Robust Optimization of Forest Transportation Networks: A Case Study*

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Abstract
Forest transportation costs are the major cost component for many forest product supply chains. In order to minimize these costs, many organizations have turned to optimization models to guide decisions that are extremely complex in nature. These models generally assume that input parameters are known with certainty, but in reality they are associated with a high degree of uncertainty. One way of dealing with uncertainty is through robust optimization, which is capable of generating near-optimal solutions that are relatively unaffected by the surrounding uncertainty. This we will illustrate by means of a case study that employs a robust optimization approach. Our approach will employ a two phase approach. The first phase will create a more tractable problem by limiting the search to those solutions that are near optimal and feasible. The second phase will simulate the affect of uncertainty on the solutions isolated in the previous phase. The resulting simulation results will then be evaluated for robustness by means of seven robustness performance measures. Our research will show that (1) the deterministic solution is extremely unstable and highly reliant on a particular realization of uncertainty, that (2) the robust solution is dependent on the robust performance measure selected, and (3) that the true robust solution is different from the deterministic solution for our case study.

1. INTRODUCTION

The transportation of forest products from infield locations (stand) to ultimate point of sale (mill) is generally considered to be the foremost cost element of most forestry supply chains. In the southern United States it has been found that these costs can amount to roughly half of total mill-delivered cost (McDonald et al, 2001). Even in cases where other costly activities such as pruning and pre-commercial thinning were applied, transportation still accounted for 20 to 30% of the discounted seedling to mill cost (Carson, 1989). Minimizing the cost associated with transportation is therefore of paramount importance to the profitability of any forestry organization. This has led to the development of various transport optimization methods and tools through the years. One, the Integrated Resource Planning Model, IRPM (Kirby et al., 1981) is a mixed integer programming model developed for the USDA Forest Service that simultaneously solved the harvest scheduling, road building and transportation problem, but was limited in size due to the number of integer decision variables to represent construction project choices. Others used some form of heuristics. The Timber Transport Model developed by the United States Department of Agriculture (USDA) Forest Service, used a heuristic combination of mixed-integer and network programming to solve the road construction and forest transportation problem (Sullivan, 1974). N-shortest (lowest variable cost) routes were generated using network programming and these became the decision variables for the mixed integer programming

problem. Other heuristics using network programming include NETCOST (Weintraub, 1985), NETWORK (Sessions, 1987), and NETWORK 2000 (Chung and Sessions, 2003).

These techniques however all assume that model parameters are known with certainty. The reality however is that most decisions are made under conditions of uncertainty (Wallace, 2000) and that some degree of uncertainty exists as to the true value of model parameters. This is especially true in forest product supply chain problems, where one has to contend with the uncertainty related to harvest age, stand volume, product mix, transportation cost, road cost, mill volumes and market prices. Uncertainty is also not limited to the parameter values, but also extends into the realm of modeling approximation (Wallace, 2000). Every model is an abstraction of the real world. Abstraction requires the generalization of a real world phenomenon in order for it to be squeezed into a particular model. This generalization results in uncertainty, since no model can capture all the detail present in the real world. Models are often also quite complex, resulting in logical modeling errors that are difficult to detect.

In dealing with uncertainty, many practitioners resort to sensitivity analysis to evaluate the sensitivity of a given solution to uncertainty. This approach generates an area of optimality, where a “large” area will point to a stable solution and vice versa (Wallace, 2000). The problem with this technique is that it does not actively search for a stable solution, but merely reports on the stability. Other practitioners have employed worst-case analysis, where parameter values are set to the worst possible expected value. This enables the evaluation of the feasibility of the worst possible outcome, but also leads to sub-optimal and overly conservative results (Sörensen, 2002).

Uncertainty is therefore an unavoidable factor of decision making and optimization, regardless of the industry or discipline. Numerous Operational Research (OR) methods have been developed over the years to deal with uncertainty. These include stochastic linear programming, dynamic programming, and chance constrained methods (Bai et al, 1997). With regards to these techniques, Bai et al notes that “despite the presence of uncertainty in critical real-world problems, optimization based systems on the whole fail to address risk aversion as specified in classical decision theory” (Bai et al, 1997). That is, these techniques do incorporate uncertainty, but do not necessarily minimize the effects of the uncertainty.

This is exactly where the strength of robust optimization lies, since its goal is to find a “near optimal solution that is not overly sensitive to some realization of uncertainty” (Bai et al, 1997). Robust solutions therefore have two distinguishing characteristics. First, they are close to optimal (Mudchanatongsuk, 2005), where the degree of optimality is referred to as “absolute robustness” (Carr et al, 2006). Second, they exhibit limited deviation from a given robust solution under considered variation, a condition known as “robust deviation” (Carr et al, 2006).

In this paper, we present a two-step procedure for finding robust solutions to real-world forestry transportation problems. We will also present seven different measures of robustness and will highlight how these measures influence the ultimate decision through a case study. The most similar work in this area was reported by Moore (1987) and Moore et al. (1988) who examined the sensitivity of transportation solutions to changes in fixed and variable costs for several network algorithms.
2. METHODS

We will begin this section with a description of the chosen study area. This will be followed by discussion of the two-step robust optimization technique and subsequent robustness evaluation measures.

2.1 Study Area

The area selected for this study is a small plantation forest called Tainui-Kawhia, located on the west coast of New Zealand’s north island. The landholding has an area of ±900 ha, of which ±895 is planted to Pinus radiata. Data was originally collected in the 1980’s for use in a New Zealand forest industry workshop on forest transportation analysis. The area has subsequently been harvested.

Harvest age ranged from 25 to 31 years, and the total expected volume over an 11 year harvest period was expected to be 391,000 m³. The coefficient of variation for total volume was set at 2.5%. Since the silvicultural regime included pruning and pre-commercial thinning, this area is capable of producing pruned veneer logs, pruned saw logs, un-pruned saw logs and pulp logs. It was expected that these products would respectively represent 10%, 24%, 55% and 11% of the total volume. The coefficients of variation for these percentages were respectively set at 12.5%, 7.5%, 5.0% and 12.5%.

Six possible markets existed for the logs, which were located in Auckland, Hamilton, Tokoroa, Taumarunui, New Plymouth and Wellington. Veneer logs were accepted by mills located at Auckland, Tokoroa or Wellington. Pruned saw logs were accepted by mills at all six locations. Un-pruned saw logs were accepted by all mill locations, except Wellington. Pulp logs were only accepted by the mill located at Tokoroa. Mill-delivered prices for these respective products were US$83/m³, US$66/m³, US$40/m³ and US$33/m³ (1 US$ = 1.5 NZ$). The respective coefficients of variation for these prices were 6.67%, 6.67%, 11.11% and 6.67%.

Since the plantation was established on flat coastal sand dunes, the entire area could be harvested with ground based systems. The original road infrastructure was constructed to a standard that facilitated light use for silvicultural and management purposes. The road system therefore had to be upgraded to consider logging transportation. In addition, ±70 landings had to be constructed. The internal transportation network linked with the external transportation...
network at three locations; an existing road exit at the south end of the plantation, a proposed coastal marine barge exit at the south end of the plantation (a log storage and barge loading facility had to be constructed), and a proposed road exit at the north-east corner of the plantation (right-of-way had to be purchased and a linking road constructed).

From these exit points, three alternative transportation options existed:

- Truck all the way to the mill
- Barge to either Auckland or New Plymouth, followed by truck to the mill
- Truck to a rail loading facility, rail to an unloading facility, truck to the mill

Tokoroa was the only mill with direct linkage to a rail network. Transport cost elements and associated coefficients of variation were as follows:

**Table 1:** Estimates of transport cost elements and their associated coefficients of variation.

<table>
<thead>
<tr>
<th>Cost Type</th>
<th>Cost Element</th>
<th>Cost</th>
<th>Coefficient of Variation (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable Costs</td>
<td>Log and Load</td>
<td>US$8/m³</td>
<td>15.0</td>
</tr>
<tr>
<td></td>
<td>Road Transport</td>
<td>US$0.14/m³/km</td>
<td>7.5 to 20</td>
</tr>
<tr>
<td></td>
<td>Rail Transport</td>
<td>US$7/m³ to US$37/m³</td>
<td>5.5 to 6.5</td>
</tr>
<tr>
<td></td>
<td>Rail Load</td>
<td>US$1.33/m³</td>
<td>±3.5</td>
</tr>
<tr>
<td></td>
<td>Barge Transport</td>
<td>US$8/m³ to US$9/m³</td>
<td>±5.0</td>
</tr>
<tr>
<td></td>
<td>Barge Load and Unload</td>
<td>US$4/m³ to US$5/m³</td>
<td>±2.5</td>
</tr>
<tr>
<td>Fixed Costs</td>
<td>Landings</td>
<td>US$8,400</td>
<td>±20.0</td>
</tr>
<tr>
<td></td>
<td>Roads</td>
<td>US$4,600/km to US$18,800/km</td>
<td>±20.0</td>
</tr>
<tr>
<td></td>
<td>Barge Landing</td>
<td>US$70,000</td>
<td>±6.5</td>
</tr>
</tbody>
</table>

### 2.2 Robust Optimization Procedure

The robust optimization procedure that will be proposed here has two distinct phases, namely the scenario generation phase and the scenario evaluation phase. During the scenario generation phase 100 trials were performed on the input data to isolate a set of candidate robust solution scenarios. First step was to create ten unique transportation networks from the original network, by allowing the variable and fixed costs of each network link to deviate a random number of standard deviations from the mean. Next, ten sets of sales volumes were created by allowing the overall stand volume and product mix of each stand to deviate a random number of deviations from the mean. In both cases, the deviations were limited to 3 standard deviations from the mean along an assumed normal distribution. Then, by pairing the set of ten transport networks with the set of ten sales volumes, 100 unique trials were generated. Network 2000, a heuristic network analysis package (Chung and Sessions, 2003), was then used to determine the optimum transport mode, route and sales destination for each trial. Optimality was based on maximized NPV, using a discount rate of 7%. The 100 solutions obtained were then grouped into similar solutions, with similarity defined as those solutions that sent the same products to the same destination via the same transport mode. This rendered the overall problem more tractable, since it was reduced to those candidate solutions that were both feasible and potentially optimal. This step is especially important when dealing with real-world problems, since the complexity contained therein can often render the problem both computationally and logically difficult to solve.
During the scenario evaluation phase, each of the candidate scenarios identified above were subjected to a set of 1,000 simulations. For each simulation the variable and fixed cost of each network link was randomly varied, as well as the total volume and product mix of each stand. Once again deviations were limited to 3 standard deviations from the mean along an assumed normal distribution. The 1,000 trials for each scenario were then used to calculate the scenario’s robustness, based on seven robustness performance measures.

In addition to the above, the NPV of the optimal deterministic solution was also determined. This was established by using the means of all input parameters in Network 2000.

2.3 Robustness Performance Measures

In order to ascertain the robustness of each candidate scenario, seven robustness performance measures were evaluated. The first performance measure was calculated from data collected during the scenario generation phase, while the rest was calculated from the scenario evaluation phase data. They were:

- Most Frequent Solution: Candidate scenario that was found to be optimal by Network 2000 the highest number of times.
- Highest Average NPV: Candidate scenario that had the highest average NPV.
- Lowest Variation in NPV: Candidate scenario with the lowest standard deviation from the average NPV.
- Best Worst-Case NPV: Candidate scenario with the highest minimum NPV.
3. RESULTS

The scenario generation phase identified ten unique candidate scenarios. Two of these were near similar to two others with respect to markets supplied, transport modes and routes taken. These were subsequently grouped together, resulting in eight candidate scenarios being taken forward to the scenario evaluation phase. These will be labeled scenarios 1 to 8 for future reference.

Following the scenario evaluation phase, only two scenarios (1 and 3) displayed strong robustness as measured by the seven robustness performance measures. Scenario 1 had the highest average NPV (US$5.552 million), best worst-case NPV (US$5.334 million) and lowest threshold probability (15.1%). It equaled scenario 4 with respect to the most frequent solution (20). It was also identical to the deterministic solution with regards to markets supplied, transport modes and routes taken.

Scenario 3 however ranked best in the three remaining robustness performance measures. It had the lowest NPV standard deviation (US$0.196 million), highest NPV signal-to-noise ratio (27.43) and the highest weighted NPV sum (0.975). Scenario 3 persisted to have the highest weighted NPV sum until the weights were changed to 0.90 and 0.10, after which scenario 1 had the highest value.

Table 2: Robustness performance measures evaluated for the eight scenarios examined in the scenario evaluation phase.

<table>
<thead>
<tr>
<th>Performance Measure</th>
<th>Scenario 1</th>
<th>Scenario 2</th>
<th>Scenario 3</th>
<th>Scenario 4</th>
<th>Scenario 5</th>
<th>Scenario 6</th>
<th>Scenario 7</th>
<th>Scenario 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Most Frequent Solution (%)</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>Highest Average NPV (US$ millions)</td>
<td>5.552</td>
<td>5.490</td>
<td>5.365</td>
<td>5.335</td>
<td>4.952</td>
<td>4.923</td>
<td>4.838</td>
<td>4.729</td>
</tr>
<tr>
<td>Lowest Variation in NPV (US$ millions)</td>
<td>0.275</td>
<td>0.293</td>
<td>0.196</td>
<td>0.334</td>
<td>0.371</td>
<td>0.249</td>
<td>0.598</td>
<td>0.762</td>
</tr>
<tr>
<td>Highest NPV Signal-To-Noise Ratio</td>
<td>20.23</td>
<td>18.74</td>
<td>27.43</td>
<td>16.00</td>
<td>13.35</td>
<td>19.75</td>
<td>8.10</td>
<td>6.20</td>
</tr>
<tr>
<td>Highest Weighted</td>
<td>0.928</td>
<td>0.908</td>
<td>0.975</td>
<td>0.867</td>
<td>0.801</td>
<td>0.861</td>
<td>0.735</td>
<td>0.703</td>
</tr>
</tbody>
</table>
In addition, scenario 1 and 3 were substantially different with regards to markets supplied, transport modes and routes. With scenario 1 veneer logs would be sent by barge to Auckland, pruned and un-pruned saw logs would be sent by road to Hamilton and pulp logs would be sent by road to Tokoroa. In this scenario about 10% of the volume would be transported by barge and 90% by road.

For scenario 3 veneer logs, pruned saw logs and about one third of un-pruned saw logs would be transported by barge to Auckland. The remaining un-pruned saw logs would be transported by road to Hamilton, while the pulp logs would be transported by rail to Tokoroa. In this scenario about 54% of the volume would be transported by barge, 35% by road and 11% by rail.

4. DISCUSSION

The management of forestry enterprises requires the simultaneous consideration of numerous supply chain factors to remain cost efficient and competitive. This is especially true for transportation optimization, since the selection of the optimal practice is contingent on factors ranging from harvest age through to mill demands. In this study we evaluated the effect of stand volumes and product mixes, the variable and fixed costs associated with various transport modes, and mill revenues. To consider all of these factors at once, many practitioners are turning to various optimization models. These models however typically do not account for the variation and uncertainty that is inherent to the practice of forestry. These uncertainties can however have a profound effect on the ultimate optimal solution, and by using robust optimization, decisions can be made that are substantially more immune to uncertainty.

Our first finding from this study was that uncertainty can give rise to numerous solutions that seem optimal. This was evident in the fact that our deterministic solution procedure (scenario generation phase) delivered eight distinctly different solutions when the expected input values were varied. The optimal solution of our case study was therefore highly sensitive to variations in the input data (uncertainty) and therefore unstable. This is hardly a desirable situation, since a minor error in input data could lead to the wrong transport strategy being selected.

Our second finding was that the robust solution is dependent on the selection of robust performance measure. Here we evaluated seven robustness measures, and found that they isolated two potentially robust solutions (scenario 1 and 3). To isolate the most robust solution we need to return to the principles of robust optimization, and isolate those robust performance measures that truly adhere to those principles. Robust solutions typically display two characteristics. They are near-optimal (absolute robust) and display a low degree of deviation from their mean value under uncertainty (robust deviation, low regret) (Bertuccelli et al, 2004) (Carr et al, 2006). It is the combination of these two characteristics that constitutes the definition of a truly robust solution. In this regard, we found that scenario 1 only displayed absolute robustness, since it only ranked high with those measures that were contingent on the absolute
value of the NPV. Scenario 3, on the other hand, displayed both absolute robustness and robust deviation, since it ranked highest with those measures that incorporated both the absolute NPV and its standard deviation. Of particular interest is the high ranking of scenario 3 with regards to the signal-to-noise robust performance measure, since this ratio is often used in practice to evaluate robustness (Al-Aomar, 2002) (Chen et al, 1999). We can therefore conclude that scenario 3 is the most robust of all the scenarios evaluated.

Our third, and final, finding was that our inclusion of uncertainty in the optimization process for our case study did lead to a different solution than the deterministic solution. Scenario 1 was the deterministic solution for this study. However, by incorporating a measure of robustness our optimal solution was scenario 3.

Robust optimization is therefore an optimization technique that could lead to better decision making in forestry. Much work however remains to be done. First, future studies should investigate the scenario generation phase employed in this study. Its purpose was to break the problem down to a more tractable one, but limiting the scenario generation to a pool of 100 candidates could have narrowed the search down prematurely. Larger pools, or other techniques to isolate candidates, should be investigated. Also, whenever heuristics are used to solve a problem, caution must be used in interpreting solutions. Heuristic rules may trap solutions in a local optimum over a range of inputs thus underestimating variances in solutions as well as underestimating the optimal value of the deterministic solution. Second, it was assumed that all parameters varied along a normal distribution from the mean. However, normal distributions might not adequately describe the actual distributions. Other distribution forms and their affect on overall results should therefore also be investigated. Third, the model should be expanded to incorporate the effect of additional supply chain factors. These might include placing an upper and lower limit on mill demand, and varying the final harvest age of stands. Fourth, the source and cost of uncertainty could be examined. For example, the origin of uncertainty about log prices may be different than the uncertainty concerning road, landing, and harvest costs. Log prices may depend on exogenous factors, while the variation in road, landing, and harvest costs may be dependent upon the quality of planning. Therefore the source of the uncertainty may need to be examined.

5. LITERATURE CITED


