Dynamics of the Multi-Depot Pickup and Delivery Problem

Thomas Huth **Dirk C. Mattfeld**

Chair of Business Administration - Information Systems

Technical University Braunschweig

Abt-Jerusalem-Straße 4, 38106 Braunschweig, Germany

fax.: +49-531-391-8144, e.mail: t.huth@tu-braunschweig.de

May 15, 2007

Abstract

This contribution gives an introduction to an integrated vehicle routing and resource allocation problem. We refer to it as the Swap Trailer Problem and formulate the mathematical model. After the analysis of dynamic decision problems and the development of a framework for this problem, we highlight the dynamic aspect of the problem. Two different solution strategies are supposed. Special properties of these strategies lead to deliberations about degrees of freedom and their exploitation. This way, we propose sophisticated methods to solve the Swap Trailer Problem.

keywords: multi-depot multi-period pickup and delivery problem, resource allocation, swap trailer, model integration, multi-stage transportation problem

1 Introduction

We deal with a real-world routing and allocation problem. The allocation part of this problem comes from charge carriers, so called swap trailers, which have to be balanced within a network over time. Additionally, the swap trailers are used to transport items between hubs in the network. Our Swap Trailer Problem (STP) can be modeled as a generalization of Savelsbergh and Sol's General Pickup and Delivery Problem [SS95].

Because of the two regarded sub-problems, routing and allocation, an integrated view can be fruitful. A lot of literature is available for each of these problems. A recent contribution on pickup and delivery problems can be found in [PDH06a, PDH06b]. Some literature on empty container allocation are [CGD93, CC98, CCK02]. But the application of two independent models neglect possible synergies arising from an integrated view of these problems. Geoffrion provides some conceptional considerations concerning model integration, which can help understanding relationships between these problems [Geo89, Geo99]. Solution strategies can be found by deriving the appropriate conclusions from these relationships.

The outline of this paper is as follows. In Section 2, we focus on a real-world vehicle routing and swap trailer allocation problem (2.1) and provide a mathematical model (2.2). After this, we generalize this problem following the model of Minkoff [Min85] in Section 3. In order to get a solution for the dynamic, mutli-period version of the STP, we introduce the mathematical model of the tactical allocation sub-problem in Section 4. Section 5 presents some conclusions about the two strategies and their properties 5.2 by analyzing integration methods 5.1.

2 Problem Description

2.1 A Real-World Problem

Today, large parcel service providers operate in hub-and-spoke networks [GS00], [HM07b]. Customers are located in particular service regions and are assigned to hubs. We consider the daily hub to hub transports occurring between all hubs. Transports are performed by swap trailers, i.e. vehicle independent units comparable with containers, which have a standardized size and can be easily deposited. One transportation request is represented by one swap trailer. A trailer truck can transport at most two swap trailers, a sufficient number of swap trailers is available. Between every pair of hubs, one or more swap trailers are shipped by one or more trucks. Transports are performed by 3rd party carriers paid on the basis of transportation routes only.

One goal is the construction of routes, connecting hubs. Another goal is to provide swap trailers in a sufficient number at the hubs over time. Swap trailers have to be allocated according to the demand of the forthcoming periods, determined by the forecasted requests. To satisfy the demand at a hub, the currently available swap trailers minus outgoing requests plus incoming requests are considered. Additionally, deadheads may be required to meet the demand. The origin hub of deadheads is subject of selection by the parcel service provider.

Next to deadheads, our approach considers, empty swap trailers can be transported as a by-product in the calculated routes (if there is capacity available). Costly deadheads can be saved by detours and assignments of requests to trucks. This should minimize the overall traveled distance during routes and deadheads.

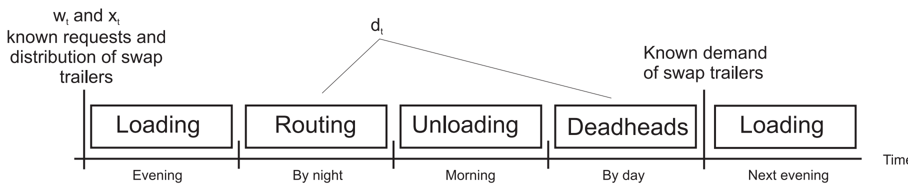

Figure 1: The Swap Trailer Problem in the course of time

This problem in the course of time is shown in Figure 1. The goals of the service provider are the minimization of traveled distances and the matching of availability and demand of swap trailers.

2.2 Model Building

This section provides the mathematical formulation of the STP. We introduce an adapted pickup and delivery model of Savelsbergh and Sol [SS95], to formulate the routing problem and integrate the allocation problem. This can be found in [HM07b].

The STP is defined on a graph G containing nodes N and edges E. All hubs are in N. A Request $a \in TA$ consists of a pickup Node R^+ and a delivery Node R^-. $R = R^+ \cup R^-$ and $R \subseteq N$. Requests of empty swap trailers (possible allocations to match the future demand) form the set TA_{empty} and requests of loaded swap trailers form the set TA_{load}. $TA = TA_{empty} \cup TA_{load}$. All possible deadheads are subject of the selection. The trucks $k \in K$ have an origin depot D^+ and a destination depot D^-. $D = D^+ \cup D^-$ and $D \subseteq N$.

The set of pickup and delivery locations are determined by the pickup and delivery nodes of all requests $R^+ := \bigcup_{a \in TA} R_a^+$ and $R^- := \bigcup_{a \in TA} R_a^-$. The needed capacity for a swap trailer is equal to one, decreases the available capacity of the trucks in pickup locations and increases the available capacity of the trucks in delivery locations $q_a = \sum_{i \in R_a^+} q_i = -\sum_{i \in R_a^-} q_i = 1 \;\; \forall a \in TA$. To ensure that each node starts and ends in arbitrary nodes, each node is associated with a depot. The origin depots of trucks are located in the origin Node k^+ and the estination depots are located in the destination Node k^-. This can be described as follows $D^+ := \{k^+ | k \in K\}$ and $D^- := \{k^- | k \in K\}$. Different binary decision variables have to be introduced. Sequence decision variable

x_{ij}^k holds if Truck k travels from Node i to Node j. Selection decision variable y_a holds if Request a is accepted for routing and Vector y finally forms the request set to be routed. Assignment decision variable z_a^k holds if Request a is assigned to Truck k.

Now, the model can be formulated as follows:

$$\sum_{i \in R \cup D} \sum_{j \in R \cup D} \sum_{k \in K} x_{ij}^k c_{ij} \to \min! \tag{1}$$

subject to:

$$\sum_{k \in K} z_a^k = 1 \qquad a \in TA \tag{2}$$

$$\sum_{j \in R^+ \cup D^-} x_{k^+ j}^k = 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{i \in R^- \cup D^+} x_{ik^-}^k = 1 \qquad \forall k \in K \tag{4}$$

$$\sum_{i \in R \cup D} x_{li}^k = \sum_{i \in R \cup D} x_{il}^k = z_a^k * y_a \qquad \forall l \in R_a^+ \cup R_a^- \ ; \ a \in TA \ ; \ k \in K \tag{5}$$

$$d_p \leq d_q \qquad \forall p \in R_a^+, q \in R_a^-, a \in TA \tag{6}$$

$$x_{ij}^k = 1 \Rightarrow d_i + t_{ij} \leq d_j \qquad \forall i, j \in R \cup D, k \in K \tag{7}$$

$$d_{k^+} = 0 \qquad \forall k^+ \in D^+ \tag{8}$$

$$d_i \geq 0 \qquad \forall i \in R \cup D \tag{9}$$

$$x_{ij}^k = 1 \Rightarrow l_i + q_i = l_j \qquad \forall i, j \in R \cup D, k \in K \tag{10}$$

$$0 \leq l_i \leq 2 \qquad \forall i \in R \cup D \tag{11}$$

$$\sum_{a \in TA} e_{ab} y_a = 1 \qquad \forall b \in T \tag{12}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall i, j \in R \cup D, k \in K \tag{13}$$

$$y_a \in \{0,1\} \qquad \forall a \in TA \tag{14}$$

$$z_a^k \in \{0,1\} \qquad \forall a \in TA, k \in K \tag{15}$$

The objective function is the minimization of the total traveled distance of all trucks between request and depot nodes with the distance coefficient c_{ij}. A Request a is assigned to exactly one Truck k (2). Origin and destination node of Truck k are the depots (3 and 4). Furthermore, a truck does not drive if there is a direct connection between depots or no request is assigned to this truck. (5) ensures, that a Truck k leaves or enters a Node l if an request exists (y_a and z_a^k hold).

The auxiliary variable for time balance d_i describes the exact point of time in which Node i is visited. The departure time at the pickup Node p is greater or equal to the arrival time at the corresponding delivery Node q (6). The time at pickup Node i plus travel time t_{ij} between i and j results in the arrival time at Node j (7). The next constraints set up start time to zero and prevent negative times at every node (8 and 9).

The auxiliary variable for load balance equation l_i maps the used capacity at Node i. Equality (10) ensures, that the load at Node i plus the request at Node i is equal to the load at Node j if the edge between these nodes is traveled. All loads must be less or equal two, the trucks capacity. Negative loads are not permitted (11).

e_{ab} is the set partitioning matrix with all necessary tasks $b \in T$ to fulfill the load requests and to satisfy the demand of empty swap trailers. All requests $a \in TA$ can fulfill at least one of these tasks. The transport of empty swap trailer to the demand node is possible from more than one node in the hub network. Because of the bijective relationship between a and b in a load request, there is only one possibility to chose y_a. In contrast, the set partitioning constraints (12) prohibit selecting more requests with empty swap trailers than needed. The constraint ensures, that each task $b \in T$ is fulfilled exactly once. The calculation of costs captures the pickup and delivery model. Therefore, an extra objective function is not needed. Finally, the result will be detours in routes to take along empty swap trailers.

Additionally, there is more than one request (swap trailer) per node. We have to adapt the model to incorporate this property. The most basic way is the insertion of virtual nodes. These nodes will be located at the same coordinates and must be integrated for every extra request at the same node. This can be achieved with an enlargement of the distance matrix. Connections between nodes have to be rated on the basis of their coordinates. The distance matrix can be adapted to incorporate precedence constraints. Basically, one may forbid direct connections between delivery nodes and pickup nodes of the same request and in this sequence. In a preprocessing step, these distances can be set infinite.

Because the depot locations and the request locations are within the hubs, we must adapt the distance matrix once again. In this way, a model adaptation can be avoided. Every hub can be a depot and a request node. Distances are calculated and are preprocessed as follows:

- 0 if the depot is located at the coordinates of pickup or delivery node
- ∞ between depots
- ∞ between pickup and depot and between depot and delivery
- ∞ if Node i = Node j

The introduced pickup and delivery model is now able to operate with this data structure. Hence, as a consequence of the distance matrices and the model, for one request we need two hubs and one truck. Because we consider a carrier with a sufficient number of trucks, one truck in every pickup node of a request is needed and every truck has two depots.

3 Dynamic Decision Problems

This section generalizes the above sketched problem as a dynamic decision model according to [Min85]. Altered problem characteristics like infinite decision horizon, rolling planning horizon, problem updates, and so on, can be found in Psaraftis [Psa88, Psa95]). Such a model consists of a sequence of system states x_t (position of the swap trailers and information about the hubs) and decisions or state transitions d_t (routing and deadheads). Additionally there are exogenous factors w_t (e.g. requests) which are not influenced by the planner. Figure 1 shows the incorporation of these components into the problem specific context.

Because of the rolling planning horizon, a description of the system progress is needed. The state x_{t+1} is the functional value of the state, the decision and the exogenous factors in t (17). f_t is the transition function which updates the state of the system. A decision depends on the planners model based decision function D_t (18).

In the dynamic case, time horizons are typically infinite. A sub-problem is described by a state, a decision and the exogenous factors within a certain time. The expectation of the objective function value of g with subject to the external factor w_t will be minimized. We have to choose the right d_t to support this goal.

$$min_{d_t}\ E_{w_t}\left[g(x_0, d_0, w_0, x_1, d_1, w_1, ...)\right] \tag{16}$$

subject to

$$x_{t+1} = f_t(x_t, d_t, w_t) \tag{17}$$

$$d_t = D_t(x_t) \tag{18}$$

Figure 2 illustrates interactions between the mentioned components of the decision problem in the framework. External events (w_t) are taken up from the component ‘Dynamic’ in combination with data from the real or rather object world (x_t). The tasks of the ‘Control element’ are updating the state of the system and coordinating the function of all components. This includes choosing the adequate solving procedure which is the transition function f_t. What we call 'Model' is the model based decision function of the planner. This function is independent of the above introduced goal of dynamic problems.

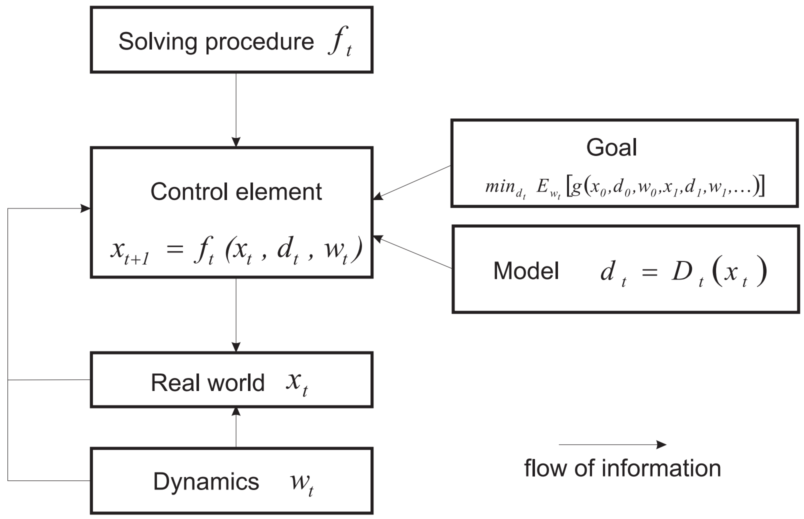

Figure 2: A framework for dynamic decision problems

The key issue of an approach for solving dynamic decision problems is how to address this goal and how to deal with dynamics. There are different approaches to integrate dynamics in vehicle routing problems. Each approach tackles the problem in another way by adapting the model D_t or the solving procedure f_t. A comprehensive overview, how to solve dynamic vehicle routing problems can be found in [HM07a].

In the described STP, the dynamic comes from the multi-period property. The allocation problem for empty swap trailers can be solved by the routing solution. This means interdependencies between decisions on the tactical and operational level. A current decision for the routing problem has an unpredictable impact on the allocation sub-problem in future periods. The same holds the other way. Thus, a perfect anticipation of future decision can not be made and we get a dynamic problem.

The sub-problems are deterministic and the objective function can be the minimization of the routing distance. An expectation term in the objective function and the component 'Dynamic' is not needed. This way, the long-term decisions about allocation of empty swap trailers are neglected. Though the allocation for the next period is taken into account, this must not be the right decision in the long run. Consequently, we have to introduce a different goal for the problem in a single period than for the overall problem. This means, the 'Goal' in the framework is not the goal of the decision maker coded in the model D.

Hence, the question is, how the STP can be solved. One possibility is the usage of the static model presented in Section 2.2. The single period problem is solved repeatedly in a rolling planning horizon. But this proceeding neglects the findings of the last paragraph. A more sophisticated method is the integration of tactical knowledge from the allocation problem. Thus, we have to formulate a adapted transportation problem and integrate that's results in the operational routing model. So, there is no need to adapt the model of the STP.

4 Capacitated Multi-Stage Transportation Problem

The above introduced model can be applied to a rolling planning horizon in order to meet the requirements of a multi-period environment. However, effects of balancing deadheads between periods cannot be achieved this way. Therefore, we propose a coarse-grained model for allocation decisions [Bel58, Pow03].

Within a multi-period environment demand at all nodes and in all periods has to be determined. This is achieved by a multi-stage transportation model and is exemplary given in the time-space network in Figure 3. In order to balance workload and to receive deadheads connecting nodes over more than one period, a capacity constraint for ton-kilometer (routing and deadheads) per period is necessary. This can be achieved with a deadhead from Node 2 to Node 1 in Period 1, so the capacity constraint in Period 2 holds (Figure 3).

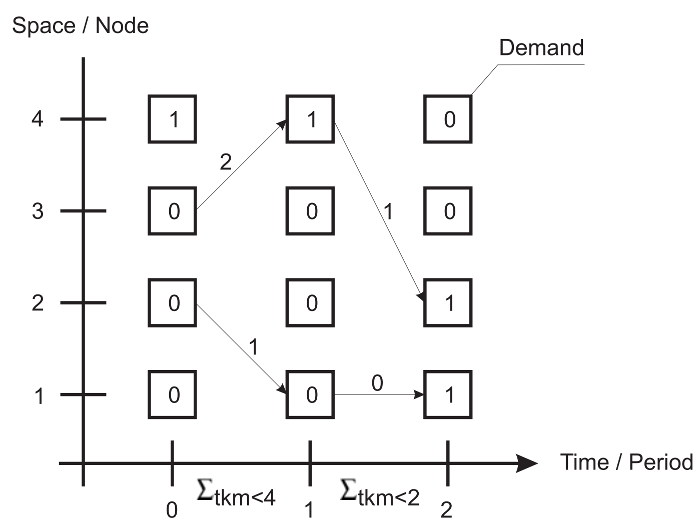

Figure 3: Time space network for the allocation problem

Special properties of the considered transportation model compared to Hitchcock-Koopmans transportation problem are:

- There can be more supply than demand. A dummy-node or an adapted balancing constraint can overcome this.
- All nodes can be origins and destinations of swap trailers.
- Because of the multi-period property, additionally all nodes can be transshipment nodes.
- There are capacity constraints for swap trailers which can be shipped in one period.

In order to cope with these properties, we need the distance matrix, that is given in Table 1 with the following explanations. A value of 0 means no transport respective a transport between these nodes is waiting time. c_{ij} are euclidean distances between Node i and Node j. If Node i = Node j, the footnote (a) is added. The value with footnote (b) leads to no connection between nodes in the same period. Because of the values marked with footnote (c) no transportations back in time are possible. Finally, the (d)-flag prohibit transportations over more than one period without a transshipment node.

Table 1: Distance matrix of the transportation problem

$node_{period}$	1_1	2_1	1_2	2_2	1_3	2_3
1_1	$\infty^{(a)}$	$\infty^{(b)}$	0	c_{12}	$\infty^{(d)}$	$\infty^{(d)}$
2_1	$\infty^{(b)}$	$\infty^{(a)}$	c_{21}	0	$\infty^{(d)}$	$\infty^{(d)}$
1_2	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(a)}$	$\infty^{(b)}$	0	c_{12}
1_2	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(b)}$	$\infty^{(a)}$	c_{21}	0
1_3	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(a)}$	$\infty^{(b)}$
1_3	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(c)}$	$\infty^{(b)}$	$\infty^{(a)}$

In Period 1 the demand has to be zero because there is no period before to deliver nodes. A Node i in one period has a certain supply a_i and demand b_i. In order to avoid a second index, we can copy the nodes. After this, they can be numbered consecutively. Nodes with the same location but different demands and supplies in different periods form the set of nodes for the transportation problem.

$$\sum_{i\in N}\sum_{j\in N} x_{ij}c_{ij} \rightarrow \min! \tag{19}$$

subject to:

$$-\sum_{h\in N} x_{hi} + \sum_{j\in N} x_{ij} \leq a_i - b_i \qquad \forall i \in N \tag{20}$$

$$\sum_{i,j\in N} x_{ij} \leq 2 \qquad \forall i,j \in N \tag{21}$$

$$x_{ij} \in 0,1 \qquad \forall i,j \in N \tag{22}$$

The balancing constraint in (20) ensures that the demand at Node i is fulfilled by qualified (with respect to other constraints and the distance matrix) supplier nodes. Predecessor nodes (in a time manner) have to have a sufficient supply of swap trailers. The capacity constraint in (21) ensures the transport of less or equal than 2 swap trailers at once. x_{ij} are the binary decision variables (22).

The solution on this tactical level for the next period goes into the above swap trailer model. We have to distinguish four different types of requests in the solution of the swap trailer model.

1. Load requests of the next period TA_{load} which must be fulfilled.
2. Requests of empty swap trailers in TA_{empty} which are needed for demand in the next period. Deadheads must be realized for these requests.
3. Requests of empty swap trailers in TA_{empty} which can be transported without deadheads. These are requests, carried on trucks in unity with load requests TA_{load}.
4. Requests of empty swap trailers in TA_{empty} which are needed in a forthcoming period but nut in the next period.

In case of non-deterministic events, like mentioned in Minkoff's model, these requests have to be treated in different ways.

5 Properties of the Model Integration Approach

5.1 Model Integration Analysis

As described in Section 3, we solve the introduced STP by model adaptation. Therefore, the tactical problem and the operational problem have to be integrated. Geoffrion distinguishes between two types of integration: deep integration and functional integration [Geo89, Geo99]. Reasons for model integrations are the consolidation of management functions, cooperation between companies and the consideration of different goals on different decision levels (operational, tactical, strategic) [GP95, Geo99]. In our STP, there are two decision levels, the tactical allocation decision and the operational routing decision. Furthermore, the goal of the allocation is to match the demand of swap trailers, the goal of the routing is to minimize the traveled distance. The consolidation of these management functions in one model and the collaboration with the carrier should create synergies and a benefit for the overall problem.

Deep integration combines two models and creates a new one. This new model must describe the two problems like the two separate models before. The advantage of the simultaneous treatment of the two problems is the global optimal solution. We have introduced a deep model integration approach with the swap trailer model. The allocation problem (actual a transportation model) is modeled as a set partitioning problem. The selection decision concerning origins of empty swap trailers is represented by this term and connected with the pickup and delivery model by constraint (5). The tactical decision is done by the operational model and provides synergies (extra degrees of freedom). A weakness of this approach is the absence of tactical knowledge. The swap trailer model only considers routing and allocation aspects in a single period.

Functional integration approaches use the given models for every single problem and combine them by a coordinating mechanism. This is a formal description of the sequence and the information exchange relationships between the models. Mostly the output of one model is the input of the other model. The idea for the STP is: Fruitful tactical knowledge can be integrated into the operational routing decision by hierarchical decision making. In our case, the selection of origin-destination pairs for the allocation of empty swap trailers is the output of the transportation problem described in Section 4. The swap trailer model (without the set partitioning formulation and the model connector) gets the input from the transportation model. So, the set of transportation requests is enlarged by new requests concerning these empty swap trailers. The solution of the routing problem becomes the initial situation of the transportation problem of the next period. Such a procedure is needed by a functional integration approach.

As well as the deep integration, the functional integration has a weakness. Preceding the selection decision, functional integration loses the synergies available in the swap trailer model with deep integration. The routing decision is not made with the degree of freedom provided by the selection. However, we achieve another synergy, the tactical knowledge or rather the demand of further periods are used in the operational decision making. The next subsection provides some ideas, how we can overcome the weaknesses of the deep and the functional integration approach.

5.2 Ideas to Overcome Integration Weaknesses

The following observations can be made. Both integration approaches address the balancing and selection decision in the STP. Either the allocation or the routing decision is neglected by one of the approaches. An evaluation of certain issues can be made as follows:

- The balancing of empty swap trailers is solved by the transportation model to optimality. Because of the multi-period consideration, we get the best allocation decision in each point in time. The one-period view of the swap trailer model neglects further periods and cannot make an optimal decision for the whole planning horizon.
- Selection of origin-destination nodes is an operational issue. Therefore, the swap trailer model with the set partitioning formulation takes advantage of the synergies of our deep integration approach. A transportation model selects origin-destination pairs only on a direct node-to-node connection basis. Within a routing model, these are not the true costs and the solution of the combined problem will be falsified.

The question is now: How can we adapt the solution procedure or the models to overcome these weaknesses? Two possible answers are given below.

In **deep integration** future requests can be anticipated by model adaptation on the operational level. Knowledge of the distribution of swap trailers can be introduced in the swap trailer model. We give more attractiveness to solutions creating a certain distribution of swap trailers at the end of the period. This can be done by adding extra constraints (forbid not suitable solutions and shrink the solution space) or adapting the objective function (reward/penalize solutions). In order to respect the heuristic approach of this distribution assumption, we recommend the objective function trade-off between distance term and distribution term. The latter term can be provided measuring the deviation of the wanted distribution. Afterwards, both terms must be normalized because they are not naturally connected.

Within the **functional integration**, a sensitivity analysis with the solution of the transportation model can be made. As an output, such a sensitivity analysis can provide borders in which a certain plan is still optimal. Other usefull information are different plans with a similar rating but different selections of origin-destination pairs for the distribution of empty swap trailers. The OD pairs of all these (similar rated) plans are the input of the swap trailer model. A final selection is done by the set partitioning formulation on the operational level based on this degree of freedom. So the synergies of the deep integration approach can be exploited without full lost of tactical knowledge.

The two sketched ways of solving the STP have advantages and disadvantages. The discussion of the solution approaches and their properties leads to an open question. We face the choice - which is the more promising strategy. Only a computational study with different scenarios can answer this question.

6 Conclusion

This paper introduces an integrated vehicle routing and resource allocation problem. In a multi-period situation, the problem becomes dynamic. One may deal with these dynamics by hierarchical decision making or neglecting the changed situation. Therefore, a deep integration and a functional integration strategy are developed. Both strategies induce advantages and disadvantages.

The swap trailer model can be solved up to six requests, so real-world instances are not computable. Compared with this, it is possible to solve problem instances up to 750 nodes with the proposed transportation model. Thus, a problem with 30 nodes and 25 periods can be tackled. That implies, different settings of solution methods for the two strategies are possible.

1. For deep integration, which means the single period problem is solved repeatedly in a rolling planning horizon, a metaheuristic is needed.

2. For functional integration, which means a hierarchical approach, the transportation problem can be solved to optimality and the following routing decision is made by a metaheuristic (successive approach). Another option is a heuristic selection of OD pairs within the metaheuristic (simultaneous approach).

After the development of benchmark instances, the three settings of solution methods will be tested and compared. As a next step, the proposed ideas concerning the weaknesses of these strategies will be put into praxis. Finally, the impact of dynamic and stochastic requests will be investigated.

References

[Bel58] R. Bellman. Notes on the theory of dynamic programming - transportation models. *Management Science*, 4(2):191–195, 1958.

[CC98] R.K. Cheung and C.-Y. Chen. A two-stage stochastic network model and solution methods for the dynamic empty container allocation problem. *Transportation Science*, 32(2):142 – 162, 1998.

[CCK02] S.T. Choong, M.H. Cole, and E. Kutanoglu. Empty container management for intermodal transportation networks. *Transportation Research Part E*, 38:423–438, 2002.

[CGD93] T.G. Crainic, M. Gendreau, and P. Dejax. Dynamic and stochastic models for the allocation of empty containers. *Operations Research*, 41(1):102–126, 1993.

[Geo89] A.M. Geoffrion. Integrated modeling systems. *Computational Economics*, 2(1):3–15, 1989.

[Geo99] A.M. Geoffrion. Structured modelling: Survey and future research directions. *Interactive Transactions of ORMS*, 1999.

[GP95] A.M. Geoffrion and R.F. Powers. Twenty years of strategic distribution system design: An evolutionary perspective. *Interfaces*, 25(5):105–127, 1995.

[GS00] T. Grünert and H.-J. Sebastian. Planning models for long-haul opertions of postal and express shipment companies. *European Journal of Operational Research*, 122(2):289–309, 2000.

[HM07a] T. Huth and D. Mattfeld. Dynamische Tourenplanung - Problemformulierung und Literaturüberblick. In *submitted to Logistikmanagement*, 2007.

[HM07b] T. Huth and D.C. Mattfeld. Integration of routing and resource allocation in dynamic logistic networks. In *submitted to International Conference on Dynamics in Logistics*, 2007.

[Min85] A.S. Minkoff. *Real-time dispatching of delivery vehicles*. PhD thesis, Massachusetts Institute of Technology, 1985.

[PDH06a] S.N. Parragh, K.F. Doerner, and R.F. Hartl. A survey on pickup and delivery models part i: Transportation between customers and depot. Technical report, University of Vienna, 2006.

[PDH06b] S.N. Parragh, K.F. Doerner, and R.F. Hartl. A survey on pickup and delivery models part ii: Transportation between pickup and delivery locations. Technical report, University of Vienna, 2006.

[Pow03] W.B. Powell. Dynamic models of transportation operations. In A.G.de Kok and S.C. Graves, editors, *Supply Chain Management: Design, Coordination and Operation*, volume 11 of *Handbooks in Operations Research and Management Science*, pages 451–516. Elsevier Science Publishers B.V., 2003.

[Psa88] H.N. Psaraftis. Dynamic vehicle routing problems. In B.L. Golden and A.A. Assad, editors, *Vehicle Routing: Methods and Studies*, pages 223–248. Elsevier Science Publishers B.V. (North Holland), 1988.

[Psa95] H.N. Psaraftis. Dynamic vehicle routing: Status and prospects. *Annals of Operations Research*, 61:143–164, 1995.

[SS95] M.W.P. Savelsbergh and M. Sol. The general pickup and delivery problem. *Transportation Science*, 29(1):17–29, 1995.