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A simulated annealing algorithm to solve the log-truck scheduling problem

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Introduction

In this paper, we present a simulated annealing (SA) approach for solving the log-truck scheduling problem, which is an extension of the timber transport vehicle routing problem with time windows (TTVRPTW). The problem is characterised by a heterogeneous fleet of trucks that depart from their corresponding depots and must perform a number of daily transport tasks to move log products between wood pickup (harvest areas) locations and industrial customers, such as pulpmills and sawmills. Commencing at their depots, each truck must perform a number of successive transport tasks, each one charaterised by a trip between a designated harvest area and an industrial customer, until the number of daily working hours is completed (Karanta 2000, Audy et al. 2012). The objective of the model is to minimise total empty travel time for the whole fleet as well as waiting times at wood pickup locations. In addition, time windows and accessibility to harvest areas and customers, must be taken into account.

Material and Methods

In order to provide the inputs to solve the truck scheduling mathematical model, the daily transport tasks must be predefined. A task corresponds to a truck load or transport order that must be performed to obtain a feasible solution. The problem structure with tasks occurring at depots and customers reduces the number of constraints and variables considerably, as opposed to vehicle routing problems without predefined transport tasks.

The mathematical model corresponds to an adaptation of the formulation presented by Gronalt and Hirsch (2007) and Oberscheider et al. (2013), and it is formulated as a standard multiple depot vehicle routing problem with pickup and delivery (MDVRPPDTW). The model optimally allocates a fleet of logging trucks to transport tasks assuming a centralised transport system is in place to provide schedules for trucks and ensure that their utilisation is maximised.

Our solution approach to solve the truck scheduling problem is based on a standard SA procedure, and it was implemented and programmed in Visual C++ using an object-oriented design. It includes the SA heuristics as an optimisation engine in combination with a deterministic discrete event simulation to emulate the movement of trucks throughout the day. In addition the simulation model keeps track of all the performance metrics associated with the daily tasks performed by the trucks, and provides general metrics for the whole fleet.

Our solution approach consists of the following steps:

1. Determination of the SA cooling schedule, including parameter testing
2. Construction of an initial feasible solution with a greedy heuristic
3. Solution improvement by applying four different search improvement methods

The cooling schedule of the SA algorithm implemented is fully defined by the following components: Initial temperature (T0), final temperature (FT), temperature reduction factor (α), and iterations at each temperature (niter). Four SA search improvement methods were implemented: single task insertions, single task swaps, task insertions for a set of n-trials, task swaps for a set of n-trials. A small set of problem instances generated from real-life data was used to test and validate our algorithmic approach. The instance consisted of a sub-set of 30 transport tasks and 10 trucks, taken from an original data set comprising more than 150 transport tasks, 60 trucks, 25 wood pickup locations, and eight customers. Our SA algorithmic approach was implemented and programmed with Visual C++, while the mathematical model formulation was implemented and solved with the software GAMS® v. 24.1.3 and the solver CPLEX®.

Results

Table 1 shows the per cent deviation between the average solution (five runs) in each cooling scheme and the best single SA solution obtained for a total of 180 runs. The best single SA solution was obtained with an initial temperature of 20000, a temperature reduction factor of 0.999, and 1000 iterations per temperature. The maximum deviation between the average solution and the best single SA solution was 3.6%.

Table 1: Per cent deviation between the average solution in each cooling scheme and the best single SA solution

	Temperature reduction factor											
	0.8			0.95			0.99			0.999		
	Initial temperature			**Initial temperature**			**Initial temperature**			**Initial temperature**		
Iterations per temperature	20000	40000	100000	20000	40000	100000	20000	40000	100000	20000	40000	100000
500	3.0	3.5	3.6	2.7	2.9	2.6	2.2	2.1	2.0	1.1	1.3	1.3
1000	3.2	2.8	3.0	2.7	2.0	2.4	1.6	2.1	1.7	0.9	1.2	1.1
1500	2.7	3.6	2.8	2.4	2.2	2.1	1.6	1.6	1.5	1.3	1.0	1.1

In order to compare the efficiency of our SA heuristics, we also compared the best SA solution obtained in each temperature adjustment factor group with the optimal solution obtained with the optimisation software GAMS® and the solver CPLEX®. The mathematical formulation of the problem solved with an optimisation solver consisted of more than 16,000 integer variables and 17,000 constraints.

Table 2 shows the results for the problem instance evaluated. A neighbourhood structure with 60% probability of insertions and 20% of swaps was used to perform the comparisons. The best SA solution (2660) was obtained with a temperature reduction factor of 0.999, an initial temperature of 20000, and 1000 iterations per temperature. This solution is 0.4% away from the optimal solution (2648) obtained with GAMS® and CPLEX®.

Table 2: Comparison between SA and optimal solutions.

Parameters SA			**SA solution**	
Temperature adjustment factor	Initial temperature	Iterations per temperature	Solution value	Deviation (%)
0.8	20000	1500	2711	2.4
0.95	40000	1000	2692	1.6
0.99	40000	1500	2683	1.3
0.999	20000	1000	2660	0.4

Conclusions

In this paper, we have presented a simulated annealing algorithm to solve the log truck scheduling problem, which is a variation of the timber truck vehicle routing problem with time windows (TTVRPTW). Given the computational complexity of the truck scheduling problem, a SA heuristics has been developed, implemented, and tested for a small problem instance, consisting of 30 transport tasks and 10 trucks. Our results show that the best solutions are obtained when the temperature is reduced very slowly (reduction factor of 0.999) in combination with reduced initial temperatures (20000) and number of iterations per temperature (1000). In addition, the convergence of the algorithm is improved when a slow cooling scheme is implemented (slower temperature reduction factor), which results in more stable solutions and lower variance of the deviations in relation to the best single SA solution. Considering all the scenarios evaluated, our best SA solutions resulted in maximum deviations of 3% in comparison with the optimal solutions obtained with commercial optimisation solvers.

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