

5.3 Comparison of strategies

We expect that more efficient solutions can be obtained by anticipated planning in comparison to myopic planning. We have already seen that in AP-stochastic repositioning moves can be largely avoided. To some extent, synergies in routing can be exploited by the detouring and entrainment feature. In the following, we compare the results gained for AP-stochastic with MP, AP-deterministic and AP-expected. The experiment is performed as shown in Table 5.

Table 5. Experiment to compare myopic and anticipating planning approaches

Parameter	**Characteristic**	**Count**
Network	R101; C101; RC101	3
Distribution	uniform; normal; clustered	3
Strategies	MP; AP-deterministic; AP-expected; AP-stochastic	4
Instances		10
Number of runs		360

Its results observed are depicted in Table 6 for the four strategies in accordance to the application scenarios considered and the types of legs performed. The mean distance of the itinerary and the improvement against MP is given for the anticipating strategies. This experiment allows us to answer the three questions raised at the end of Section 1.3.

Huth and Mattfeld: *Myopic and Anticipated Planning in Stochastic Swap Container Management*
IJOR Vol. 8, No. 1, 3–22 (2011)

Table 6. Comparison of myopic and anticipating planning approaches for the SSCP

Types of leg	MP	AP-deterministic	AP-expected	AP-stochastic
Uniform distribution				
Transport	5,927	5,813	5,807	5,800
Repositioning	2,386	2,358	2,389	2,355
Entrainment	0	144	156	201
Anticipated alloc.	0	397	413	594
Repair allocation	516	0	199	19
Sum	8,829	8,712	8,964	8,969
Improvement		1.3%	-1.5%	-1.6%
Normal distribution				
Transport	5,523	5,352	5,336	5,226
Repositioning	3,090	2,099	2,162	2,044
Entrainment	0	268	286	344
Anticipated alloc.	0	1,946	2,352	2,193
Repair allocation	2,773	0	360	49
Sum	11,386	9,665	10,496	9,863
Improvement		15.1%	7.8%	14.4%
Clustered distribution				
Transport	9,291	9,202	9,294	9,190
Repositioning	8,502	3,717	3,485	3,534
Entrainment	0	101	80	134
Anticipated alloc.	0	5,610	7,369	6,859
Repair allocation	8,023	0	475	117
Sum	25,816	18,630	20,703	19,834
Improvement		27.8%	19.8%	23.2%
Overall				
Sum	56,815	46,706	50,248	48,289
Improvement		17.8%	11.6%	15.0%

5.3.1 Anticipation is advantageous

By comparing anticipating with non-anticipating solution approaches, we can state that anticipation is worth the effort. In general, anticipating approaches perform superior if the request distribution produces an imbalanced swap container fleet. The consideration of future demand situations and the integration of TR and AR result in benefits for the overall problem. As expected, the ex-post approach AP-deterministic outperforms all other approaches due to complete knowledge of future data. This serves as benchmark for the possible impact of anticipation. When considering stochastics, AP-stochastic performs almost as good as AP-deterministic whereas AP-expected does produce improvements over MP only. Altogether, the ranking can be stated as follows: AP-deterministic > AP-stochastic > AP-expected > MP.

5.3.2 Consideration of stochastics is beneficial

Stochastics may be incorporated in different ways; AP-stochastic is the most elaborate one. Is this complex approach worthwhile the effort spent?

As summarized in the last two rows of Table 6, the ex-post approach AP-deterministic with known realizations is not as dominant as may have been expected. Despite perfect information, AP-deterministic outperforms AP-stochastic by just a few percent. Although AP-stochastic may produce imperfect allocations, the subsequent routing model is capable of adopting the allocation solution which may be implemented for free or comparatively low priced. This observation is also shown at the bottom of the recourse factor analysis. Some additional AAR (higher value for R) does not necessarily lead to inefficient itineraries. On the contrary, RAR can be saved that are carried mostly on a direct way between supply and demand hub and a repositioning on the way back.

5.3.3 Advantages are confined to non-uniform distributions

The second question concerns different settings of request distribution. Results show, there is no solution approach that can be successfully applied to all settings.

Planning with *uniform* distributed requests does not induce many AR because of uniformly distributed empties. That is depicted in the allocation rows of Table 6. The MP approach shows a distance of 515 whereas allocations in AP approaches are between 397 and 612 units. Concerning only the allocations, anticipation is not beneficial with uniform distributed requests because of the minor potential of integration. In fact the variation against MP shows rather a deterioration of performance than an improvement.

For *normal* distributed instances, the variation against MP is convincing for all anticipating approaches. If expected values are used, the AA and RA exceed the corresponding legs of the other approaches. It seems that AP-expected overestimates the demand (AP-expected: 2.352; AP-deterministic: 1.946; AP-stochastic: 2.193) and moreover does not anticipate necessary allocations (AP-expected: 360; AP-deterministic: 0; AP-stochastic: 49). The more precise recourse model in AP-stochastic and the demand considered known in AP-deterministic outperforms the deterministic model with expected values because of these two types of legs. Other legs feature nearly the same distance.

Unlike this, *clustered* distributed instances show a lot of allocations to be made and consequentially longer overall distances. Here another interesting effect can be observed. Because of geographical separated regions, AAR are paired on their direct way from supply to demand hubs. Thus just a very few entrainments take place. However, the joint consideration of TR and AAR allows decreasing the number of repositioning moves. On one hand, full swap containers are transported from pickup to delivery hubs and on the other hand empties are balanced on the same way back. No extra repositioning moves need to be implemented.

5.3.4 Analysis of runtimes

The runtime of CPLEX does play a minor role only, because of the planning horizon of only two periods. Thus, the mean runtimes in Table 7 represent the effort of LNS that depends on the size of the considered request sets. MP does not integrate the routing decision, so both types of requests are routed separately whereby routes for a few RAR are calculated very fast. Longer runtimes of AP-stochastic are caused by the time to build the model and calling CPLEX from Java; the deterministic models in AP-deterministic and AP-expected consume less time (c.f. column uniform in Table 7). Normal distributed instances result in many AAR and so in longer runtimes of LNS. However, for normal distributed instances with clustered pickups and deliveries the mean runtimes decrease significantly. AAR produced in these instances are difficult to adopt from the routing model by pairing them with TR because of the spatial segmentation. LNS can barely improve the solution of the transportation model that leads to a fast convergence of the metaheuristic.

Table 7. Average runtimes of the approaches in seconds

Strategy	Uniform	Normal	Clustered
MP	15	14	12
AP-deterministic	31	75	26
AP-expected	30	85	25
AP-stochastic	55	93	25

6. CONCLUSION

The introduced Stochastic Swap Container Problem is a complex logistic problem and addresses tactical and operational issues in parcel transportation networks. Methods of solving this twofold problem in a myopic and anticipated way are proposed. The myopic solution approach performs inferior because of neglecting future allocations and missing integration effects. Anticipation is introduced in two ways on the tactical level (transportation model): We use 1) expected values and 2) probabilities in order to describe the demand of empty swap containers in future periods. As expected, the recourse model with more detailed information about stochastics outperforms the expected value transportation model. Primarily, the appropriate parameterization of the integration approach by adjusting the recourse factor of the transportation model makes a contribution to the good results by enabling an appropriate integration of TR and AR. Additionally, it could be shown that a dynamic stochastic transportation model does not benefit from anticipating events in the remote future.

Further attention may be put on more sophisticated methods of solving the models in order to transfer our findings on real world problems. Moreover, the principle integration ideas in a stochastic environment may be beneficial in similar problems like railway operations.

REFERENCES

1. Ahuja, R.K., Orlin, J.B. and Magnanti, T.L. (1993). *Network Flows: Theory, Algorithms & Applications*. Prentice Hall.
2. Angelelli, E., Speranza, M.G. and Savelsbergh, M.W.P. (2007). Competitive analysis for dynamic multiperiod uncapacitated routing problems. *Networks*, 49(4): 308-317.
3. Aronson, J.E. (1989). A survey of dynamic network flows. *Annals of Operations Research,* 20(1): 1–66.
4. Assad, A.A. (1987). Multicommodity network flows: a survey. *Networks,* 8(1): 37-92.
5. Bellmore, M., Eklof, W.D. and Nemhauser, G.L. (1969). A decomposable transshipment algorithm for a multiperiod transportation problem. *Naval Research Logistics Quarterly,* 16(4): 517-524.
6. Birge, J.R. and Wets, R.J.-B. (1986). Designing approximation schemes for stochastic optimization problems, in particular for stochastic programs with recourse. *Mathematical Programming,* 27: 54-102.
7. Chen, C. and Chen, S. (1993). A dynamic container allocation model. Tech. rep., National Chen Kung University, Taiwan.
8. Cheung, R.K. and Powell, W.B. (1996). An algorithm for multistage dynamic networks with random arc capacities, with an application to dynamic fleet management. *Operations Research,* 44(6): 951-963.
9. Chong, E. (1991). On-line stochastic optimization of queueing systems. Ph.D. thesis, Princeton University.
10. Choong, S.T., Cole, M.H. and Kutanoglu, E. (2003). Empty container management for container-on-barge (COB) transportation: Planning horizon effects on empty container management in a multi-modal transportation network. *National Transportation Library*.
11. Crainic, T.G. (2003). Long-haul freight transportation. R.W. Hall, ed., *Handbook of Transportation Science*. Kluwer Academic Publishers.
12. Crainic, T.G., Gendreau, and Dejax, M. P. (1993). Dynamic and stochastic models for the allocation of empty containers. *Operations Research,* 41(1): 102-126.
13. Ermoliev, Y. (1983). Stochastic quasigradient methods and their application in systems optimization. *Stochastics* 9: 1–36.
14. Ermoliev, Y. (1988). Stochastic quasigradient methods. Y. Ermoliev, R.J-B. Wets, eds., *Numerical Techniques for Stochastic Optimization Problems*. Springer, pp. 141-185.
15. Ford, L.R. and Fulkerson, D.R. (1958). Constructing maximal dynamic flows from static flows. *Operations Research,* 6(3): 419-433.
16. Ford, L.R. and Fulkerson, D.R. (1962). *Flows in Networks*. Princeton University Press.
17. Frantzeskakis, L.F. and Powell, W.B. (1990). A successive linear approximation procedure for stochastic, dynamic vehicle allocation problems. *Transportation Science,* 24(1): 40-57.
18. Gruenert, T. and Sebastian, H.-J. (2000). Planning models for long-haul operations of postal and express shipment companies. *European Journal of Operational Research,* 122(2): 289-309.
19. Hillier, F.S. and Liebermann, G.J. (2005). *Introduction to Operations Research*. 8th ed. McGraw-Hill.
20. Hitchcock, F.L. (1941). The distribution of a product from several sources to numerous localities. *Journal of Mathematics and Physics,* 20: 224-230.
21. Holmberg, K. (1995). Efficient decomposition and linearization methods for the stochastic transportation problem. *Computational Optimization and Applications,* 4(4): 293-316.
22. Huth, T. and Mattfeld, D.C. (2009). Integration of routing and resource allocation in a dynamic logistics network. *Transportation Research Part C: Emerging Technologies,* 17(2): 149-162.
23. Jaillet, P. and Wagner, M.R. (2004). Competitive and asymptotic analysis for online traveling salesman problems in euclidean space. Tech. rep., MIT.
24. Jaillet, P. and Wagner, M.R. (2006). Online routing problems: Value of advanced information and improved competitive ratios. *Transportation Science,* 40(2): 200-210.
25. Jaillet, P. and Wagner, M.R. (2008). Online vehicle routing problems - a survey. B. Golden, S. Raghavan, E. Wasil, eds., *The Vehicle Routing Problem*. Springer, pp. 221-238.
26. Kall, P. aand Wallace, S.W. (1994). *Stochastic Programming*. John Wiley & Sons.
27. Klein, M. (1967). A primal method for minimal cost flows with applications to the assignment and transportation problems. *Management Science,* 14(3): 205-220.
28. Klein, R.S., Luss, H. U. and Rothblum, G. (1995). Multiperiod allocation of substitutable resources. *European Journal of Operational Research,* 85(3): 488-503.
29. Krumke, S.O. (2001). Online optimization - competitive analysis and beyond. Ph.D. thesis, Technische Universitaet Berlin. Habilitationsschrift.

30. Nanry, W.P. and Barnes, W. (2000). Solving the pickup and delivery problem with time windows using reactive tabu search. *Transportation Research Part B: Methodological,* 34: 107–121.
31. Parragh, S.N., Doerner, K.F. and Hartl, R.F. (2008a). A survey on pickup and delivery models part I: Transportation between customers and depot. *Journal fuer Betriebswirtschaft,* 51(1): 81–117.
32. Parragh, S.N., Doerner, K.F. and Hartl, R.F. (2008b). A survey on pickup and delivery models part II: Transportation between pickup and delivery locations. *Journal Betriebswirtschaft,* 51(1): 21–51.
33. Powell,W.B. (1988). A comparative review of alternative algorithms for the dynamic allocation problem. B.L. Golden, A.A. Assad, eds., *Vehicle Routing: Methods and Studies*. Elsevier Science, pp. 249-291.
34. Powell, W.B. (2007). *Approximate Dynamic Programming: Solving the Curses of Dimensionality*. John Wiley & Sons.
35. Powell, W.B., Jaillet, P. and Odoni, A. (1995). Stochastic and dynamic networks and routing. M.O. Ball, T.L. Magnanti, C.L. Monma, G.L. Nemhauser, eds., *Network Routing, Handbooks in Operations Research and Management Science*, vol. 8. Elsevier Science.
36. Psaraftis, H.N. (1988). Dynamic vehicle routing problems. B.L. Golden, A.A. Assad, eds., *Vehicle Routing: Methods and Studies*. Elsevier Science, pp. 223-248.
37. Psaraftis, H.N (1995). Dynamic vehicle routing: Status and prospects. *Annals of Operations Research,* 61: 143-164.
38. Ropke, S. and Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science,* 40(4): 455–472.
39. Savelsbergh, M.W.P. and Sol, M. (1995). The general pickup and delivery problem. *Transportation Science,* 29(1): 17-29.
40. Solomon, M.M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations Research,* 35(2): 254-265.
41. Vladimirou, H. (1991). Stochastic networks - solution methods and applications in financial planning. Ph.D. thesis, Princeton University.
42. Wagner, H.M. (1969). *Principles of Operations Research*. Prentice-Hall.
43. Wets, R. (1982). Stochastic programming - solution techniques and approximation schemes. M.G.A. Bachen, B. Korte, eds., *Mathematical Programming - The State of the Art*. Springer, pp. 566-603.
44. White, W. and Bomberault, A. (1969). A network algorithm for empty freight car allocation. Tech. rep., IBM Systems Journal.
45. Wieberneit, N. (2008). Service network design for freight transportation: A review. *OR Spectrum,* 30(1): 77-112.