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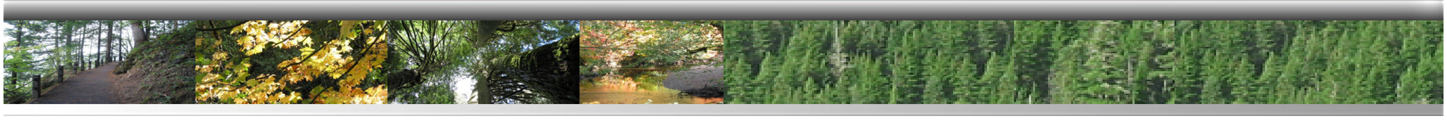

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Going Retro: Forest planning like its 1989

Karl R Walters

In 1986, I started graduate school at the University of New Brunswick under the guidance of a new professor there, Mark Jamnick. Mark was finishing up his doctoral thesis at UC Berkeley where he was comparing the effects of stratum-based and area-based harvest scheduling models using FORPLAN. As an undergraduate, I had been exposed to less-advanced LP-based harvest scheduling models (Timber RAM and MUSYC), and while linear programming had been used by the forest industry in the U.S. for years, it had not made many inroads into Canadian forestry. LP-based models were perceived as “black boxes” that few foresters understood, and reluctance to employ them over the more familiar inventory projection models was strong. Although the FORMAN model did not employ a binary search algorithm directly, in practice it was used in an analogous manner.

In 1990, Mark wrote a paper that compared the FORMAN and LP approaches to harvest scheduling and was able to show in a rather convincing way that the more complicated the planning problem, the more effective an optimization model was relative to rule-based inventory projection models (and by extension, binary search). In the 20 years that have elapsed since that paper, forest planning has become far more complex than just determining a sustainable allowable cut or reasonable levels of precommercial thinning or planting programs. Yet we still encounter managers of timberland who use relatively simplistic forest planning models like binary search, spreadsheet-based area-regulation and others even today! When we ask why they don’t employ more sophisticated models they usually say something like, “we considered it but we didn’t think it was worthwhile since we only manage X thousand acres”. If X = 1, it makes sense to stay simple, but if X = 50, 100, 250 or more, then it is time to rethink things!

Suppose that forest land in the U.S. southeast goes for $1500 per acre (a conservative value these days – a recent transaction went for $1895/acre); an ownership of 100,000 acres is then worth 150 million dollars!! Now suppose that you could improve the net present value of that land by 5% through management employing optimization methods (again, a conservative estimate), the payback on that investment in optimization would return $7.5 million!! Just to keep the arithmetic simple, suppose you were willing to spend $100,000 on forest analytics. You’d still see a return on that investment of 7400% even if NPV was only improved 5%. In reality, you’d spend far less on the analytics and you’d likely reap bigger gains, so what’s holding people back?

Part of the issue is familiarity. Often, the task of harvest scheduling falls to the same individual who is responsible for maintaining the inventory system and/or GIS. These folks have enough work to do as it is, without taking on the task of learning a new planning model, particularly if their tool set already includes a “harvest scheduler.” Since they are already familiar with how it works, the desire to stray outside the familiar interface is muted at best. Moreover, with a long history of using such a system, the results tend to be consistent over time and expected; if a radically different answer comes out of an analysis, it is generally assumed that the new analysis is wrong rather than a better answer has been found. In many ways, the situation remains similar to the one described by Jamnick in 1990. Maybe it’s time to revisit the issue with an updated analysis.

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Methods

One of the difficulties with comparing the results of different models is the ability to make apples-to-apples comparisons. To that end, I conducted the analysis using Woodstock because it is able to formulate planning models using optimization or inventory projection (with or without binary search). A binary search model is an extension to the inventory projection model. The name binary search emerges because 1) there is one decision variable per period (a target output level) and 2) there are only two choices for the decision variable (either increase or decrease the level of output).

A hypothetical forest planning model was developed using Remsoft's Woodstock software. There are four actions defined in the model (clearcut, site preparation, natural regeneration and planting), corresponding to activities undertaken to manage the forest: final harvest, site preparation, stand establishment. The model is formulated to track timber harvest volumes and revenues by log sort and origin (logging system/elevation), harvest and silvicultural treatment acres, costs by treatment and non-silvicultural costs. Three outputs are particularly important since they are either output targets in the binary search models, or objective function/constraint components in the LP models. These are conifer log volume, total inventory and discounted net revenue.

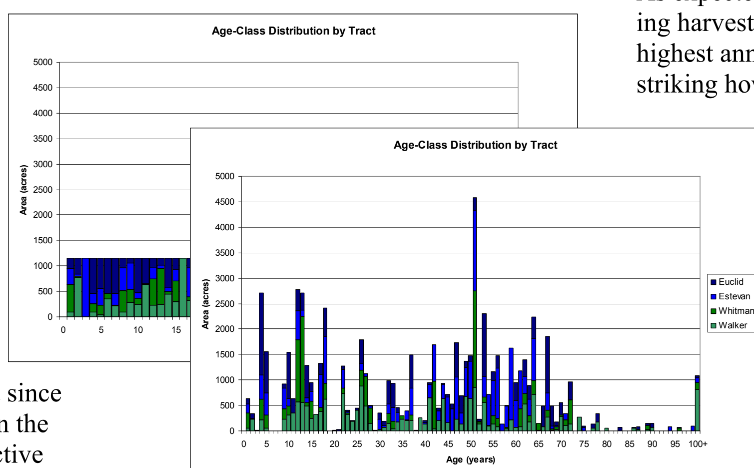
For the binary search models, three harvest rules were employed: highest volume first, highest value first, slowest-growing first. For silvicultural activities, the oldest existing stands were treated first. Since no real limits were placed on these activities, the net effect is to regenerate all cutover stands. For the LP models, the requirement to reforest cutovers was an explicit constraint. A planning horizon of 100 years was used throughout.

Table 1. Descriptions of the model runs.

Run	Type	Harvest Rule	Target/Objective	By Tract
BinVal	Binary Search	Highest Value First	Max even-flow volume	No
BinVol	Binary Search	Highest Volume First	Max even-flow volume	No
BinGro	Binary Search	Slowest Growing First	Max even-flow volume	No
LPVol		n/a	Max even-flow volume	No
LPNpv		n/a	Max PNV st even-flow volume	No
BinGroTE	Binary Search	Slowest Growing First	Max even-flow volume	Yes
LPVolTE		n/a	Max even-flow volume	Yes
LPNpvTE		n/a	Max PNV st even-flow volume	Yes

The binary search models all attempted to maximize an even-flow of conifer log volume in every planning period. The only limiting output target was a requirement that the ending inventory be at least as high as the initial inventory.

The LP models explicitly constrained conifer log volume to be even-flow, and ending inventory to be greater than or equal to the initial inventory. All other costs, yield coefficients, and so forth were identical for both binary search and LP models.



Two forests were modeled in this analysis, both typical of forests in the Pacific Northwest. The first exhibited a balanced age class structure up to age 60; the second exhibited a more typical age class structure with significant variations and gaps, and stands of advanced age. The total acres in each forest were the same, and both forests were divided into four tracts.

A total of 8 model runs were completed for each forest. Three of the runs incorporated even-flow constraints on harvest volume at the tract-level. These are denoted by the TE suffix on model names as shown in Table 1.

Due to space considerations, a more detailed explanation of how the harvest rules work and their explicit definition is not possible here. However, you may download the complete white paper from our website by clicking here.

Results

The results of the 8 runs for each forest are presented in Table 2 on the next page.

Harvest Volume

As expected, the LP model maximizing harvest volume produced the highest annual harvest levels but it is striking how poorly the binary search models performed overall.

Considering that Forest 1 already has a balanced age-class structure, it might be expected that the binary search models would perform quite well and without significant variations among harvest rules because the slowest-growing stands are generally those with the highest volumes and values. While the highest-volume-first (BinVol) and slowest-growing-first (BinGro) harvest rules performed almost identically well, they yielded an even-flow harvest about 10% lower than the LP optimum (9.9% and 10.3%, respectively). The highest-value-first (BinVal) harvest rule yielded exceedingly poor results, with a harvest volume 18.9% lower than the optimum. If harvest volume truly is your management objective, using a binary search model to determine the harvest schedule could be costly even with a well-balanced age-class distribution.

Table 2. Net present value, annual harvest and average inventory for 8 model runs.

Forest 1 Model Runs

	BinVal	BinVol	BinGro	LPVol	LPNpv	BinGroTE	LPVolTE	LPNpvTE
Net Present Value ($million)	172.1	176.9	178.2	198.7	206.4	170.2	193.7	202.0
Annual Harvest (MMBF/yr)	42.4	47.1	46.9	52.3	51.0	44.5	50.4	49.5
Avg Inventory (MMBF)	1,138.9	976.8	936.9	921.6	892.3	1,123.5	895.1	870.9

Forest 2 Model Runs

	BinVal	BinVol	BinGro	LPVol	LPNpv	BinGroTE	LPVolTE	LPNpvTE
Net Present Value ($million)	206.3	202.7	211.4	233.3	247.2	209.1	232.6	244.8
Annual Harvest (MMBF/yr)	51.8	53.2	55.1	60.4	58.9	54.0	59.7	58.5
Avg Inventory (MMBF)	1564.2	1436.3	1428.9	1383.3	1351.9	1467.1	1375.7	1345.3

Most forests that occur in the real world do not have perfectly balanced age-class distributions; rather, they are more likely to resemble Forest 2. Again, the binary search models performed less well but with more variation across the different harvest rules. The best solution applied the slowest-growing-first rule (BinGro) and yielded an even-flow harvest 8.8% lower than the LP optimum; with reductions in harvest of 14.3% (BinVal) and 11.8% (BinVol), the other harvest rules performed significantly worse.

Applying even-flow at the tract level had a real impact on harvest levels from Forest 1. The constrained version of the volume maximizing LP model (LPVolTE) yielded a total harvest of 50.4 MMBF/year, so the cost of the constraints was 3.5%, a not insignificant amount. The constrained version of the slowest-growing-first binary search model (BinGroTE) yielded a total harvest of 44.5 MMBF/year, a loss of 14.8% relative to the unconstrained maximum, and a 5% reduction relative to the unconstrained BinGro model.

The results for Forest 2 were quite different, and the impact of the constraints was minimal using LP (1% reduction for LPVolTE). The constrained binary search model (BinGroTE) performed significantly better on Forest 2, suffering only a 10.5% reduction in annual harvest relative to the unconstrained maximum and a 2% reduction relative to the unconstrained BinGro model.

Net Present Value

As expected, LPNpv model produced the highest discounted cash flows. For maximizing net present value, the slowest-growing-first (BinGro) harvest rule performs best overall among the binary search models, although still significantly less well than the LP models. Considering the effect of discounting on PNV, the ideal is to harvest stands growing slower than the hurdle rate. Unfortunately, the rule cannot make trade-offs among the different planning periods and so it will harvest the stands with the slowest growth rates regardless of whether they exceed the hurdle rate or not.

In the volume results, BinVal was consistently the worst performing harvest rule for volume objectives. However, for maximizing net present value, the results for BinVol and BinGro were mixed, with NPV from BinVol exceeding that of BinVal by 2.8% on Forest 1, but lagging that of BinVal by 1.8% on Forest 2. As Jamnick (1990) suggested, LP models significantly outperform binary search models when economic criteria are important: the binary search results in both cases trailed their corresponding LP model results by over $35 million. That is $458 on a per-acre basis when Pacific Northwest timberland currently sells for around $3200/ac!

Applying even-flow at the tract level had a modest impact on NPV from Forest 1. The constrained version of the volume maximizing LP model (LPVolTE) yielded a total NPV of $206 million, so the cost of the constraints was 2.2%; the constrained version of the slowest-growing-first binary search model (BinGroTE) yielded a total NPV of $170.2 million, a loss of 17.6% relative to the unconstrained maximum, and an additional loss of 4.5% reduction relative to the unconstrained BinGro model.

The results for Forest 2 were similar, though the impact of the constraints was a bit less (1% reduction for LPVolTE). As before, the constrained binary search model (BinGroTE) performed worse than the unconstrained BinGro model on Forest 2, suffering a 15.4% reduction in annual harvest relative to the unconstrained maximum but only 1.1% worse than the unconstrained BinGro model. For Forest 1, the additional even-flow constraints were far more onerous than on Forest 2, which exacerbated the performance gap between LP and binary search.

Standing Inventory

For each of the 8 model runs for Forests 1 & 2, the standing inventory was calculated in each planning period. As expected, the LP model maximizing NPV produced the lowest average standing inventory levels. Even with a constraint that requires an ending inventory equal to the initial inventory, the most economically efficient management scheme retains just enough standing timber to meet constraint requirements; inventory levels higher than this indicate a degree of inefficiency. The BinVal results for Forest 1 and Forest 2 exhibit inventory surpluses of 27.6% and 16.3% relative to the NPV maximizing LP models.

On Forest 1, the tract-level even-flow constraints required an inventory surplus of over 25% for the binary search model (BinGroTE), a significant increase over the unconstrained version (BinGro). What this likely indicates is the presence of an age-class gap in one or more of the tracts. Because the overall harvest cannot be made up for by harvesting in other tracts, the even-flow constraint keeps the harvest level below the average growth rate, resulting in inventory accumulation over time.

Discussion

Since this analysis was inspired by the work of Jamnick (1990), it is instructive to repeat some of his conclusions since they are replicated by our results:

> *These two models represent somewhat opposite extremes at looking at the harvest scheduling*

problem. With [inventory projection models], the analyst is interested in examining the effects of particular forest management scenarios on one or more outputs (usually harvest level). With LP, the analyst is interested in finding the best or optimal management scenario selected from a given set of management activities for a particular objective function and constraint set… The fact that LP is able to find better solutions than [binary search (inventory projection)] does is not a surprising result. Since [it] is a sequential, iterative model, it cannot make trade-offs between choices that span different planning periods. It is unable, therefore, to generate globally optimal solutions over the entire planning horizon in situations where present harvests can be foregone for a higher harvest later.

Another problem with inventory projection/binary search models is that they will attempt to meet output targets by applying the specified treatment in each iteration to all eligible stands, up to the target level. The problem with such targeting is that the model may generate inferior solutions in which the marginal value of the treatment is zero. Although I did not explore it in this analysis, consider what would happen if I had included planting noble fir on high elevation sites as an alternative to natural regeneration.

In the LP model, this would have presented no difficulties because the trade-offs between natural regeneration and planting would have been considered and the better alternatives selected in each planning period. Without knowing the optimum solution ahead of time, an analyst would specify area targets for planting noble fir based on his/her best judgment and if it were possible, the binary search model would plant the full number of acres each period. Conversely, the LP model may not necessarily plant the full amount in each period, thus avoiding an expense that does not provide additional harvest volume later. Thus, in these cases, the binary search solution would be not only inferior with respect to harvest levels, but it is also economically inefficient.

Historically, inventory projection models (including binary search) have played an important role in determining harvest schedules. When LP models were only available on mainframes, forest planning amounted to little more than determining an allowable cut and constraints were few, so binary search was an effective planning tool. But today, forest models are far more involved than 20 years ago, even without considering the complexity of spatial restrictions. Simple heuristics like binary search are insufficient to the task: even with the admittedly simple examples explored in this analysis, binary search failed to come within 5% of the optimum. In this economy, no one can afford such poor performance from their forest planning methodology.

References

JAMNICK, M. S. 1990. A comparison of FORMAN and linear programming approaches to timber harvest scheduling. Can. J. For. Res. 20:1351-1360.

Download the full white paper from our website by clicking here. For a more detailed look at what can be done using LP, download the final report and analytical spreadsheets as well.

Columbia River Gorge in winter.
(Photo courtesy K.R. Walters)

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