# Spatial Adaptive Large Neighborhood Search for Wood Supply Chain Optimization

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## ABSTRACT

*A Supply Chain describes a system flow from the raw product to the final product that is delivered to a customer. Hence, the participating organizations, people and transport processes are part of a Supply Chain. The Wood Supply Chain denotes a special Supply Chain that describes the flow of timber. This work focuses on the logistic operations from timber production to the first processing step in a saw or paper mill, and seeks to optimize the Wood Supply Chain with Adaptive Large Neighborhood Search. By introducing spatial amendments to Adaptive Large Neighborhood Search it is capable of solving the spatial-temporal problem of Wood Supply Chain optimization. A comparison of the obtained results and initial results give evidence that the optimization approach with spatial amendments results in an increase of the objective function of the given problem.*


*Keywords:* *Real-time Spatial Optimization; Vehicle Routing Problem; Operations Research; Heuristics; Supply Chain, Spatial-temporal optimization*

## INTRODUCTION

Spatial optimization is a subfield of geography contributing – among others – e.g. to the field of transportation, location modeling or land use planning (Tong & Murray, 2012). Spatial optimization relies on mathematical optimization techniques to structure and solve problems with an inherent spatial context. Thus, any spatial optimization problem is an optimization problem where the spatial dimension is a crucial part and is part of the optimization problem itself. Such a geographical nature of an optimization problem can be reflected either as spatial variables and coefficients but also in terms of spatial relationships. Examples for such relationships are e.g. distance, adjacency, connectivity, containment, intersection or pattern (Tong & Murray, 2012). The importance of spatial optimization stems from the practical usage and the various application contexts of spatial problems. Due to contemporary available computing power we are able to model and solve complex spatial problems which are regarded computationally intensive. Hence, spatial optimization can help in decision making contexts, by delivering solutions to complex spatial problems.

The spatial optimization problem addressed in this paper is summarized in the term Wood Supply Chain. The Wood Supply Chain (WSC) is a special Supply Chain that characterizes the flow of timber starting at the production of the raw material and ends at the customer. To describe the WSC the stakeholders are listed: forest enterprises, saw mills, haulage companies and associated vehicles (see Figure 1) which are connected. In the WSC under investigation there are two distinct processes that have to be considered: transportation and timber trade. Timber trade in the WSC takes place at the saw mill where the delivered timber is measured. This process generates a monetary value in the supply chain which is refunded to the forest enterprise delivering the timber. This value is denoted as turnover in the following paragraphs. Transportation describes the process of timber haulage from forest enterprises – where timber is piled up at forest roads – to the saw mill, where the timber trade process follows. In order to carry out transportation, the resulting costs have to be considered. The contemporary WSC works as follows: timber is produced and piled up in the forest, and subsequently sold to a saw mill by contract. The saw mill organizes the haulage of the timber without considering surrounding conditions - e.g. timber piled up nearby that is ready for haulage. In addition, Austria is dominated by small scale forestry, with only small quantities of timber to be hauled – often less than the capacity of a truck. In order to overcome the shortcomings of the traditional WSC, an optimization process that considers the spatial-temporal dimension is developed. The cooperation of the stakeholders of the WSC can be enhanced, by altering today's WSC in a significant manner. Timber is not sold to a specific saw mill as it is piled up in the forest (see Figure 1). Forest enterprises can notify the optimization system of a new supply point, as well as saw mills can notify the system of their timber demand. The spatial optimization system allocates the vehicles and plans their routes so that the overall profit (turnover minus haulage costs) of the WSC is optimized. This requires that the timber selling process is done 'on-the-fly' during the planning process and not beforehand. Additionally, the demands of the saw mills and the forest enterprises have to be fulfilled.

The objective of this paper is to evaluate on the performance of a spatial-temporal amended heuristic to solve the WSC in comparison to an initial solution that behaves similar to a human dispatching manager. The evaluation is based on two test instances and using different Planning Horizons, that are described in the paper. Therefore, a mathematical model is created that is the foundation for the optimization itself, which relies on theory from Geographical Information Science (GISc) and Operations Research (OR).

Due to the fact that the study does not cover all aspects of the WSC, there are a number of limitations that are described here. First, the paper deals with the WSC starting from timber piled up at the roadside in the forest and ending at the saw mill. In addition, the paper seeks to optimize the timber haulage from the forest to the saw mills. In addition, each saw mill has a specific timber demand over time that has to be fulfilled and the forest enterprises need timber to be picked up at latest at a certain point in time. Hence, the paper concentrates more on the demand side – to fulfill their needs accordingly – by also considering that timber has to be removed from the roadside in the forest. In addition, we do not take any managerial and market processes into account. Thus, the model is not suited to calculate the maximum overall revenue for forest owners or saw mills.

*Figure 1 (about here). Simplified illustration of the Wood Supply Chain*

## RELATED WORK

The related work in this area is focused on three topics: Geographic Information Science and Technology (GIS&T), Operations Research (including Graph Theory) and Forestry Decision Support Systems. A combination of GIS&T and OR is capable of generating a solution for the given spatial-temporal problem of WSC optimization. The recent advances in Forestry Decision Support Systems are targeted towards the analysis and creation of strategic and tactical Decision Support Systems (DSSs) even in the field of WSC management.

### Geographic Information Science and Technology

Looking at spatial-temporal processes of the WSC, time geography is one of the relevant principles for the movement objects in space (Hägerstrand, 1970). This principle allows the creation of 3D-matrices with three axes: time, activity and position. Each activity of an object can be traced using space-time paths, which are a trajectory of movements in physical space over time. In addition, Lenntorp (1977) incorporated the idea of transportation. It is possible to model the potential area that can be reached in a given amount of time starting from the actual position based on a network on which movements can be done. This continuous space in the space-time coordinate system is named space– time prism. When projected onto a two–dimensional space the resulting region is called potential path area, which represents an outlook of possible future movements by actors. This has been used by Raubal et al (2007) for selecting host-client combinations in shared–ride trip planning. In this context the determination of timber that is potentially reachable for a particular vehicle can be modelled with time geography. The approach is described in detail in Scholz & Bartelme (2011).

In order to model the "movement" of timber and vehicles, network flows are of importance. They are mentioned by Ahuja et al. (1993) and Fohl et al. (1996). Goodchild (1998) distinguishes three different types of flows: flows allocated to the data model, flows between origins and destinations where flows exist between two places in both directions (square case), flows between origins and destinations similar to the square case, but where the set of origins is different than the set of destinations (rectangular case). For WSC management the rectangular case is of importance and has to be modeled accordingly, due to the similarity of the rectangular case and the WSC.

To model and solve complex spatial-temporal problems in a GIS environment Murray (2010) reviewed the possibilities of spatial analysis and associated areas in the context of locational analysis. Murray (2010) mentions solution approaches to complex locational problems. Among them a combination of GISc and mathematical solution techniques (independent if exact or heuristic approaches are used) for given spatial problems are highlighted (see e.g. Liu et al., 2006, Bender et al., 2002, Delmelle et al., 2012). Tong and Murray (2012) coined the term *spatial optimization* for optimization problems with an explicit spatial component to solve. Hence, a spatial optimization problem is an optimization with spatial decision variables. Early works in the area of optimization in geography are published by Garrison (1979) Scott (1971), Beaumont (1972) and more recently Church (2001) or Delmelle et al. (2012). The integration of optimization models and GIS has been of interest for multi-objective decision making (Malczewski, 2006).

### Operations Research

Operations Research including Graph Theory provides the methodology for modeling the problem using a mathematical formulation and to optimize a given problem accordingly. The modeling of the given problem – the WSC – is based on the definition of a specific instance of a Vehicle Routing Problem (VRP). Toth and Vigo (2002) elaborate on VRPs and the VRP variants in terms of mathematical definitions as general linear programs. In general, to solve VRPs a number of methodologies and algorithms exist, that are mentioned in literature (e.g. Toth & Vigo, 2002). Exact techniques provide optimal solutions to given problems, while they are not capable of solving big problem instances. In comparison, heuristics are able to cope with great problems but do not provide an exact solution. Additionally, the quality of the result – denoted as factor $\epsilon$, where $s' = \epsilon * s$ ($s$ indicating the optimum and $s'$ the result of the heuristic) – cannot be determined by a heuristic, which is explained by Voss (2001). Due to the ability to deal with great problem instances in reasonable computing time, heuristics are of importance for optimizing the WSC. Ropke (2005) published a heuristic for VRPs with Pickup and Delivery and Time Windows (VRPPDTW) that relies on Variable Neighborhood Search (Mlacenovic & Hansen, 1997) and Large Neighborhood Search (Shaw, 1998). The methodology is called Adaptive Large Neighborhood Search (ALNS) and relies on the Ruin and Recreate (Schrimpf et al., 2000) and Ripup and Reroute approach (Dees & Karger, 1982). ALNS was tested using problem instances published by Li and Lim (2003) and Nanry and Barnes (2000). The results show that ALNS improves more than half of the solutions. In addition, for 80% of the problems the achieved solution is at least as good as the previously best known solution (Ropke & Pisinger, 2006).

### Forestry Decision Support Systems

Forestry Decision Support Systems are a current research topic in forest science, that focus on (spatial) decision making for forest related problems. One problem class that is under investigation is the ”optimal” planning of timber transport from forest to saw mills, using basic GIS technology and methods from Operations Research. Forsberg et al. (2005), Andersson et al. (2008) and Flisberg et al. (2009) show operational, tactical and strategic planning with the help of Tabu Search (Glover & Laguna, 1997), a technique that searches through a solution space of a given problem for an optimal solution. In addition, this method stores search moves in a memory structure in order to avoid making unsuccessful search moves again. These approaches use a VRP with Time Windows to model the WSC and make use of a two stage process to optimize the problem. The Tabu Search is packed into a Decision Support System (DSS) that makes use of basic GIS techniques and spatial data, e.g. on the forest road network. The results of these systems show that DSSs can improve the performance of the WSC, even if they are only modeled with consideration of transport costs (Andersson et al., 2008).

## MATHEMATICAL FORMULATION AND PROBLEM DESCRIPTION

The WSC, as described in this paper, has a number of characteristics that influence the VRP variant for modeling the problem accordingly. Two main things have to be considered:

- vertices have to be serviced – being either pickup or delivery
- vertices have to be visited within a given time interval

As both characteristics of the WSC can be modeled with the VRPPDTW (Toth & Vigo, 2002; Ropke, 2005) – which is a variant of the standard VRP – the WSC is treated as VRPPDTW. To model the problem in a machine readable manner it has to be formalized as Linear Program (LP). The LP will not be formulated here, due to fact that this is not supporting the understanding of the problem in this context. Hence, the problem with the objective function and the constraints is described in natural language in order to provide an understandable formulation of the problem.

The LP consists of an objective function that seeks to optimize the VRPPDTW by maximizing the profit of the system. The profit is defined here as sales revenue for delivered timber minus haulage costs, where haulage costs are defined as fixed rate per kilometer travelled by all trucks in the supply chain. Generally, the mathematical problem describes the flow of timber from supply to demand points using a limited fleet of vehicles with specific capacity. The problem formulated in this paper models the WSC in a way that timber suppliers are cooperating, due to the fact that more than one supply vertex can be serviced by one vehicle. In addition, it is mandatory that saw mills cooperate, because every vehicle may visit more than one saw mill with one specific truckload. Thus, each haulage company and/or vehicle is not bound to a specific forest enterprise and/or saw mill, which increases the flexibility of the WSC at hand.

In the model we consider an undirected weighted Graph $G = (V, E, w)$, where the weight w is denoted as length of an edge. Consecutively, $w_{n,m}$ denotes the weight of edge $(n, m)$. The set of vertices $V$ can be split up into three subsets: set of delivery vertices, set of pickup vertices and the set of depots. From a defined list of timber assortments $Q$ – quality classes – each single assortment $q$ can be identified. The pickup vertices have, for each $q$, a given quantity to be picked up, a start date/time when timber is ready to be picked up, a due date/time when timber has to be fully removed and a price – denoted as time window. Delivery vertices have a defined quantity for each quality class, a start date/time when timber delivery should start, an end date/time when timber delivery should be finished and a price. $T$ denotes the set of trucks, which consists of a number of single vehicles $t$. Each $t$ has the following parameters: capacity, load time per m3 timber, a daily working time start and daily working time end (a single driver per truck is assumed). A route $r$ denotes the route of a vehicle starting and ending at the depot. For formal reasons each $r$ is broken down into single truckloads, which describes the timespan of a vehicle starting from a depot or directly after having delivered timber to a delivery vertex, loading timber at one or more supply points and delivering that timber to one or more saw mills and/or traveling to the depot if the working time limit is ending (see Figure 2).

To model a VRP accordingly, delivery and pickup vertices have to be connected. Thus, the amount of timber loaded at a pickup vertex – with respect to quality and the respective truck - and the volume of timber unloaded at a delivery node are to be determined. If a vehicle visits or services a vertex the arrival and the leaving time are calculated with respect to the shortest path in the road network. The actual load of a vehicle at a vertex is determined in order to see if the node is visited within the defined time window. To decide on the movement of a vehicle from vertex $u$ to $v$ the binary – i.e. [0, 1] – decision variable $x$ is used that denotes the movement of a vehicle over a certain edge with a given truckload. In order to model the driving time from vertex $u$ to $v$ a certain variable is used throughout the model. To limit the timber delivered to saw mills, a constraint regulates that there is not more timber arriving in saw mills than demanded. Special consideration has to be paid that that no timber gets lost after the pickup process and generally in the WSC. Thus, the amount of timber flowing out of pickup vertices has to be equal to timber amount flowing into delivery vertices. One constraint defines that timber at a certain vertex must not be lower than zero – in order to prohibit that timber is removed from piles although nothing is left. From the constraints and is obvious that each timber pile and each saw mill – represented by a vertex – can be visited more than once, which causes additional complexity to the representation of the WSC as VRPPDTW. Delivery and pickup vertices are visited by vehicles as long as timber is present at the timber pile (for pickup) or timber can be delivered to the saw mill (for delivery vertices). For a consistent terminology the term request is introduced. It describes the process of a vehicle visiting two vertices in a certain order – i.e. pickup and delivery - in order to transport timber from one vertex to the other.

*Figure 2. (about here) A route of one vehicle starting and ending at the Depot(D) servicing a number of vertices. The numbers near the arrows indicate the temporal sequence of the vehicle's movements. All vertices starting with C are locations with pickup, except for vertex C7 - a delivery vertex.*

## SPATIAL ADAPTIVE LARGE NEIGHBORHOOD SEARCH

Ropke and Pisinger (2006) propose Adaptive Large Neighborhood Search (ALNS) as a heuristic to optimize a given VRPPDTW. It relies on the concept of modifying a given solution of a VRP and an evaluation if it satisfies criteria from Simulated Annealing (SA). ALNS is a heuristic that performs at least as good as 80 % of the best known solutions of standardized problem instances (Ropke & Pisinger, 2006; Ropke, 2005). As ALNS has been successfully tested on non-spatial problems, it is applied to a spatial problem in this paper. In addition, the optimization heuristic ALNS is enveloped in a spatial data infrastructure in this approach, which is outside of the scope of this paper. A description of the ALNS approach can be found in Scholz & Bartelme (2010) and in Figure 3. The optimization process starts with the generation of an initial solution, which is described in section “Generation of an initial solution”. Based on an initial solution ALNS tries to improve the solution by modifying it with the help of spatial relations like nearness and/or position, which are described in detail in the section “Spatial Adaptive Large Neighborhood Search for Wood Supply Chain Optimization”. In order to cope with the temporal dimension of the WSC the Rolling Schedule Approach (e.g. Wagner & Whithin, 1958) is employed, which helps to decrease the problem complexity and uncertainty in terms of data quality. This increases the accuracy of the obtained results (see section “Rolling Schedule approach” for details).

*Figure 3. (about here) ALNS workflow (from Scholz & Bartelme (2010))*

### Generation of an Initial Solution

An initial solution is necessary in order to start the ALNS process. Due to the fact that the first solution has to be feasible in terms of the given constraints, the quality – i.e. optimality – of the solution is not of any particular interest. In order to provide such a solution in a short time heuristics are applied. Classical heuristics for the generation of an initial solution are savings heuristics that “gradually build a feasible solution while keeping an eye on solution cost, but they do not contain an improvement phase per se” (Laporte & Semet, 2002). Clarke and Wright (1964) introduced the class of savings heuristics that is implemented in the approach presented in this paper. This construction heuristic constructs routes that serve exactly one customer at first hand. In a following phase these routes are merged with consideration of user defined criteria. Thus Traveling Salesman Problems as well as VRPs can be solved accordingly.

In this publication, a heuristic for generating an initial solution is used that is similar to savings heuristics. First, routes are created that start and end at a depot, pick up timber at exactly one pickup point and deliver it immediately to a saw mill. The routes from the depot to a pickup point, from pickup point to saw mill and back to the depot are shortest paths with respect to minimum travel time. Secondly, these routes are merged until no more routes can be merged. The merging process involves a process comparable to human behavior. First it selects pickup locations that are geographically near, having the same type of timber or the same delivery point (sub-route merging). In addition, the algorithm has an eye on the current loading of the truck, thus avoiding overloading of a vehicle. Finally, the generated routes are combined so that each vehicle performs a number of turns between pickup and delivery points per day (tour merging). If the number of resulting routes exceeds the number of available vehicles, routes are deleted until the number of routes is lower than or equal to the number of vehicles. Routes are deleted based on the value of the objective function, starting with the route having the lowest value. This approach is similar to the way human dispatching managers plan routes.

### Spatial Adaptive Large Neighborhood Search for Wood Supply Chain Optimization

Spatial ALNS for WSC optimization relies on ALNS published by Ropke (2005). As mentioned before, ALNS modifies a given solution in order to optimize it. Generally speaking, it enhances Local Search by adding several heuristics to modify the given solution. Thus, new solutions are created by partly destroying and repairing the given solution, by deleting a number $q$ of requests and inserting $q$ requests at another position to generate a new solution. Such new solutions are accepted if they satisfy Simulated Annealing (SA) – a metaheuristic introduced by Kirkpatrick et al (1983). A more detailed description of ALNS is found in literature (e.g. Ropke, 2005; Ropke & Pisinger, 2006).The heuristics available to alter a given solution are divided into destroy and repair heuristics. The destroy heuristics are: Shaw Removal, Random Removal and Worst Removal. The repair heuristics are: basic Greedy Heuristic, Regret-2 and Regret-3 heuristic.

Shaw Removal alters the current solution by deleting a certain request (i.e. a vertex) – being either pickup or delivery – based on a similarity value of two requests $i$ and $j$. Equation (1) shows the relatedness measure $R_{i,j}$. The variable $d_{i,j}$ represents the distance between nodes $(i,j)$, whereas $T_i$ denotes the time when $i$ is visited and $l_i$ shows the timber quantity of request $i$. $q_{i,j}$ shows the timber quality similarity of the requests (see equation (2)) and $t_{i,j}$ denotes the request type similarity (see equation (3)). $C$ is a constant with a high numeric value, whereas φ, ϕ and ψ are parameters to weigh the parts of equation (1). The higher the relatedness measure $R_{i,j}$ is, the lower is the similarity between the requests $i$ and $j$.

$$R_{i,j} = \varphi(d_{i,j}) + \phi(|T_i - T_j|) + \psi(|l_i - l_j|) + q_{i,j} * C + t_{i,j} * C \quad (1)$$

$$q_{i,j} = \begin{cases} 0 & if\ q_i = q_j \\ 1 & if\ q_i \neq q_j \end{cases} \quad (2)$$

$$t_{i,j} = \begin{cases} 0 & \text{if request types } i,j \text{ are equal} \\ 1 & \text{if request types } i,j \text{ are not equal} \end{cases} \quad (3)$$

Random Removal selects a number $q$ of requests based on randomness and removes them from the solution $s$. Worst Removal deletes “expensive” requests, i.e. requests that worsen the objective function most. Thus, by removing such "bad" requests and inserting them at another position the objective function may result in a better numeric value, due to reduced vehicle travel distances.

The first repair heuristic mentioned in this paper is the basic Greedy heuristic. This heuristic repairs a given solution, but is solely interested in increasing the overall profit - sales revenue minus haulage costs. $\Delta f_{i,k}$ denotes the difference when inserting request $i$ in route $k$ at the position that results in the highest increase of the objective function. If $i$ cannot be inserted in route k then $\Delta f_{i,k} = \infty$. The value $c_i$ is defined as the profit of inserting request $i$ at its best position, where $c_i = \max_{k \in K}\{\Delta f_{i,k}\}$. This position is called the maximum profit position, where the request $i$ is selected that fulfills the function: $\max_{i \in U} c_i$. $U$ denotes the set of unplanned requests. The process continues until no more requests can be inserted or all requests are inserted.

The family of Regret Heuristics forms a class of heuristics that inserts requests to the given solution based on a selection process that tries to overcome problems caused by a pure Greedy approach. Thus, Regret Heuristics incorporate a look into the future to detect "hard" requests, that the system regrets most if they are not inserted now. In order to determine "hard" requests the variable $x_{ik} \in \{1, \dots, m\}$ represents the route for which request $i$ has the $k$ th highest increase of the objective value where $m$ is the number of vehicles. Mathematically defined, this can be denoted as $\Delta f_{i,x_{ik}} \geq \Delta f_{i,x_{ik'}}, for\ k \leq k'$. $\Delta f_{i,x_{ik}}$ $c_i$ can defined as $c_i = \Delta f_{i,x_{i1}}$. Subsequently, the regret value $c_i^*$ is defined as $c_i^* = \Delta f_{i,x_{i1}} - \Delta f_{i,x_{i2}}$. Hence, the regret value is the difference in the profit of inserting a request in its best and second best route. In each iteration the request $i$ is chosen that fulfills equation (4) and this request is inserted at its maximum profit position.

$$\max_{i \in U} c_i^* \tag{4}$$

The Regret Heuristics form a family of inserting heuristics – the Regret-k Heuristics. In the prior paragraph the Regret-2 heuristic is explained, which calculates $c_i^*$ with respect to the 2nd best $\Delta f_{i,x_{ik}}$ value. By considering the $k$ th best route $c_i^*$ has to be calculated in the following way:

$$c_i^* = \sum_{j=1}^{k} \left(\Delta f_{i,x_{i1}} - \Delta f_{i,x_{ij}}\right) \tag{5}$$

Adaptive Large Neighborhood in this paper is restricted to Regret–3 and Regret–2 Heuristic and we intentionally omit other Regret–k Heuristics. The selection of a removal and insertion heuristic for the next iteration is based on a roulette wheel selection principle (Baker, 1987). Weights $w_i \ , i \in \{1, \dots, k\}$ are assigned to each of the $k$ heuristics. The roulette wheel procedure selects the heuristic $i$ with probability:

$$w_u \big/ \textstyle\sum_{i=1}^{k} w_i \tag{6}$$

The update of the weights is done automatically in every ALNS iteration in order to measure the performance of each heuristic. Thus, the algorithm keeps track of the success of each heuristic and determines their score. Ropke (2005) divides this process into segments of 100 iterations. At the beginning of each segment the score is set to zero, and each time a heuristic creates a solution the score is increased by values $\alpha_1$, $\alpha_2$ or $\alpha_3$ based on the following cases:

- $\alpha_1$: a new global best solution is found
- $\alpha_2$: a solution that has not been accepted before is found, and

objective value is better than in the current solution

- $\alpha_3$: a solution that has not been accepted before is found, the objective value is not better than in the current solution

Due to the fact that in every iteration one remove and insert heuristic is applied, the algorithm cannot distinguish which heuristic is responsible for the generated solution. Hence, both heuristics – remove and insert – are updated by the same values $\alpha_1$, $\alpha_2$ or $\alpha_3$. At the end of each segment $j$ the weight $w_{i,j}$ of each heuristic $i$ is updated – which equals $w_u$ from equation (6). Thus, the weight for heuristics in the next segment $j+1$ is obtained using equation (7). In this formula $\pi_i$ denotes the score of the heuristic $i$ achieved and $\theta_i$ represents the number that heuristic $i$ was used in the last segment. The variable $r = [0,1]$ – a reaction factor – controls the inertia of the system. A low value of $r$ results in a slow change of $w_{i,j+1}$ and vice versa.

$$w_{i,j+1} = w_{i,j}(1-r) + r\frac{\pi_i}{\theta_i} \qquad (7)$$

As mentioned previously and in Scholz and Bartelme (2010), ALNS makes use of Simulated Annealing (SA) to overcome local optima in order to reach a global optimum. SA makes use of an analogy between the cooling schedule of metals with minimum energy crystalline structure and mathematical optimization (Kirkpatrick et al., 1983). The main advantage of SA is described by the fact that the technique avoids becoming "trapped" in a local optimum. As metaheuristic it accepts solutions that improve the objective function, but also solutions that do not improve the objective function as such. The acceptance of non-improving solutions is depending on the current temperature of the process – where the temperature is gradually cooled down. In general, the cooler the temperature gets the lower is the probability for accepting non-improving solutions.

Mathematically, SA accepts a new solution $s^*$ if the objective value is "better" than the objective value of the current solution $s$. If $f(s^*)$ denotes the value of the objective function of a new solution $s^*$ then "good" moves of ALNS are accepted when $f(s) < f(s^*)$. For the case $f(s) \geq f(s^*)$ SA decides if $s^*$ is accepted, which is implemented according to Kirkpatrick et al. (1983) and van Laarhoven and Aarts (1987), using equation (8), where $R$ is a random number. The start temperature for SA is determined using equation (9). By using equation (9) the start temperature is defined so that a new solution that is $w$ worse than an initial solution $s_{initial}$ is accepted with a probability of 0.5. $w$ is set to 0.05 in this context. The termination criterion of ALNS is set to a maximum number of iterations. Here it is set to a value of 25000, which is also used by Ropke (2005).

$$e^{\frac{-f(s)-f(s^*)}{T}} > R \quad \text{where } R = \{x \in \mathbb{R} | (0 \leq x < 1)\} \qquad (8)$$

$$T_{start} = \frac{-\left(f(s_{initial}) - f(s_{initial}) * (1-w)\right)}{\ln 0.5} \qquad (9)$$

### Rolling Schedule Approach

Modeling and Simulation of dynamic systems requires any system to cope with uncertainty. Especially for WSC optimization, the system has to work with the assumption that reality conforms exactly to the optimized solutions. The further the system attempts to develop a global optimal solution looking far into the future the more uncertain the results are, due to data not existing or being only partly accurate (e.g. vehicle breakdown, weather or changed demands of customers). Thus, the system optimizes only for a given time period where uncertainty is low. In addition, this approach reduces the complexity of the problem which reduces computing time. Such approaches are discussed in literature (Teng et al, 2006; Spitter, 2005; Wagner & Whithin, 1958), which are called Rolling Schedule approaches (RSAs). In detail, a RSA divides time into discrete time periods $P_1 ,..., P_n$ and discrete time intervals – the Planning Horizons – which contain one or more time periods. RSAs work as follows (see Figure 4):

1. divide time into n time periods (e.g. days, months)
2. define planning horizon, i.e. the number of time periods the systems plans ahead
3. solve the optimization task for planning horizon starting at period $p = 1$
4. after period p = 1 is over roll horizon forward by one period, i.e. $p = p + 1$
5. repeat (3) and (4) until a given stop criterion

In addition, the Rolling Schedule Approach the dynamic adjustment of the optimization system with the real situation with the help of e.g. mobile devices located on the vehicles and the saw mills. The mobile devices act similar to a sensor delivering (near) real-time information on the status of the supply chain. Hence, at each end of a period the digital representation of the supply chain to be optimized can be updated with respect to the real status.

Generally, rolling schedule approaches result possibly in non-optimal solutions, the procedure is relevant for real-life situations (Spitter et al., 2005; Bertrand et al., 1990; Blackburn & Millen, 1980). The justification for the real-life relevance is given by the fact that demands and supply might change over time and can be regarded as fixed in the near future. In order to react to such changes rolling schedules are employed in industry related optimization systems (e.g. in material requirements planning). Teng et al (2006) report on rolling schedule heuristic results for a TSP problem. There the solution found by the rolling schedule heuristics is on the average 2.5% worse than the upper bound (i.e. best solution) for the problem.

## EXPERIMENT SETUP

To conduct an experiment to evaluate the performance of ALNS applied to the WSC compared to an initial solution a SDSS following a service-oriented architecture has been created, which is not stressed in this paper. In this chapter, the focus lies on the generated test instances and spatial data which are the basis for the evaluation of ALNS in the context of WSC optimization. For testing spatial ALNS we employ street network data from a commercial vendor. These data contain the geometry of public roads with additional attributes, e.g. on average and allowed speed on a certain road segment. Due to the fact that public data on forest roads are not available in Austria, the experiments are limited to the public road network served by the commercial vendor. Thus, timber piles to pick up and saw mills are strictly modeled as vertices in the road network. The area of interest is in the province of Styria (Austria) (see Figure 5). The size of the test area is approximately 5018 km2 and it contains 55308 road segments with a total length of 15090 km. In order to evaluate ALNS with respect to WSC optimization two test instances are created. Test instance one ($TI_1$) consists of ten piles, 28 assortments, four saw mills, 38 different demands of timber and 35 trucks located in six haulage companies. A map of the spatial objects of $TI_1$ is given in Figure 6(a). $TI_2$ has 20 timber piles, 80 assortments in the timber piles, four saw mills, 43 different demands of timber and 35 vehicles in six haulage companies. In Figure 6(b) a map of $TI_2$ is shown. The positions of haulage companies as well as the positions of saw mills are the same for both test instances. A detailed description of $TI_1$ and $TI_2$ can be found in Scholz (2010). The data of the test instances, which are spatial and non-spatial in nature, are stored in a PostGIS database. In order to perform shortest path calculations on the road network within the database, pgRouting (Orkney, Inc., 2013) is employed. In detail, the A*-Algorithm (Hart et al, 1968) is used for shortest path calculations in the given road network.

*Figure 4. (about here) Rolling Schedules approach illustration (from Scholz (2010)). The timeline is divided into discrete time periods $P_1, \ldots, P_n$ and a Planning Horizon - abbreviated "Horizon" – that defines the duration that the system plans ahead. After $P_1$ is over the Horizon is rolled forward by one time period*

*Figure 5. (about here) The test area for WSC optimization marked with the dark grey box – the overview in (a) and the detailed map in (b)*

*Figure 6. (about here) Map with the entities present in TI1(a) and TI2 (b) – piles, saw mills and haulage companies*

## RESULTS

Using ALNS for WSC optimization with the test instances described in chapter 5 leads to a comparison of an initial solution and an optimized solution for the WSC instances at hand. Due to the fact that RSA is employed in optimizing any test instance, specific Planning Horizons (PHs) are defined. $TI_1$ and $TI_1$ are evaluated with respect to the following two PHs:

- $PH_1$ : start: September 23rd; end: September 25th
- $PH_2$ : start: October 21st; end: October 23rd

In addition, the performance of ALNS is tested with different q values - i.e. number of requests that are deleted and reinserted. The evaluation is done with $q = \{2, 4, 8, 20\}$. The results are displayed in Table 1. The Table shows results for given *TIs*, *PH*s and for given values of $q$. The objective values of the initial solutions are given in column $s_{initial}$, and the objective values of the best solutions computed with ALNS are visualized in column $s_{best}$. The relative increase of the objective value with respect to the initial solution is given in column *inc*[%].

*Table 1 Results of ALNS applied to test instances T I1 and T I2 for the defined P Hs. ndenotes the problem size (number of timber piles), the number of vehicles is represented by v, s initial is the objective value of the initial solution, and sbest denotes the objective value of the best calculated solution. The relative increase of the objective function is denoted with inc[%]*

| *TI* | *PH* | *q* | *n* | *v* | $s_{initial}$ | $s_{best}$ | *inc*[%] |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 43 | 35 | 17,130.64 | 19,318.36 | 12.77 |
| 1 | 2 | 2 | 24 | 35 | 897.64 | 5,090.90 | 467.14 |
| 1 | 1 | 4 | 43 | 35 | 17,130.64 | 19,061.98 | 11.27 |
| 1 | 2 | 4 | 23 | 35 | 897.64 | 5,060.06 | 463,71 |
| 2 | 1 | 2 | 93 | 35 | 223,453.98 | 219,196.25 | -1.91 |
| 2 | 2 | 2 | 64 | 35 | 160,282.85 | 158,135.80 | -1.34 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2 | 1 | 8 | 93 | 35 | 223,453.98 | 274,182.55 | 22.70 |
| 2 | 1 | 20 | 93 | 35 | 223,453.98 | 245,483.75 | 9.86 |

*Table 2 Test instances and iteration number of the best achieved optimization result –denoted as "#iteration" – which gives an indication of the optimization speed*

| ***TI*** | ***PH*** | ***q*** | ***N*** | ***#iteration*** |
|---|---|---|---|---|
| 1 | 1 | 2 | 43 | 1825 |
| 1 | 2 | 2 | 24 | 164 |
| 1 | 1 | 4 | 43 | 3709 |
| 1 | 2 | 4 | 23 | 252 |
| 2 | 1 | 2 | 93 | n.a. |
| 2 | 2 | 2 | 64 | n.a. |
| 2 | 1 | 8 | 93 | 8078 |
| 2 | 1 | 20 | 93 | 1487 |

## CONCLUSION

In this paper the foundations for optimizing a certain representation of a WSC are described. In order to overcome the traditional shortcomings of a contemporary WSC – which mostly manifests itself in the lack of cooperation between the stakeholders both horizontally and vertically – the approach published in this paper facilitates a transparent cooperation within the supply chain. The WSC itself can be characterized by a mathematical problem class, namely the VRPPDTW. This problem class allows the mathematical formulation of the WSC as a LP, which can be optimized using heuristical algorithms. In this context ALNS is chosen as appropriate optimization method, due to the fact that heuristics have a better performance than exact optimization methods.

To apply ALNS to the spatial problem WSC optimization, ALNS has to be enhanced by the spatial domain. Thus, ALNS is augmented in order to consider the spatial-temporal domain of the problem, which is necessary for:

- spatial-temporal "localization" of timber piles, saw mills and vehicles
- determination of validity of created solutions
- determination of travel distances and travel times – i.e. transport costs
- calculation of similarity of requests
- determination of requests that are reachable for a particular vehicle located at a certain position – here time geography can be employed (Scholz & Bartelme, 2011)

To be able to cope with the uncertainty in simulating future events, a rolling schedule approach is used. Rolling schedule approaches reduce the complexity of the optimization problem by strictly looking at a given planning horizon and optimizing the remaining problem within this time slice. The length of a planning horizon can be arbitrarily chosen, but has to be set in a way that the base data for the optimization are not pure speculation. The mathematical model and optimization methodology is applied to two problem instances with varying planning horizons and parameters $q$. A comparison with the initial solutions of a given problem gives evidence, that ALNS with spatial amendments is capable of optimizing the

WSC with respect to initial solutions. Crucial for the optimization process itself are the control parameters – e.g. *q* or start temperature of Simulated Annealing. They are crucial for the chance to find an optimized solution within the course of the algorithm and for the speed of the optimization. Future research items comprise a comparison with real-world WSCs, a detailed evaluation of optimization control parameters as well as a generalizability of the results in order to be applied e.g. in other Supply Chains accordingly. Through a monitoring of real-world WSCs the system could be fine-tuned. Additionally, a comparison with real-world data could give more insight in the quality of the optimized results.

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