

Chapter 2

Transport Processes and Uncertainty

This chapter addresses the management of transport processes in volatile environments. In particular, we analyze how the supply consortium coordinator agent and the fleet management agent can be integrated despite the contradicting objectives concerning the planning of transport operations.

We start with a classification of different types of decision problems and decision models (Section 2.1). In particular, we explain the differences between a static and a dynamic decision problem. Generic approaches for mapping the uncertainty (related to dynamic decision situations) into formal decision models are presented and classified.

Demand peaks are a major source of transport process disturbance. A compilation of approaches to cope with this specific interference is presented in Section 2.2. We investigate whether demand peak management concepts for production scenarios can be transferred to transportation planning.

In order to prepare the setup of a simulation study of a transport process planning scenario in a volatile environment, we introduce a specific planning problem in Section 2.3.

2.1 Formalization of Uncertainty within Decision Problems

A decision problem P is called *static* if it can be solved completely at one time point t_0 (Sellmaier, 2007). In all other cases, a decision problem is called a *dynamic problem* or an *online (decision) problem*. Such a decision problem is characterized by the need for repeated decision making and decision revision at consecutive times $t_1, t_2, \dots$ (Brehmer, 1992). Consequently, a dynamic decision problem P can be expressed as a sequence $P_0, P_1, \dots$ of static decision problems. The decision problem P_{i+1} represents P_i enriched by the additional data acquired between time t_i and time t_{i+1} . A dynamic decision problem is referred to as *real-time decision problem* if the time to re-compute a solution (deliberation time) of the instance P_i of the online problem is limited (Séguin et al., 1997). Decision problems are often dynamic

because decision-relevant information is missing at a decision time t_i (Lund et al., 1996). Typically, decisions made at time t_i have impacts on to the decision alternatives available in later decision situations (Bussemeyer, 2001). If the appearance of future events can be approximated by probability distributions then a dynamic decision problem is called a *Markov Decision Process* (Littman et al., 1995). The portion of information revealed after the initial decision time t_0 is expressed by the *degree of dynamism* (Larsen et al., 2008; Lund et al., 1996).

In transportation logistics, dynamic assignment problems (McKendall Jr. and Jaramillo, 2006; Fleischmann et al., 2004b; Mitrović-Minić et al., 2004; Pankratz, 2002; Powell and Cheung, 2000; Lund et al., 1996; Powell, 1996; Madsen et al., 1995) as well as combined dynamic vehicles routing and scheduling problems (Rego and Roucairol, 1995) are major research fields. Furthermore, dynamic emergency team relocation problems (Rajagopalan et al., 2008) are in the focus of scientific interest. Surveys on the differences between static and dynamic vehicle deployment problems are given in (Psaraftis, 1995, 1988). If all data that are considered for the definition of the decision problem P are assumed to be given then P is called a *deterministic* (Illa, 1966) decision problem, otherwise P is named *non-deterministic* (Munera, 1984).

Let M be a decision model for the decision problem P . The model M is called a *static model* if the realization time of a decision is irrelevant for the feasibility and the evaluation of the decision (Saéz et al., 2008; Sellmaier, 2007). The mixed integer linear program formulation of the traveling salesman problem (Garfinkel, 1985) is a representative example for a static model: Only the originating and the terminating node determine the costs for traveling along an arc but not the time when the arc is traversed. If a model M is not a static model then M is called a *dynamic model* (Sellmaier, 2007) that is applied if e.g. capacity availabilities or realization costs alter over time. Dynamic optimization models are used to represent routing tasks if time or costs to pass through roads or paths alter over time (Moreira et al., 2007; Potvin et al., 2006; Fleischmann et al., 2004a; Ichoua et al., 2003). Other applications of dynamic models comprise (among others) core control in computer sciences (Ramamritham and Stankovic, 1994) or machine scheduling (Seiden, 1996). If uncertain data are described by probability distributions then M is called a *stochastic decision model* (Laux, 1982). Let M_i denote a decision model for the instance P_i of an online decision model. The sequence of decision models $M_0, M_1, \dots$ is called an *online decision model* for the online decision problem $P_0, P_1, \dots$.

2.2 Operational Management of Peaks in Transport Demand

The generated transport processes specify the transport services to be carried out. Pickup locations, delivery locations, quantities to be moved and operation times are determined so that the deployed transport resources are used with highest efficiency. However, the completion of the processes is in danger of being compromised

by uncertainty resulting from the occurrence of unforeseen events (e.g. additional requests) as discussed above.

Independent of the type of uncertainty, the incomplete knowledge of the complete and exact planning makes the planning of transport processes more difficult. During a decision making process the degree of uncertainty (e.g. event probabilities) has to be considered in the evaluation of decision alternatives. In addition, strategies to manage events that have not been expected but which nevertheless have been appeared have to be available in order to ensure that the operations remain running even under unexpected circumstances. In this section, we direct our interest to concepts discussed to ensure that a transport process planning remains effective even if a significant workload increase suddenly happens as a result of capacity uncertainty. A specific situation is investigated in which not only the time and location of the additional requests but also the number of additional requests released at a certain time is unknown in advance. Actually, a balanced stream of requests, regularly entering the request pool, is enriched by a temporary workload peak that begins at a previously unknown time and lasts over an unknown period. During the peak period, the number of incoming requests at a certain time is significantly higher than before or after the peak period.

If the capacity of the available transport resources is already exhausted by the so far known requests then the additional requests cannot be integrated into the processes. The flexibility of the processes is in danger of being decreased (Schönberger and Kopfer, 2009c), which means that the probability for serving the additional requests in compliance with customer time window requirements runs the risk of being decreased, too.

Obviously, the reservation (blockage) of *emergency capacity* for the vehicles belonging to the controlled fleet supports the compensation of workload peaks. However, two aspects compromise this remedying idea. (i) The additional resources are not profitable during off-peak periods. Therefore, it is not possible to maintain such an extra capacity over a longer period. (ii) If none of the vehicles with emergency capacity is located in the nearer surrounding of the request-associated location(s) then reserving additional capacity only for peak situations is futile.

How to cope with an overloading of the own fleet? The acceptance and exploitation of shortfalls and under-capacity situations is proposed (Zäpfel, 1982) but, due to the currently customer-dominated transportation market, not enforceable. Also temporal staffing arrangements (temporary workers) (Kalleberg et al., 2003; Zäpfel, 1982) cannot remedy transportation capacity bottlenecks since additional vehicles must be available, too. Additional deliveries and postponement are also proposed (Zäpfel, 1982) but, again, not applicable in freight transportation logistics with supply function. In-time and complete deliveries are unconditional necessary in order to keep the process performance on a high level. Deferred deliveries corrupt the flow of goods through the value creation stages. The spatial pre-distribution of deliverable goods over the operations area and a pre-loading of trucks is proposed and evaluated in Calza and Passaro (1997). However, these approaches are very capital-intensive. Pre-peak resource build-ups (Ronen et al., 2001) are also impossible since the peak occurrence is not predictable and transport services cannot be

stored. These previously mentioned strategies to mitigate the negative impacts of demand peaks have their origin in production management and exploit the special conditions in this sector. In particular, the significant larger geographic extent of transportation networks prevents the ad-hoc short-term re-allocation and increase of transport resources. For this reason, the strategies successfully applied in production applications within factories or concentrated locations cannot be transferred into the area of goods transportation.

Instead of holding or blocking a certain amount of capacity constantly in readiness, a temporal and demand-oriented provision of additional transport capacity is preferable (external procurement, third party supply, externalization). LSPs (External forwarders or transport service providers) are incorporated in order to execute selected requests (subcontracting). The LSPs provide capacity in their transport resources (e.g. vehicles). Thus, the intensification of the usage of the subcontracting cluster in transport resource dispatching is the preferred activity to achieve a quick capacity expansion in response to a beginning demand peak. As a consequence, high service reliability is ensured even during a demand peak disturbance.

In order to ensure that the subcontracting opportunity is available whenever and wherever it is needed, a consortium coordinator sets up and maintains longer term contracts with one or more transport service providing companies (the LSPs). Their transport networks cover the considered area of service (Ronen et al., 2001). The set up contracts specify the provided capacities and the fees which are paid to the service providers. A survey on subcontracting arrangements can be found in (Kopfer and Krajewska, 2007).

With respect to the incorporation of LSPs in transport request fulfillment, we make the following assumptions for the sequel of this research.

- The fleet managing agent and a sufficiently large number of logistic service providers have agreed respective contracts on a request-oriented base (Krajewska and Kopfer, 2008; Kopfer and Krajewska, 2007). According to such a contract, each single request can be given to an LSP. The fleet managing agent has to decide which requests are subcontracted.
- Only one LSP can be chosen to fulfill a certain request so that no provider selection becomes necessary for the fleet manager. Immediately after a request has been transferred to the corresponding LSP the service provider starts with the execution of the request and ensures a timely fulfillment.
- We refrain from explicitly considering preparation or setup times for incorporating an LSP.
- A previously fixed fee is paid by the coordinator agent to the LSP for each selected request.

The contracts with the LSPs secure the fleet manager agent an opportunity to make use of the resources of the LSP immediately if necessary. Thereby, the fleet managing agent has the *right but not the obligation* to choose LSP services. For this reason, the externalization (subcontracting) of a request in the context of the aforementioned contracts is interpreted as an *option* (Wöhe, 1993). The supply consortium (by means of the fleet managing agent) is enabled to exert this option at any

time during the duration of the contract (*American option*). It is possible that such an option remains unused. The price for exercising the option is fixed at the time when the contract is signed (*call option*) as explained in Black and Scholes (1973).

Prices to be paid to the LSP in case those options are used are quite high, because the prices must include the costs for hedging the LSP's risk that the fleet-manager does not exercise an option. If both the own fleet and the options are available then the first mentioned alternative would be preferentially selected by the fleet manager. However, if the own resources are exhausted then the higher LSP-fee is justified and acceptable because the timely request execution supports the goal to keep the quota of reliably completed customer orders high.

2.3 A Dynamic Vehicle Routing Problem with Subcontractor Options

We want to study the impacts of a demand peak on transportation processes within simulation experiments. Therefore, we introduce a specific dynamic transport process planning scenario. The environment in which the planning decisions are made is outlined in 2.3.1. Next, the goals and interests of the involved agents and proposals for the consolidation and integration of the aims are discussed (2.3.2) and the planning task of the transport service agent is described (2.3.3). We conclude the scenario introduction with the description of the generation of parameterizable artificial test instances for the described scenario (2.3.4).

2.3.1 General Scenario Outline

We assume that the supply consortium coordinator has agreed a contract with a customer. This customer specifies demand and submits this demand irregularly and at unpredictable times to the coordinator. Immediately after the reception of the demand, the coordinator specifies the consortium orders and inserts the generated orders into the order pools of the involved service agents.

In order to enable the supply consortium to execute the necessary transport of goods between the partners, the coordinator sets up a temporary contract with one (and only one) transport service partner (service agent). The transport service agent receives a certain amount as a budget. From this budget it has to pay its costs for fulfilling the necessary transport orders (travel expenditures and fees to be paid for subcontracted shipments). The difference between the overall budget and the request fulfillment costs remain as profit at the service agent.

According to the contract between the customer and the coordinator a service degree is fixed, e.g. a given percentage p^{target} of the customer's transport demand has to be fulfilled within the customer specified time restrictions. The current process punctuality rate p_t is defined by $p_t := \frac{f_t^{punc}}{f_t}$ (representing the current reliability

of the transport system). There are f_t requests whose completion times (already realized or scheduled) fall into the period $[t - 500, t + 500]$ (moving time window). Among these f_t requests the number of f_t^{punc} requests is completed within the previously agreed time windows. If the reliability requirement is met then the quotient p_t must not fall below the threshold value p^{target} . This quota can be explained as follows: Each demand comprises goods necessary to keep the production processes at the customer's factories running and goods used to build up security stocks. The first kind of goods must be provided in time while the second kind of goods can be delivered later without causing corruption of the running production processes.

For the reason of simplification, we assume that each transport order is an executable task. Hence, neither capacity nor temporal nor loading conflicts occur and each transport order is copied into the request pool of the transport service agent immediately after the order has been inserted into the order pool. A request instructs a transport resource to visit a given location during a customer specified time window. Examples, in which such a kind of request occur are related to situations in which a large number of small-sized packages is loaded at the beginning of a day-trip so that packages (like spare parts) can be delivered to a large number of customers without the necessity to re-visit a loading berth. Other applications are the collection of used consumable items (collection of used laser or ink-cartridges during office-hours) and the dispatching of service crew and repairmen dispatching (Madsen et al., 1995). For a summary of further related scenarios we refer to Beullens et al. (2004)).

We investigate the impacts of request uncertainty. A stream of arriving requests must be served. Additional requests are released regularly and the requests must be integrated reactively into the existing transportation plans (processes). Whenever an additional request corrupts the execution of the so far followed processes a process revision (re-planning) becomes necessary. Typically, the processes of several transport resources have to be updated because a re-assignment of requests is necessary if the originally selected vehicle is no longer scheduled to fulfill one or more requests as decided in the last plan update. Subsequently arriving requests are handled by updating the existing transportation plan. Therefore, the planning situation outlined above is a dynamic decision situation (Brehmer, 1992). The decision problem is formulated as an online decision problem. Each instance P_t of this problem is static and deterministic (all data relevant at the re-planning time t_i are assumed to be known).

2.3.2 Coordinator's and Service Agent's Interest Integration

The two considered agents follow different and to a certain extent contradicting planning goals. While the transport service agent aims at maximizing his profit by keeping costs as low as possible the coordinator agent targets the fulfillment of the promised least punctuality degree ($p_t \geq p^{target}$). The endeavor to minimize the operational costs restrains the transport service providing agent from investing additional expenditures to increase the punctuality rate if this rate has fallen below the threshold value. For this reason, the contract between the coordinator and the service agent

must contain some specific measures in order to ensure that the service agent's endeavor for profit maximization does not lead to a negligence of the coordinator's requirements.

2.3.2.1 Reference Configuration

The direct way to ensure the achievement of the desired least punctuality rate is to force the service providing agent to generate only processes fulfilling the least punctuality requirement. Every process proposal which does not observe the least punctuality condition and which leads to a lower punctuality will be rejected by the coordinator. The minimization of costs is only addressed as a second ranking desire. It is not a mandatory planning requirement. The achievement of least punctuality is the superior planning goal. We refer to this configuration as the hard condition configuration (HARD-configuration) of the investigated supply consortium scenario.

The least punctuality rate has been agreed between the coordinator and the transport-providing partner. Therefore, an average workload has been assumed while deriving the agreed service level p^{target} . A significant increase in the number of customer sites (workload peak) augments the process costs and therefore lowers the profit of the transport partner. It is quite unfair that the additional expenses are not shared with the coordinator (and thereby among all supply consortium partners). Thus, a strict enforcement of the least punctuality discriminates the transport partner and enforces him to leave the consortium as soon as possible in order to avoid serious financial damage. For this reason, the HARD configuration is neither realistic nor applicable. We use it as reference configuration to provide comparable results for simulation experiments. These reference results enable an estimation of the costs necessary for ensuring the achievement of the service goal.

2.3.2.2 Penalization of Late Arrivals

Actually, the coordinator must provide incentives to each service providing partner in the supply coalition in order to act in the sense of the common goals instead of acting only in the sense of its own interest. For each partner, a major motivation to participate in the supply consortium is to maintain or increase the own profit. Vice versa, the endeavor of a partner to maximize its profit enables the supply consortium controller to influence and regulate the behavior of a partner. The partner is promised a higher benefit if it acts in accordance with the common supply consortium goals but its profit is reduced if the partner acts otherwise.

The supply consortium coordinator receives fees paid by the customers for the fulfillment of the customer orders. Using the sum of earned fees, budgets are funded that are used to cover the material flow process costs specified by the service agents. In order to stimulate a partner agent to determine processes of highest efficiency, the difference between the budget and the process costs remains at the service partner as its gain (profit). The main idea of the penalty configuration (PEN-configuration)

is to penalize the transport partner for each request whose on-site fulfillment starts with a delay. Thereby, this partner is motivated to fulfill as many requests as possible on time so that the punctuality rate p^{target} can be guaranteed. If a demand peak occurs then the service-providing partner can freely decide whether to accept the profit reduction or to spend more effort on maintaining or even increasing the service level. Here, the negative impacts of a workload peak are shared between the coordinator (and therefore among all partners) and the transport partner: The latter pays penalties for late arrivals but the supply chain consortium accepts a temporarily reduced punctuality.

2.3.3 Dispatching Task of the Fleet-Managing Agent

The coordinator receives customer demand continuously over time. Every Δt time units he generates orders from the customer demand and the resulting requests are to be executed by the transport providing partner. The reception of additional requests triggers a process revision to incorporate the additional requests into the so far followed transport processes. The process-planning problem of the transport service providing agent is therefore a dynamic decision problem, which is solved in online fashion, e.g. a process revision is carried out in event-driven fashion in response to the additionally submitted requests. Consequently, a sequence of concatenated decision problems is defined. Each instance is formulated as an optimization model. Solving such a model means to find the most profitable process decisions for the transport operations considering the so far actually known planning data. Each instance represents a generalized common vehicle routing problem with time windows (Solomon, 1987). It is the multi-vehicle version of the traveling repairman problem (Irani et al., 2004), which is additionally extended by subcontracting. The transport partner's dynamic decision problem has been previously formulated and investigated in Krumke et al. (2002).

A release of one or more additional requests initiates the revision of the so far constructed routes for the own vehicles. If needed, some requests which are so far assigned to the self-fulfillment cluster, are excluded from the routes of the own vehicles and forwarded to an LSP. A re-assignment of requests formerly assigned to the subcontractor cluster into the self-fulfillment cluster is not possible.

The arrival times at some customer sites may be postponed in order to serve one or several additional customers earlier by the same vehicle. Furthermore, the number of additionally released requests temporarily increases unpredictably, so that workload peaks occur from time to time. In a *high quality (HQ) period* the requirement for the least punctuality is fulfilled ($p_t \geq p^{target}$) but in a *low quality (LQ) period* the required punctuality rate is not attained ($p_t < p^{target}$).

Subsequently arriving requests are accepted and handled by updating the existing transportation plan. A sequence of transportation plans $TP_0, TP_1, TP_2, \dots$ is generated reactively at the ex ante unknown update times $t_0, t_1, t_2, \dots$ and each single transportation plan is executed as long as it is not updated. In order to determine the

transportation plan TP_i at time t_i a static decision problem P_i must be solved. The problem P_i represents the task of selecting the least cost transportation plan from the set of all possible transportation plans. Thus, P_i is an optimization problem and the sequence $P_0, P_1, \dots$ is an online optimization problem representing the dynamic decision problem of the subordinate transport service agent. In the following, we propose a mathematical model M_i for each instance P_i of this online optimization problem.

A single request r attains consecutively different states that change with ongoing time. Initially, r is known but it is not yet scheduled (K). Then, r is assigned to an own vehicle (I, short for internal fulfillment) or subcontracted (E, short for externalization). If the operation at the corresponding customer site has already been started but not yet been finished the state S (short for started request) is assigned to r . The set $R^+(t_i)$ is composed of additional requests released at time t_i . Requests completed after the last transportation plan update at time t_{i-1} are stored in the set $R^C(t_{i-1}, t_i)$. At time t_i , the recent request stock $R(t_i)$ is determined by $R(t_i) := R(t_{i-1}) \cup R^+(t_i) \setminus R^C(t_{i-1}, t_i)$. Each request belongs at each time to exactly one of the sets $R^K(t_i)$, $R^E(t_i)$, $R^I(t_i)$ or $R^S(t_i)$, in which the requests having a common state are collected.

The problem P_i of updating a transportation plan at time t_i is as follows. Let V denote the set of all own vehicles, $P_v(t_i)$ the set of all paths (sequence of visited sites beginning with the position of the vehicle at time t_i and ending with the central depot) executable by vehicle v in TP_i and let $P(t_i)$ denote the union of the sets $P_v(t_i)$ ($v \in V$). If the request r is served in a path p then the binary parameter a_{rp} is set to 1, otherwise it is set to 0. A request r , already known at time t_{i-1} that is not subcontracted in TP_{i-1} is served by vehicle v_r . The travel costs associated with path p are denoted as $C^1(p)$. Finally, $C^3(r)$ gives the subcontracting costs of request r .

In order to code the necessary decisions for determining a transportation plan in the representation M_i of P_i , we deploy two families of binary decision variables. Let $x_{pv} = 1$ if and only if path $p \in P(t_i)$ is selected for vehicle $v \in V$ and let $y_r = 1$ if and only if request r is subcontracted.

$$\sum_{p \in P(t_i)} \sum_{v \in \mathcal{V}} C^1(p) x_{pv} + \sum_{r \in R(t_i)} C^3(r) y_r \rightarrow \min \quad (2.1)$$

$$\sum_{p \in P_v(t_i)} x_{pv} = 1 \quad \forall v \in \mathcal{V} \quad (2.2)$$

$$x_{pv} = 0 \quad \forall v \in \mathcal{V}, p \notin P_v(t_i) \quad (2.3)$$

$$y_r + \sum_{p \in P(t_i)} \sum_{v \in \mathcal{V}} a_{rp} x_{pv} = 1 \quad \forall r \in R(t_i) \quad (2.4)$$

$$y_r = 1 \quad \forall r \in R^E(t_i) \quad (2.5)$$

$$\sum_{p \in P_{v(r)}} a_{rp} x_{pv_r} = 1 \quad \forall r \in R^S(t_i) \quad (2.6)$$

$$p_t \geq p^{target} \quad (2.7)$$

$$x_{pv} \in \{0, 1\} \quad \forall p \in P(t_i), y_r \in \{0, 1\} \quad \forall r \in R(t_i) \quad (2.8)$$

For the HARD-configuration the process-planning problem is represented by the mathematical optimization model (2.1)-(2.8). The costs for TP_i are minimized (2.1). One route is selected for each vehicle (2.2) and vehicle v is able to execute the selected path p (2.3). Each single request known at time t_i is either served by a selected vehicle or forwarded to the LSP (2.4) but a once subcontracted request cannot be re-inserted into the path of an own vehicle (2.5). An (S)-labeled request cannot be re-assigned to another vehicle or LSP (2.6) and overall, the percentage p^{target} of all requests must be scheduled in time (2.7).

The model (2.1)-(2.8) is NP-hard to solve since it represents the traveling salesman problem in a specific parameter setting.

$$\sum_{p \in P(t_i)} \sum_{v \in \mathcal{V}} (C^1(p) + C^2(p)) x_{pv} + \sum_{r \in R(t_i)} C^3(r) y_r \rightarrow \min \quad (2.9)$$

In the PEN-configuration the punctuality constraint (2.7) is skipped and the objective function (2.1) is replaced by the evaluation function (2.9) that incorporates the penalty payments $C^2(p)$ for lateness. Penalties associated with p are summed up to $C^2(p)$ from all late customer site visits according to p . If the request is performed in time, the penalty is zero for the associated single customer site; it increases proportionally up to 25 monetary units for a delay of 100 time units. Further delays do not lead to additional charges. According to (2.9) each late arrival at a customer's site is penalized independent of the fulfillment of $p_t \geq p^{target}$. In so doing, we have a unique quantification of the extent of lateness of the scheduled requests. We cannot uniquely identify those late requests (among all late requests) that finally cause the decrease of p_t below p^{target} . Therefore, we use the "more strict" penalization scheme coded into (2.9).

2.3.4 Generation of Parameterized Test Cases

In order to evaluate and compare the impacts of the different SC-configurations in computational simulation experiments, we have derived a set of artificial test instances. Each instance is defined by a special instantiation of a set of parameters. Different scenarios can be modeled by adjusting these parameters.

Two different kinds of dynamic routing scenarios are referred to in the literature. In the first scenario type, the workload remains stable over a specific time interval. This means that it is possible to adapt the available resources in advance so that all

additional requests can be served appropriately with own vehicles. For this reason, such a scenario is called a *balanced scenario*. In the event that the workload varies over the simulation interval, the scenario is denoted as a *peak scenario*. Here, it is hardly possible to adapt the available resources in advance.

Lackner (2004), Mitrović-Minić et al. (2004) as well as Pankratz (2002) propose artificial benchmark instances for evaluating different dispatching strategies. In all these instances the number of additional requests for a given time interval remains equal, constituting balanced scenarios.

Gutenschwager et al. (2004) and Sandvoß (2004) use real world data sets for their experiments in which the intensity of incoming demands varies over time. Such instances represent examples of a peak scenario. Neither a parameterization nor a classification of these instances is possible.

To simulate and parameterize peak scenarios we first generate a balanced stream of incoming customer demands over the complete observation time period. A second stream is generated for a part of the observation period. Both streams are then overlaid so that during the period in which the second stream is alive, the balanced stream is replaced by a higher number of requests (a peak) which must be integrated into the existing transportation plans.

We start with the generation of the balanced stream of incoming customer demands over the complete observation period $[0; T_{max}]$. Therefore, at time $t_{rel} = 0$ n_0 requests are drawn randomly from request set P . The set P is a Solomon instance (Solomon, 1987) for the vehicle routing problem with time windows comprising 100 customer requests. Next, the request release time is updated to $t_{rel} := t_{rel} + \Delta t$ and for this new release time, n_0 customer requests are drawn from P at random again. However, for each of the recently selected requests r , the release time is set to t_{rel} . The original service time window $[e_r; l_r]$ of r is replaced by $[t_{rel} + e_r; t_{rel} + l_r]$. Then, t_{rel} is increased by Δt again and additional requests are generated similarly as long as $t_{rel} \leq T_{max}$. A second stream of requests is generated in order to achieve a demand peak. Again, we iteratively increase the release time t_{rel} by Δt starting at $t_{rel} = 0$. As long as $t_{rel} \leq t_{start}^{peak}$ is met no additional demand occurs. In the event that $t_{rel} \in [t_{start}^{peak}; t_{start}^{peak} + d_{peak}]$, n_1 additional requests, drawn randomly from P , are selected to be released at t_{rel} . Again, the original service time window is shifted by t_{rel} . No requests are specified anymore within the second stream as soon as $t_{rel} > t_{start}^{peak} + d_{peak}$. Both streams are then overlaid so that during the period $[t_{start}^{peak}; t_{start}^{peak} + d_{peak}]$ an increased number $n_0 + n_1$ of requests appear.

All vehicles specified within the instance P can be used. In order to determine a competitive and comparable tariff for calculating the LSP fare F_r associated with request r , we desist from capacity constraints and set the capacity usage of each request to zero. We multiply the Euclidian distance d_r between the depot of the LSPs, situated at location $(65, 65)$, and the customer site associated with r with a normalizing factor v_r . A subcontracting of r yields costs of $F_r := d_r \cdot v_r$ monetary units. We consult the best-known solution $\mathcal{S}(P)$ of P found in the literature in order to calculate v_r . The vehicle v_r serves r according to $\mathcal{S}(P)$ and $l^{demanded}$ denotes the sum of the Euclidian distances (the demanded distances) between the depot and the

customer sites of all requests served by v_r in this solution proposal. The normalizing factor assigned to request r is now set to $v_r := \alpha \cdot \frac{l^{\text{demanded}}}{l^{\text{travelled}}}$, where $l^{\text{travelled}}$ denotes the route length of vehicle v_r (Schönberger, 2005). Scenarios with different tariff levels can be generated by modifying the factor α . If $\alpha \ll 1$ then subcontracting is cheaper than self-fulfillment, in the event that $\alpha \approx 1$ both fulfillment modes have comparable costs but if $\alpha \gg 1$ then the self completion-mode is cheaper.

Each scenario is described by the 5-tuple $(P, d_{\text{peak}}, n_0, n_1, \alpha)$. In this investigation, we use the four Solomon cases $P \in \{R103, R104, R107, R108\}$ to generate request sets with tariff levels $\alpha \in \{1, 1.25, 1.5, 1.75, 2, 3\}$. Furthermore, it is $n_0 = 50$, $n_1 = 100$ and $\Delta t = 100$ time units. The peak duration is fixed to $d_{\text{peak}} = 200$ time units starting at $t_{\text{start}}^{\text{peak}} = 1500$ time units. Finally, the total observation period lasts $T_{\text{max}} = 5000$ time units.

2.4 Conclusions

We have introduced online optimization models as a suitable formalization approach of dynamic transport process planning problems in a supply consortium. The involved decision making entities (coordinator and transport service agent) have to solve specific and interrelated online decision models in order to generate transport processes for fulfilling customer demand. Although the process planning goals of the coordinator agent and the transport service agent are partly contradicting, they have to interact in the process planning phase.

As a second major challenge in online transport process planning, the management of demand peaks has been identified. An appropriate approach to cope with significantly varying transport need is the subcontracting of parts of the maintained request pool. Depending on the amount of the costs for subcontracting a request, the goals of the two decision making units comply (low subcontracting tariffs) or they are contradicting (high subcontracting tariffs).

For preparing computational simulation experiments of the interaction between the coordinator and the service agent, we have introduced a special dynamic transportation planning scenario. Artificial test instances are proposed in which we can scale the source of dynamic as well as the subcontracting costs as the most important parameters for determining the decision behavior of the transport service agent.

Model-Based Control of Logistics Processes in Volatile
Environments

Decision Support for Operations Planning in Supply
Consortia

Schönberger, J.

2011, XII, 184 p., Hardcover

ISBN: 978-1-4419-9681-7