Spatial-enabled Adaptive Large Neighborhood Search for Optimizing the Wood Supply Chain

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1. Introduction

A Supply Chain (SC) describes a system flow from the raw product to the final product that is delivered to a customer (Wannenwetsch 2005). The Wood Supply Chain (WSC) denotes a special SC 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.

The stakeholders of the WSC are (Gronalt et al. 2005): forest enterprises, saw mills, haulage companies and associated vehicles (see Figure 1). Originating from forests, timber is harvested, piled up on the next forest road and transported to saw mills. In order to optimize this process the monetary value of timber and transport processes is considered. As forest enterprises want to maximize their profit – i.e. get the highest price for their product while delivering the timber with low transport costs – the following decisions have to be made:

- WHAT should be transported? e.g. 15 m^3 timber with quality class A, from forest enterprise 1
- WHO should transport? e.g. truck A from haulage company 1
- WHEN should it be transported? e.g. picked up tomorrow at 8.30 am
- WHERE TO? e.g. saw mill 1

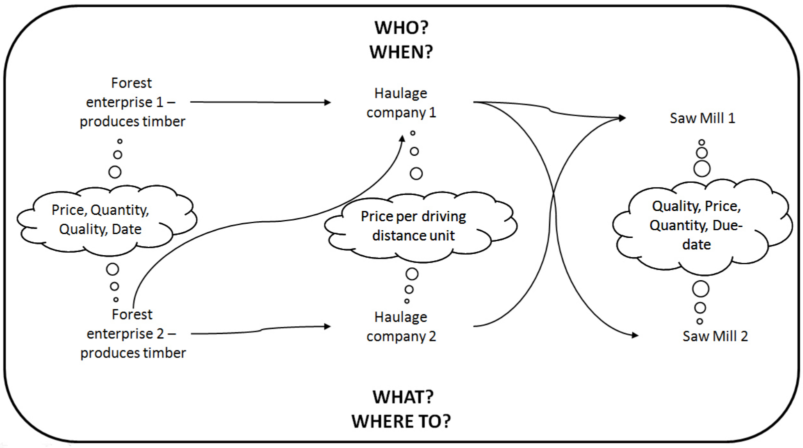

Figure 1. Simplified illustration of the WSC, with requirements and constraints that characterize each stakeholder of the WSC.

In addition, every stakeholder has constraints that have to be considered (see Figure 1). Forest enterprises producing timber, define a time window, i.e. a date and time when timber is ready for pick up and when it has to be fully removed. Additionally, the timber quality, quantity and price are important. Saw mills need the raw product at a specific date and time in order to schedule the production process, which forms a time window too. Furthermore, they demand a defined quality and quantity of timber for which they pay a certain price.

Prior to any optimization process, the problem has to be modelled accordingly, which is out of the scope of this paper. Scholz (2010) presents a mathematical model based on the Vehicle Routing Problem with Pickup and Delivery and Time Windows (VRPPDTW). To optimize the WSC, a number of heuristical algorithms are applicable – e.g. Local Search, Tabu Search or Genetic Programming – which hardly consider the spatio-temporal component of the problem. In order to optimize the WSC accordingly Adaptive Large Neighborhood Search (ALNS) is chosen, due to its superior performance compared to contemporary heuristics (Ropke and Pisinger 2006). A detailed description of ALNS and its adaption for the WSC follows in chapter 2.

This paper focuses on the spatial optimization of the WSC by ALNS. In addition, this work elaborates on ALNS amendments that are necessary to cope with the spatio-temporal dimension of the WSC.

2. Adaptive Large Neighborhood Search for WSC optimization

ALNS was first published by Pisinger and Ropke (2005). ALNS relies on Large Neighborhood Search (Shaw 1998) that modifies a given solution during an iteration of the algorithm. ALNS enhances Local Search by adding several heuristics to modify a solution. Such a new solution is accepted if it satisfies the acceptance criteria from Simulated Annealing (SA).

In order to create new solutions in ALNS, heuristics are applied that rely on the Ruin and Recreate (Schrimpf et al. 2000) and the Ripup and Reroute (Dees and Karger 1982) approach. Thus, ALNS partially "destroys" the current solution to “repair” it instantly. The destroy heuristics are Shaw Removal, Random Removal and Worst Removal, whereas the repair heuristics are Basic Greedy Heuristic and the family of Regret Heuristics (Ropke and Pisinger 2006). Due to the fact, that these heuristics do not consider the spatio-temporal dimension per se, they are enhanced in order to provide accurate optimization results.

For destroy and repair heuristics the creation of feasible solutions is of particular importance which requires Geographic Information Technology – e.g. networks with topology. Feasible solutions are designed to meet the constraints that are defined in the mathematical model by Scholz (2010: 118), which includes spatial relations as well. Of particular interest for the VRPPDTW are (Toth and Vigo 2002):

- every vehicle route starts and ends at a depot
- time windows for each node are not violated
- loaded goods do not exceed the vehicle capacity

Figure 2 shows an example VRPPDTW. In this problem instance there is one depot (node *D*), one saw mill (node C_7) and six timber piles (nodes C_1 – C_6). For each node a time window and pickup quantities (>0 for timber piles) and delivery quantities (>0 for a saw mill) are defined. Additionally, it is assumed that only one vehicle services the nodes. Figure 2 shows one possible solution for the problem by the arrow connections between the nodes. The numbering of the arrows indicates the temporal sequence in which the nodes are serviced, while fulfilling the VRPPDTW constraints.

The optimization of the WSC has the goal of increasing the overall profit, which is regarded as the timber sales turnover minus haulage costs in this paper. In addition, timber is sold – i.e. a monetary value is created – when it arrives at a saw mill. Thus, the optimization process under investigation is driven by economic considerations. Hence, the approach tries to reduce the total travel distance while increasing the sales volume. Nevertheless, a certain amount of additional kilometres are accepted if they pay off in monetary terms.

2.1 Spatial Enablement of Destroy Heuristics

Two of the destroy heuristics are spatially enhanced: Shaw Removal and Worst Removal. Shaw Removal removes nodes that have a certain similarity. Therefore the heuristic calculates a relatedness measure (1) between two nodes i and j. Variable $d_{i,j}$ denotes the distance between nodes. T_i indicates the time when vertex i is visited. l_i denotes the quantity of timber located at node i. $q_{i,j}$ denotes a factor for timber quality similarity of request i and j. $t_{i,j}$ indicates if the node types – pickup or delivery – are equal. C is a constant value. The parameters φ, χ, ψ assign a weight to each part of (1).

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

The distance is determined by shortest path calculations on a road network using the A* algorithm. The calculation of the time when nodes are visited by a vehicle is done with data on the possible average speed broken down to road segments.
Worst Removal eliminates nodes from the current solution that are “expensive” – i.e. worsen the objective function, and thus require a vehicle to drive long distances. If these nodes are inserted at another position a better value of the objective function may be reached.

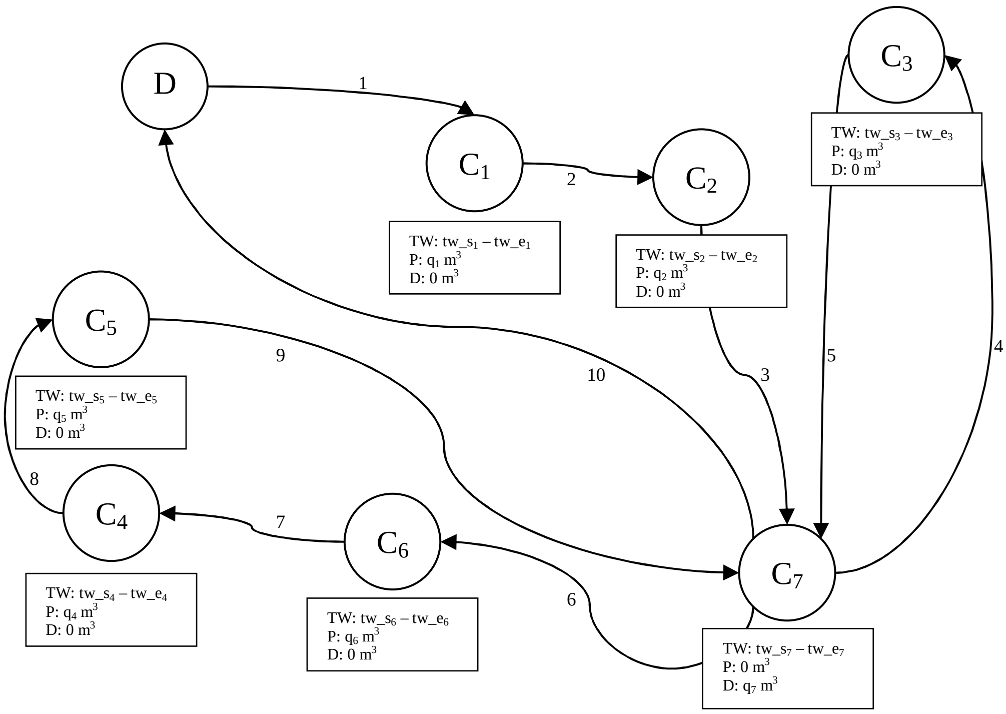

Figure 2. Visualization of a VRPPDTW as a graph with additional constraints. tw_s denotes the start of the time window (TW), tw_e the end of the TW, P marks the pickup quantity and D the quantity to be delivered within the time window.

2.2 Spatial Enablement of Repair Heuristics

Similar to destroy heuristics, repair heuristics are spatially enabled as they rely on distance and time calculations based on spatial data on a road network. For distance measures the A* algorithm and for the temporal dimension the average driving speed on a road segment is used.

Basic Greedy Heuristic determines the node that, inserted at the “best” position, improves the objective function most. The family of Regret-k Heuristics creates “what-if” scenarios in order to determine the best insert position for each node, not yet assigned. Regret-k heuristics “look into the future” and add those nodes first, that are very hard (or costly) to add later on.

2.3 ALNS optimization procedure

As mentioned in chapter 2, ALNS is an optimization heuristic that destroys and repairs a given solution and accepts non-improving solutions to a given extent due to SA. Thus, the algorithm does not get stuck in a local optimum and a global optimum can be found (Kirkpatrick et al. 1983). A basic solution outline is given in Figure 3.

Based on an initial solution ALNS seeks to optimize a problem instance by removing and reinserting nodes of a VRP instance. It makes use of destroy and repair heuristics that are competing based on statistics of the heuristics performance and a roulette wheel selection principle. Subsequently, the new solution – marked as s* – is compared with the actual solution. If the new solution is better than the actual one or accepted by SA, the new solution becomes the actual solution otherwise s* is discarded. The stop criterion is set to a number of 25000 iterations (Ropke and Pisinger 2006). After the algorithm has stopped the best solution is returned.

3. Conclusion

In this paper a concept for a spatial optimization of the WSC by an enhanced ALNS is given. Due to the fact that the problem of WSC optimization is spatial in nature and draws on spatial data the theoretical concept of ALNS is augmented with spatial operators to successfully support WSC optimization. Of importance is the generalizability, because VRPPDTWs are found in logistics and scheduling. Hence, the concept discussed here may serve as starting point for the development of Spatial Decision Support Systems in this area.

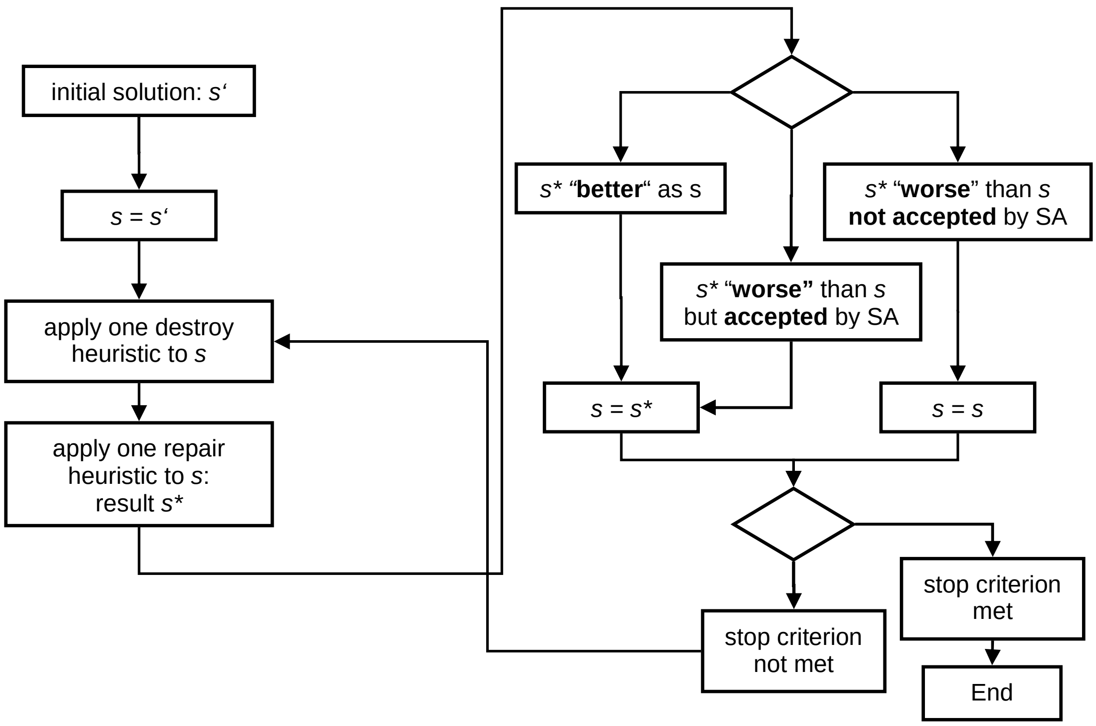

Figure 3. ALNS optimization workflow.

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