Mileage savings from optimization of coordinated trucking[1]

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Abstract

Data on mileage driven and loads delivered were collected from a log trucking firm hauling for 5 loggers to 9 consuming mills. Routes were assigned by a supervisory person and were not optimized. On average over the week of testing, the schedule achieved a loaded mileage proportion of 57%. A route optimization system was also used to assign delivery schedules and it achieved a loaded mileage proportion of 66%, significantly higher than the human-assigned dispatch ($P < 0.02$), and potentially saving the firm by up to 15,000 miles per year. Feasibility of the generated optimal schedules was a concern, but could not be directly evaluated. Instead, specific characteristics of routes that might be considered optimal and feasible were selected, and the generated solutions evaluated for whether or not they had those traits. Optimal solutions tended to a) deliver loads from multiple loggers on single days, and b) replicate a few, shorter routes between trucks, both of which were considered traits of feasible schedules. It was concluded that the optimization system was of potential benefit in reducing transport costs of coordinated trucking systems.

Introduction

Tree-length loggers of the US South have been slow in adopting technological solutions to increase efficiency of log transport. This has been despite the fact that commercial transport optimization solutions tailored to the logging industry have been developed (see e.g. Trimble BlueOx). In general, most loggers are reluctant to spend money on non-traditional technology without the certainty of a return on their investment, either in lower costs or increased hauling capacity.

Numerous studies have shown increases in log transport efficiency from application of optimization methodology (e.g., Shen and Sessions, 1989; Weintraub and others, 1996; Murphy, 2003). Most studies, however, were for situations other than found in the US South where log transport is typically structured to serve a single logger hauling to a handful of mills. The collaborative approach to hauling timber where multiple loggers use a pooled trucking resource is just now being adopted in widespread fashion, most commonly using a single human dispatcher to coordinate load

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allocation (Mendell and others, 2006). Current practice does not take advantage of the additional potential benefits of computer optimization of truck schedules.

Log truck allocation can be modeled using combinatorial methods and solution techniques to constrained optimization of the resulting problems have been proposed. Most of these methods, however, have not accounted for time in the models but rather take all trucking and load resources as being available at any time during a day (Taillard and others, 1997). This is a simplification that makes solution of the problem much more tractable, but one that also may result in solutions that are completely infeasible, i.e. schedules that cannot be implemented in practice.

This study was done to investigate the increment in log transport efficiency that might be achievable were route optimization technology implemented in a pooled log delivery system, that is a system that hauls timber from multiple loggers to any of a number of mills. The experiment was intended to assess the reduction in mileage that can be realized from application of optimization to log truck scheduling, and also to determine the feasibility of the optimal solutions. The specific objectives of the study were to:

- Characterize the baseline loaded mileage efficiency of an existing pooled log transport system using human dispatch of trucks.
- Using the identical daily delivery schedules, apply optimization methods to decrease unloaded mileage and assess the feasibility of the optimal solutions.

Methods

Data for the study were collected from a single log delivery trucking firm over the course of one week (Monday to Saturday) in February 2008. The firm operated about 12-20 trucks, depending on the day of the week. Of these trucks, a few were typically employed moving equipment or making deliveries of other commodities, but most were used exclusively for log transport. Only those trucks delivering logs were considered in this study, but there were instances where both types of deliveries were made by a single truck on one day. In those cases, that portion of the shift that was clearly log delivery was included in the analysis. Over the week, a total of 17 different trucks delivered 257 loads from 5 logging operations to 9 destinations.

All trucks were centrally dispatched by a person who did not use any form of optimization in scheduling other than their experience. Trucks varied their routines at the end of their shifts, some returning to a central yard while others ended their days at some other location, presumably at home. The trucks not returning to the yard typically were loaded at the end of the day and it was further presumed there was a mileage advantage gained by not returning to the dispatch yard at night. On any given day 4 to 9 trucks ended the shift loaded.

All movements of trucks were captured using a global positioning system (GPS) that recorded location after a truck had moved a distance greater than a fixed threshold value. Along with location, speed and time were also recorded. The raw GPS data were gone through manually to extract times and cumulative distances for each stop at either a mill or logger. Distances between mill and logger destinations were accumulated and averaged, as was travel time between the locations to calculate an average speed. Time spent at each location was also noted and averaged to come up with a logger- and mill-specific service (loading/unloading) time. Table 1 is a summary of distance and time information used as input to model the trucking system.

Table 1: Summary of mileage and service times for loggers and mills.

	Mill	Crew					Service Time
		1	2	3	4	5	(hours)
Service Time (hours)		1.09	0.67	0.7	0.89	0.88	
Distance (miles)	1	37.5	40.2	31.6	9.7	12	0.37
	2	92.7	87.4	79.5	53.4	45.6	0.49
	3	41.7	22.9	14.3	29.2	47.9	0.48
	4	26.5	25.6	40.3	19.8	28.9	0.89
	5	58.3	51.3	51	28.3	20.6	0.79
	6	52.7	47.6	28.7	26.7	45.9	0.97
	7	53.9	53	46.6	24	22.8	0.33
	8	144	122	88,4	78.8	79.1	0.52
	9	53.1	39.2	29	27.1	44	1.57

The optimization of routes was carried out on intraday truck movements only. A normal operating day began with the trucks leaving from the dispatch yard in the morning and first traveling to a logger location to pick up a load. The final movement of the day was normally a return trip from a mill to the dispatch yard. Neither of these moves were counted in the total mileage driven by a truck during the day.

The choice to not include trips to or from the dispatch yard in the optimization was made because the trucking system dispatcher seemed to make choices in route selection that were designed to minimize mileage across successive operating days. These moves typically involved leaving a truck loaded at the end of the day and not having it return to the dispatch yard. It was presumed that the operator selected a final load for some trucks for which the delivery to a mill took the driver past their home and they stopped for the night along the route. Although this was the presumed reason for some trucks not returning to the dispatch yard in the evening, this fact could not be verified. Without information on home locations of the drivers it was not possible to include these choices into the optimization scheme. Similarly, those trucks remaining loaded from the day before did not leave in the morning from the dispatch yard but went directly to a mill and these movements were not included in the optimization either. All beginning- or end-of-day moves for all trucks were therefore ignored. It was felt this comparison was the most realistic between the two dispatch systems.

The optimization of truck routes was carried out using a simulated annealing solution method for the system model as proposed in Haridass (2009). The objective function of the model was simply a summation of mileage used to deliver a set of loads and it was minimized subject to numerous constraints. The constraints restricted the solution to those that obeyed the laws of physics with regard to space and time, limited the operating time of a truck to no more than 10 hours per day, and allowed only integer numbers of loads to be delivered.

The simulated annealing solution method required a means of evaluating the relative merit of two solutions, allowing a choice to be made between them. A potential solution was evaluated using a simulator to 'run' it, then collect data on its performance. A 'fitness function' was then applied to four metrics calculated from the simulated delivery schedule. Those metrics included:

- Number of unloaded miles.
- Number of undelivered and 'phantom' loads.
- Waiting time at logging decks or mills.
- Number of trucks not meeting the constraint on working time.

Each of these metrics was multiplied by a weighting factor and summed. Those solutions having smaller penalty function values were regarded as being 'better' in some sense than those with larger values. The 'phantom' load terminology was a penalty applied to any load that was delivered but was not on the original daily schedule. These types of loads could result from the methods used to generate new solutions in the iterative simulated annealing process described below.

The simulated annealing method required a set of improvement operators by which new solutions could be derived from previous ones. These operators either added or deleted loads for a single truck, exchanged or shifted loads between trucks, or stopped a truck at a given point. New routes evaluated during the simulated annealing process were always generated from application of one or more of these operators between iterations. Once generated, a new schedule was simulated and evaluated using the fitness function then compared to the previous solution. If better, the new schedule was retained (with a certain probability) and another iteration performed until no further improvement was detected.

Results

Comparison of Observed and Optimal Routes

Loaded miles as a percentage of total driven for the non-optimized routing averaged 57 percent (table 2). This value did not include mileage to and from the first and last destinations so the overall true route efficiency would be lower. It did indicate, however, that the current scheme used to dispatch trucks was relatively effective. For static assignment of trucks, that is allocating all trucks to haul for a specific logger, this intra-day route efficiency would be near 50 percent by definition.

Application of the simulated annealing optimizer resulted in an average intra-day route efficiency of 66 percent (table 2). The overall difference in total route length between allocation schemes was about 20 miles per truck per day and was significant (P <0.02). Assuming mileage for the trucking system observed in this study was indicative of its true average weekly rate and that the reduction in unloaded miles from route optimization could be realized for the entire year, the decrease in mileage for 50 weeks of operation would be over 15,000 miles.

Table 2: Summary of mileage by day with and without route optimization.

Route Optimization	Measure	Day						Avg.
		Mon	Tue	Wed	Thu	Fri	Sat	
None	Unloaded Miles	1119	1114	668	1236	868	726	955
	% Loaded Route Mileage	58	56	60	55	60	55	57
	Min Route Length (miles)	27	40	27	40	26	80	40
	Max Route Length (miles)	261	241	201	282	203	189	230
	σ Route Mileage (miles)	74	53	52	68	51	35	56
	Median Route Segments	6	5	5	7	6.5	5	6
SA	Unloaded Miles	650	723	338	812	673	620	636
	% Loaded Route Mileage	70	66	72	65	65	59	66
	Min Route Length (miles)	37	40	37	125	89	48	63
	Max Route Length(miles)	232	235	182	213	190	215	211
	σ Route Mileage (miles)	46	58	41	24	27	59	43
	Median Route Segments	6	6	5	6	6	5.5	6

Figure 1 shows a plot of the frequency of occurrence of route distances. A 'route' in this case referred to the transport schedule over one day for one truck. The route mileage distributions for the week were quite similar for both the observed system and the optimized routing scheme. In general, the optimized transport schedule tended to shift some mileage from the longest routes to more numerous, shorter routes, but there were relatively few routes over 200 miles to begin with and the change did not dramatically shift the distribution. Variability in daily mileage between trucks, as represented by standard deviation of route length, was lower for the optimized routing (table 2) in 4 out of 6 days also indicating that the optimized system tended to allocate mileage more uniformly between trucks on a daily basis.

Larger differences in route characteristics between the two optimization schemes were observed for the number of route segments, a segment being one mill-to-logger or logger-to-mill traverse. Median number of segments per route did not vary greatly between optimization schemes, and was equal (6) for data pooled among days. The distribution, however, shown in figure 2, was quite different with the actual transport schedule showing a broad range in the number of segments and the optimized scheme tending to use a more consistent number of segments per route. Nearly 70 percent of all transport schedules assigned using the simulated annealing optimizer included 6 or 7 route segments. From a management standpoint, the route optimization scheme, in addition to reducing unloaded miles, tended to distribute trips to the mill more uniformly among drivers. It also tended to smooth daily mileage between drivers, but to a lesser extent. These characteristics could be of benefit to a trucking firm if there were issues of inequity in compensation among drivers.

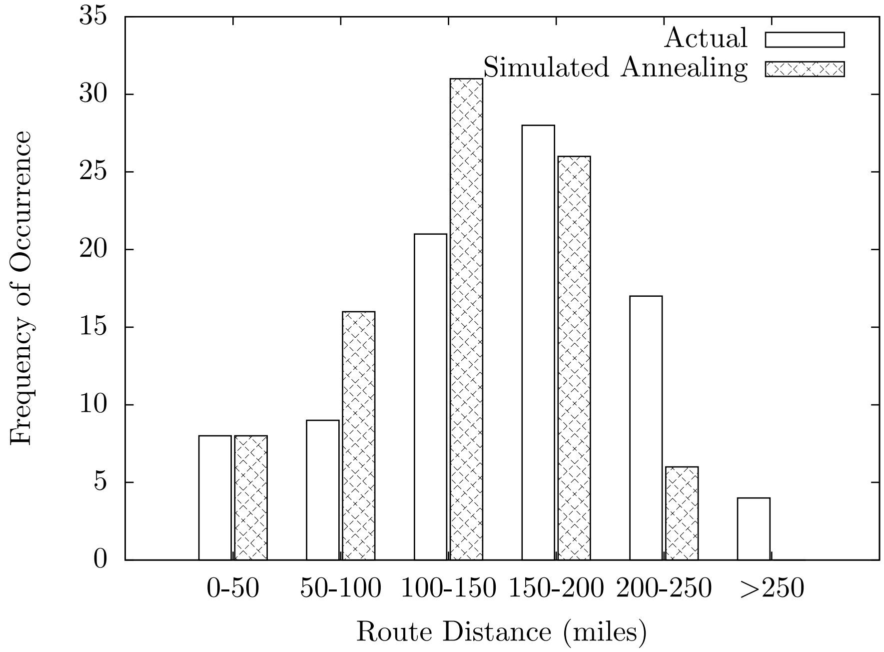

Figure 1: Frequency of routes of given lengths for original and optimized data.

The combination of a small set of loggers delivering multiple roundwood loads to a fixed (and also small) number of mills could imply that a single relatively short route applied across numerous trucks would form the core of a schedule minimizing total mileage to deliver all loads. It might also be reasonable to assume that this shortest route would, except in unusual circumstances, visit more than a single logger. An optimal delivery schedule, given these assumptions were correct, should perhaps exhibit both these characteristic of using replicated 'good' routes visiting multiple loggers on any given day. These characteristics should also be apparent when comparing optimized routes to the actual routes observed in this study and, in fact, the transport schedules generated using the simulated annealing optimizer exhibited both these characteristics. Figure 3 plots the distribution of the number of different loggers visited by each truck over the course of a day. The non-optimized routes had a high frequency of trucks (66%) that visited just a single logger during any given day. The optimized routes showed more diversity, with just under half visiting two, and 19% of routes visiting three. Table 3 shows the number of non-unique routes, meaning more than one truck drove a specific route, for a given day. For the entire week, the non-optimized schedule used four routes that were duplicated by multiple trucks. The optimized schedule used eight.

In figure 3, the number of trucks visiting zero loggers represented those that delivered a load held over from the previous day, then retired to the hub. Since there was no single 'hub' in the transport system, these beginning- and end-of-day moves were assigned in the optimization, but were excluded when calculating the mileage total. That is, the mileage to the logging deck for all final loads was counted on the day they were picked up, but the mileage to deliver the loads the next morning was never accounted for. It was interesting to note that, although there were typically five to seven of these loads held over each night, the optimizer did not prefer these zero-length

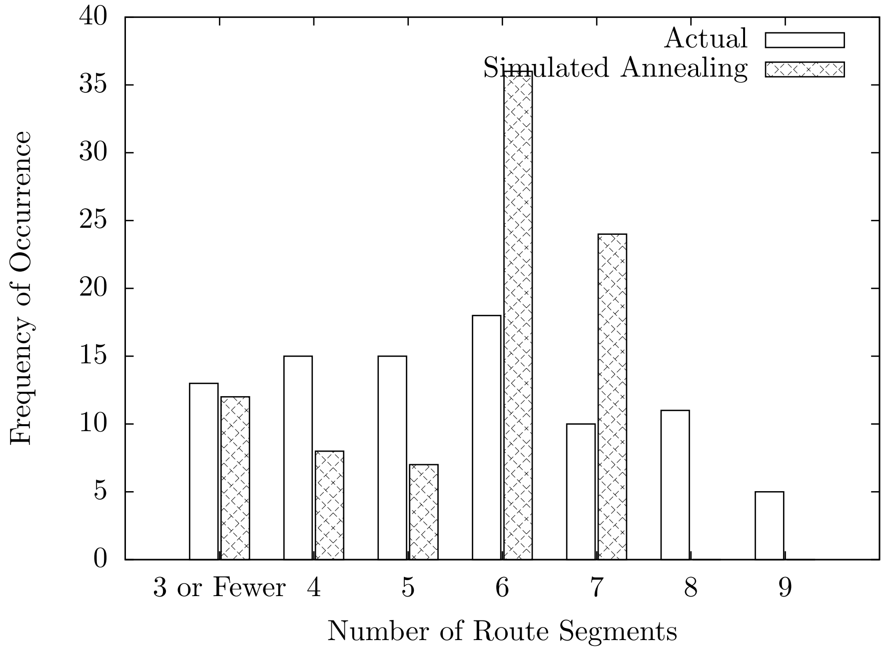

Figure 2: Frequency of occurrence of number of segments per route.

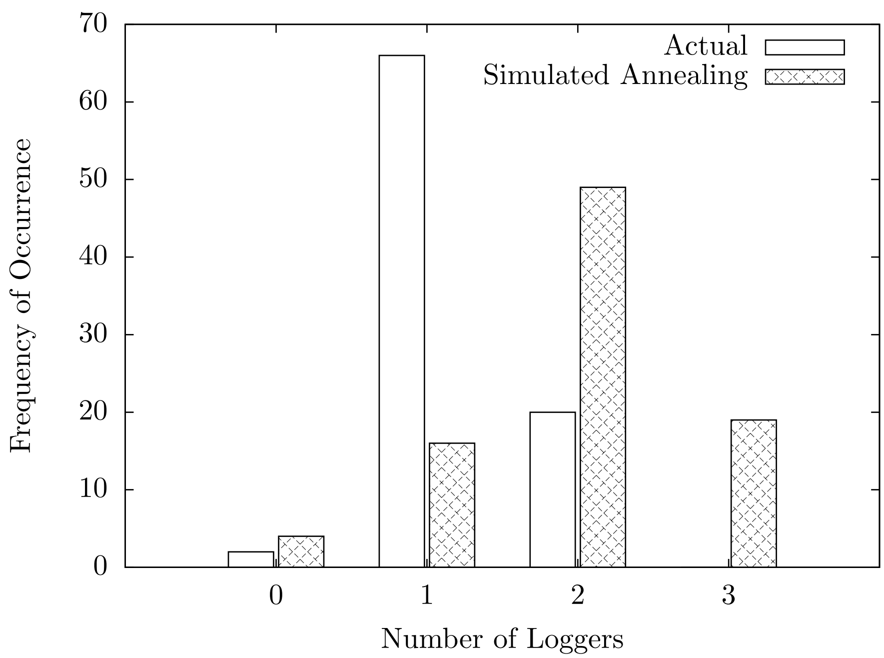

Figure 3: Frequency of occurrence of the number of loggers visited per route.

routes when generating transport schedules. In fact, the optimizer included this type of route in its schedule only two times more (4) than did the original routing scheme (2).

Effect of Waiting Time Variation

The simulated annealing route optimization scheme assigned a penalty to any waiting time spent queued either to be loaded or unloaded. The penalty affected the choice between two solutions and was included to prevent obviously infeasible solutions from being selected. In early tests of the optimizer without the waiting time penalty, for example, the solution would often send all trucks to a single logger first thing in the morning. Increasing the magnitude of the penalty, however, also negatively influenced the unloaded mileage of the optimal solution. Table 4 shows total time spent waiting and loaded travel miles percentage for a range of waiting time penalty values. The solutions were calculated for a single day (Monday). Increasing the penalty value decreased waiting time, but also decreased loaded miles percent.

The change in waiting time with penalty was large, but not linear. The largest penalty (10,000) reduced loaded mileage to just above 50 percent, indicating that the solution was almost entirely constrained. There was a large drop in loaded mileage between the penalties of 10 and 100, and waiting times also decreased by a factor of 3. Lower overall waiting time would imply higher utilization of trucks, but not necessarily earlier finishing times or lower operational costs. In fact, the largest waiting time penalty also resulted in 6 loads not being delivered in the 12-hour time window allowed for the simulations.

Effect of End-of-Day Constraints

The actual trucking system from which our operational data were derived allowed drivers to take trucks home loaded overnight presumably if it resulted in a shorter route to a delivery point the following morning. The initial optimization approach used in this study did not take advantage of these opportunities. To make the comparison between optimized and actual dispatch as fair and

Table 3: Number of non-unique pairs of individual truck routes per day, by optimization scheme.

Day	Non-Unique Pairs	
	None	of SA
Monday	1	2
Tuesday	1	3
Wednesday	1	2
Thursday	1	0
Friday	0	1
Saturday	0	0

Table 4: Change in loaded miles traveled (%) and waiting time as a function of waiting time penalty.

Waiting Time Penalty	Loaded Miles Fraction	Waiting Time (h)
0.01	0.69	61.7
0.1	0.70	44.8
1	0.70	44.0
10	0.67	32.1
100	0.53	12.3
1,000	0.52	13.6
10,000	0.51	6.3

as transparent as possible, it had been decided to look simply at intraday truck movements. The actual dispatcher had an advantage that the computer optimization system did not have, namely information about home locations and about availability of loads to specific mills at the end of the day.

Specific, end-of-day transfers could have been included in the optimization scheme but this would have reduced overall effectiveness of the approach. Forcing a specific load to be picked up last would be an additional constraint on the solution and would most often result in less effective routing. It was decided, however, to see if the additional constraint imposed by a specific end-of-day pickup dramatically reduced the advantage of the optimization scheme over the actual system.

Results from application of the additional constraint were generated for two days of operation (Monday and Tuesday) and are summarized in table 5. Intra-day efficiency of the optimized system was lower when including the final extra pickup for both approaches, and by about the same amount (4%). Changes in the other measures of system performance were similar between the two schemes, with minimum and maximum route lengths not changing by a large amount and standard deviations increasing only slightly. It was concluded that, at least for these two days, an additional constraint on the solution did not materially affect the advantage gained from the optimization system developed for this study.

The solutions found when applying the extra constraint were not the same as those identified without the constraint. There were, however, some routes that were exactly the same between the two methods, a total of 5 for Monday and 4 for Tuesday.

Summary and Conclusions

Data on mileage driven and loads delivered were collected from a log trucking firm hauling for 5 loggers to 9 consuming mills. Routes were assigned by a supervisory person and were not optimized. On average over the week of testing, the system achieved a loaded mileage proportion of 57%. A

Table 5: Summary of mileage by day with and without route optimization. The solution in this case has been constrained to ensure that specific loads are picked up at the end of the day to be delivered the following morning.

Route Optimization	Measure	Day	
		Mon	Tue
None	Unloaded Miles	1239	1276
	% Loaded Route Mileage	55	53
	Min Route Length (miles)	26	40
	Max Route Length (miles)	261	281
	σ Route Mileage (miles)	77	70
	Median Route Segments	6	5.5
SA	Unloaded Miles	799	874
	% Loaded Route Mileage	66	62
	Min Route Length (miles)	40	78
	Max Route Length(miles)	213	205
	σ Route Mileage (miles)	50	34
	Median Route Segments	6	6

route optimization system was also used to assign delivery schedules and it achieved a loaded mileage proportion of 66%. Schedules chosen using the optimization system tended to be more uniform in length and also to visit multiple loggers during any given day, as opposed to the human-assigned schedules which had higher disparity between the shortest and longest daily schedules, and which tended to send trucks to only a single logger. The feasibility of the optimal solutions was not evaluated directly, but the routes tended to be replicated among trucks and trucks tended to visit multiple loggers more often than in observed schedules, both of which were felt to be characteristics of solutions that could be practically implemented. It was concluded that the optimization system could assist dispatchers in assigning schedules that were likely to be both feasible and shorter in overall length.

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