Multi-catchment Forest Harvest Scheduling for the Eden Management Area in Australia

O. Chikumbo

The Swedish University of Agricultural Sciences, Department of Forest Resource Management and Geomatics, Umeå S-901 83, Sweden. (Oliver.Chikumbo@resgeom.slu.se)

Abstract: Different catchment areas in a region may have different forest sustainability objectives and subsequently different spatial configuration design requirements on the landscape. The common objective, applied across the whole region, maybe one of harvesting timber. In this paper a method based on the Metropolis algorithm is demonstrated for scheduling a multi-catchment forest for harvesting, where different catchments are managed independently. The Eden Management Area in the State of New South Wales, Australia is used as a case study that has eight sub-catchments in the area that require somewhat different spatial requirements.

Keywords: Harvest scheduling; Spatial constraints; Monte Carlo method; Metropolis algorithm

1. INTRODUCTION

It is becoming common practice for analysts to take into consideration the spatial configuration of a forest for any forest harvest scheduling plans such that positive environmental outcomes can be achieved as well. For example, many wildlife objectives are better met by small, dispersed openings from clear felling operations [Jones et al., 1991]. This also ensures the spread of sediment production from harvesting, preventing concentrated impact of soil erosion and subsequent pollution of streams.

Harvest scheduling addresses the following questions:

- Which stands are to be harvested?
- When should these stands be harvested; and
- What quantity should be harvested in each period?

The third question is about choosing the appropriate management option for a stand, which in turn influences the choice of management options for the neighbouring or adjacent stands. The harvesting problem is formulated with an objective function over a space that combines continuous variables and large discrete variables of possible orders of forest stands. The concept of modelling spatial configuration is clear and for small problems, conventional methods such as integer linear programming or mixed-integer linear programming can be employed to solve them.

Real world forestry problems, however, present a challenge in that the number of forest stands in the configuration space is large, making it impossible to search the space exhaustively. In some cases use of branch-and-bound algorithms with libraries that can be parallelised on a cluster of computers or SIMD (Single Instruction Multiple Data) computers can provide the computing grant required for such kinds of problems. Another issue that would be of concern is that because of the non-linearity of a harvest scheduling problem, hard constraints in a branch-and-bound formulation for the pairwise neighbourhood configuration of the forest stands, make it difficult to converge to a solution. The solution is either feasible with a guaranteed optimality or infeasible.

Heuristic search algorithms tend to provide good alternatives where conventional methods are difficult to apply especially for real world problems [Glover, 1994; Goldberg, 1989; Kirkpatrick, 1983; Press et al., 1992]. Optimality is always hard to guarantee since no exact solution exists for 'hard problems', that is,

Table 1. Sub-catchments of the Eden Management Area.

SUB-CATCHMENTS	AREA (hectares)	No. of MANAGEMENT UNITS	No. of MANAGEMENT OPTIONS
Bega	15 321	461	6 159
Coastal Central	22 210	592	7 268
Coastal North	17 754	331	4 005
Coastal South	30 438	905	7 756
Genoa	13 137	394	5 473
Snowy	8 602	177	2 531
Towomba	29 463	826	11 802
Wallagaraugh	54 773	2 048	21 622
TOTAL	**190 698***	**5 734**	**66 616**

* This total area includes the reserves.

problems were computation times for solutions increase with the number of variables, becoming increasingly prohibitive in cost.

In this paper a multi-district harvest scheduling (MDHS) problem is demonstrated using a case study area, Eden Management Area (EMA) that covers *198 000* ha in the state of New South Wales (NSW), Australia. The Metropolis heuristic search algorithm is used to find a solution and is conveniently packaged in a Java program called Habplan [NCASI-Forestry 2000].

2. EMA STUDY AREA

The EMA has a complex over storey species composition and age structure of native forest. There are four broad forest types that include the Dry Shrubby, Dry Grass, Moist and Intermediate Shrubby. The Dry Shrubby type dominated by silvertop ash (*Eucalyptus sieberi),* covers the largest area occurring in the southeast of the EMA. Moist forest occurs in the northwest (tablelands) and grassland in the southwest. Wildfires, the successional process and selective logging between the *1800*s and the late *1960*s [SFNSW, 1994] contributed to a multi-aged forest (MAF) structure. Currently there are four significant fire regrowth forests that include *1952, 1956, 1968* and *1980* age classes. Integrated harvesting (i.e. harvesting operations for both sawlog and pulpwood) has resulted in *26* age classes (1972-97) of regrowth forest. About *24 146* ha are unavailable for harvesting due to fauna, flora and stream buffer reservation.

The EMA consists of *5734* operational management units that are identifiable on ground and conveniently digitised as a GIS layer for planning purposes. A total of *29 141* ha is taken by fauna and flora reserves, and stream buffers. Production forestry is spread over an area of *168 859* ha of which *44%* is the MAF resource and the remaining *56%* regrowth forest, both managed (logging) and fire-induced. The sawlog harvesting options for each management unit of the regrowth forest were predicted from a modified stand growth model [Forest Essentials 1997], STANDSIM, originally developed for silvertop ash in Victoria, Australia [Opie, 1972]. The prediction of sawlog harvesting for MAF was derived from a combination of yield records from already harvested adjacent management units and inspection of the management units due for harvesting by State Forests of NSW. A total of *66 616* management options for all of EMA were predicted.

The EMA consists of 8 sub-catchments and Table 1 shows the breakdown by area, management units and sub-catchments.

3. PROBLEM DEFINITION

A MDHS problem for the EMA sawlog production was formulated that allowed the simultaneous control of a super-objective component of sawlog output composed of sub-objective components from the *8* sub-catchments. The super-objective sawlog output was specifically set to attain an accumulated output of *20 000*m^3 for the first *22* years and left open for the rest of the planning horizon. These years were deemed crucial because they involved harvesting mostly the MAF and in the process converting to high intensity

Table 2. Sawlog output initialisation

SUB-CATCHMENTS	INITIAL SAWLOG OUTPUT SPECIFICATION (cum)	GOAL
Bega	1400	0.5
Coastal Central	2000	0.5
Coastal North	500	0.5
Coastal South	1500	0.5
Genoa	1000	0.5
Snowy	800	0.5
Towomba	2000	0.5
Wallagaraugh	4000	0.5
Super-objective	**20 000**	**0.8**

forest production as the case with the regrowth forest. Beyond the *22*-year period, the expectation was that the yield would go higher due to intensively managed regrowth forest sawlog coming on stream.

The motivation behind the MDHS formulation was to enable the flexibility of managing each sub-catchment independently, while attaining a high level objective that depended on the accumulated sub-catchment sawlog outputs. Each sawlog objective component of the *8* sub-catchments was initialised as shown in Table 2 with goals for the sawlog outputs. A goal of *0.5* here would imply that values within *50%* of the specified starting or initial value are acceptable. Any higher goals than specified in Table 2 always resulted in the 'component weights' exceeding the limit after several hundred iterations and this meant suspending the run and resetting these weights to 1. Detail on the component weights is found in section 4 of this paper.

This initial guess was done by firstly formulating individual models for each sub-catchment with a sawlog output objective and block size (i.e., an amalgamation of adjacent management units with harvesting in the same period) constraint. The solutions to these problems provided *apriori* knowledge for initialising the goals that specify tolerance of blocks outside the size limits and constraints for the MDHS model.

For each sub-catchment the block size objective component was defined such that the total patch area harvested (i.e., clearfelled and not just thinned) would lie within specified block size limits. In each period several blocks would be harvested, and the neighbouring management units would remain untouched until after a specified 'green-up' period had expired. The green-up period allowed the cleared areas to regenerate. Table 3 shows the block size constraints for the *8* sub-catchments. A goal for each sub-catchment meant that a proportion of the blocks within *±5%* would be less than the maximum block size limit. A value of *1.0* made the maximum block size totally constraining.

Table 3. Block size constraints for the *8* sub-catchments.

SUB-CATCHMENT	MINIMUM BLOCK SIZE (hectares)	MAXIMUM BLOCK SIZE (hectares)	GREEN-UP PERIOD (years)	GOAL
Bega	20	250	2	1
Coastal Central	20	200	2	1
Coastal North	20	200	2	1
Coastal South	20	250	2	1
Genoa	20	200	2	0.5
Snowy	20	200	2	0.5
Towomba	20	250	2	0.5
Wallagaraugh	20	250	1	1

The separation of the EMA into sub-catchments was expected to give a better understanding of the impact of block size constraints on spatial configuration and subsequent sawlog output. Each sub-catchment may have a unique block size specification depending on the desired super-objective. Also in situations where it is inevitable to stay within the maximum specified block size limits, unique forest management practices may be formulated and applied to minimise any potential environmental consequences resulting from harvesting.

The final objective component that was common to all the *8* sub-catchments was specified such that the spatial juxtaposition of management options could be controlled. This was essential to ensure that harvesting operations done in the same period in adjacent stands were preferred and could lead to a minimisation of operational and haulage costs. The economic benefits from an operational point of view could not be quantified in this current MDHS model because of lack of appropriate data. The objective component here required specification of the neighbourhood structure of the management units and a pairwise management options specification with a value indicating the desired spatial juxtaposition. A goal of *0.5* was specified for the spatial objective component that meant *50%* compliance. This spatial constraint also encourages more compact and uniform blocks harvested in each period, although it may conflict with the desire to keep the block sizes small.

4. PROBLEM FORMULATION

The multi-objective function of the MDHS formulation was defined as the sum of *18* objective components. The mathematical formulation was based on the Monte Carlo simulation and is as follows:

$$E(X^r) = \sum_{j=1}^{18} w_j^{r-1} C_j(X^r) \qquad (1)$$

where

X^r = management schedule at iteration r

w_j^r = the weight based on the iteration r schedule

$C_j(X^r)$ = the jth multi-objective function component whose value is evaluated at the rth schedule.

A management schedule involves assigning a specific management option to each of the 5734 management units and therefore the vector, X^r, contains all the possible options, a total of *66 616* of them, assigned to management units *1-5734*, $x_1^r, ..., x_{5734}^r \in X^r$. The weights, which are evaluated at each iteration, are based on the user defined goals g_j, for each objective component. These weights are adjusted between the upper and lower limits defined for each goal component. Therefore, they are decreased if the goal, $g_j(X^r)$, is exceeded, or increased if the goal is not attained [Van Deusen, 1999]. Once a certain level of the weights are attained where no more changes between the upper and lower limits occur, then convergence has been achieved [Van Deusen, 1999].

This multi-objection function (1) is evaluated at each iteration where the component weight is decreased if its goal is exceeded, or increased if the goal is not attained. The Monte Carlo method takes a guess at the final schedule and then improves on the guess by an unbiased efficient, statistical sample of the vector, X^r. The schedule is represented as a parameter of a hypothetical population and using a random sequence of numbers to construct a sample of the population from which statistical estimates of the parameter can be obtained. This is why the method is called Monte Carlo, named after the famous casino in Monaco to emphasize the important role of random decisions within the method. The Monte Carlo method used for the MDHS problem was the Metropolis algorithm [Chandler 1997].

The Metropolis algorithm (MA) is a way of evolving a 'trajectory' so that the multi-objective functions (1) in the state space are visited in such a way as to reflect the Boltzmann probability distribution [Chikumbo et al., 2000]. This statistic expresses the idea that a system in thermal equilibrium at temperature T has its energy probabilistically distributed among all different energy states [Press et al., 1992]. The MA has a close resemblance to simulated annealing that uses a cooling temperature schedule to direct convergence of the MA to a single solution.

The MA is theoretically based on systems that are 'ergodic' although it can be difficult to prove that one is dealing with such a system. An ergodic system in statistical equilibrium has all the accessible states with an equal realisation. Therefore, the sampling process of the multi-objective functions (1) called importance sampling, is achieved by using the Boltzmann distribution function to assign a weight, w_j^r, to all possible multi-objective functions (1) and selecting the next multi-objective function on the basis of a scheme defined by the energetics of the system, X^r, and this weighted probability distribution.

Habplan, a Java program written specifically for handling multi-objective optimisation problems using the MA, was used in this case study. It is a landscape management and forest harvest-scheduling program.

5. RESULTS AND CONCLUSION

After *80 000* iterations there were no longer any changes in the management unit configurations and minimal shifts in the sawlog outputs of the sub-catchments. Therefore, the model was stopped after *100 000* iterations, run over a period of *2* days. A super-objective of *20 000*m^3 per year over a *22* year period was achieved. The block size objective components were satisfied as shown in Table 4. Two similar runs had been previously done, one over *4* days and the other over *3* days, that were aborted due to other computer problems. Although in all these cases the super-objective was satisfied, differences occurred in harvesting levels of the sub-catchments. Therefore, many solutions would obviously provide alternatives on a 'Pareto frontier' that decision-makers can choose from.

In all sub-catchments except the Snowy, there was a period or *2* were the maximum block size was violated, although the goals actually achieved in all sub-catchments were *0.95* or greater. The violations were due to large management units that had areas greater than the maximum block size. For example, in the Bega sub-catchment there were *2* management units, *800654* and *800662* of areas sizes *264* ha and *427* ha respectively that exceeded the maximum block size of *250* ha. The Wallagaraugh sub-catchment presented a complicated situation because the maximum block size limit in one period was exceedingly violated with a block as large as *850* ha. The regional spatial constraint was favouring larger blocks in this sub-catchment because of low yields. Only when the green-up period was changed to *1* year, did this block change down to *622* ha. Again this emphasizes the importance of multi-district scheduling.

It was easy to monitor and alter goals as deemed appropriate for the different objective components during the iterations. The different sub-catchment objective components made it possible to horn on trouble spots that did not exactly comply with the sawlog output or block size constraints.

It would be essential for SFNSW to consider subdividing the large management units greater than *250* ha so that spatial requirements are met in all the sub-catchments. In the Wallagaraugh sub-catchment, innovative silvicultural options need to be considered such that yields are higher which in turn would reduce bias towards larger than expected block sizes in some periods. The regrowth forest in this sub-catchment consisted mainly of coastal strata *4* and *9*. For coastal strata *9*, sawlog is harvested only at the final clearfelling stage, between 60 and 70 years of age of the crop. The intermediate harvesting operations only yield pulpwood.

Table 4. Results of block size constraints of the MDHS problem.

SUB-CATCHMENT	MAXIMUM BLOCK SIZE ATTAINED	ACTUAL GOAL ATTAINED
Bega	427	1.0
Coastal Central	311	1.0
Coastal North	244	1.0
Coastal South	357	1.0
Genoa	219	0.95
Snowy	190	1.0
Towomba	373	0.97
Wallagaraugh	850	1.0

MDHS has been successfully demonstrated using a real world case study, the EMA. A super-objective sawlog output of *20 000*m^3 per year for the first *22* years has been achieved whilst meeting unique objective components of sawlog output and block size constraints. A regional spatial constraint also ensured that uniform and compact block sizes were preferred, although this caused a distinct violation of the maximum block size constraint in one of the catchments (in *2* periods), due to low yields.

6. ACKNOWLEDGMENT

I am thankful to the Bureau of Rural Sciences (PO box E11, Kingston, ACT 2604, Australia) for allowing me to use their data and Mr Ian Frakes (Bureau of Rural Sciences) for generating the neighbourhood files for the sub-catchments of EMA.

7. REFERENCES

Chandler, D. *Introduction to Modern Statistical Mechanics*, New York, NY, Oxford University Press, 1977.

Chikumbo, O., R.H. Bradbury, and S. Davey. Large-scale ecosystem management as a complex systems problem: multi-objective optimisation with spatial constraints. In: *Applied Complexity-From Neural Nets to Managed Landscapes*. S. Halloy and T. Williams (eds), New Zealand Institute for Crop & Food Research Ltd, Christchurch, New Zealand. p124-155, 2000.

Forest Essentials, Validation of Eden Timber Resources Data, Sydney, Australia. Report to RACD and SFNSW: 16 p., 1997.

Glover, F., *Tabu search fundamentals and uses*, CU Boulder, University of Colorado at Boulder, 1994.

Golberg, D.E. *Genetic Algorithms in Search Optimisation and Machine Learning*, University of Alabama. Addison Wesley Longman, Inc., 1989.

Jones, J.G., B.J. Meneghin, and M.W. Kirby., Formulating adjacency constraints in linear optimisation models for scheduling projects in tactical planning. *Forest Science*, 37(5): 1283-1297, 1991.

Kirkpatrick, S., C. D. Gelatt and M. P. Vecchi., Optimisation by simulated annealing. *Science* 220(4598): p 671-680, 1983.

NCASI-Forestry, Habplan:Software for Forest Harvest Scheduling - Documentation, National Council for Air Stream Improvement Inc., 2000.

Opie, J. E. O., STANDSIM: A general model for simulating the growth of evenaged stands. Third Conference, Advisory Group of Forest Statisticians, IUFRO, Paris, France, 1972.

Press, W. H., S. A. Teukolsky, W. T. Vetterling and B. P. Flannery., *Numerical Recipes in C: The Art of Scientific Computing*, New York, NY, Cambridge University Press, 1992.

SFNSW, Proposed Forestry Operations in the Eden Management Area: Environmental Impact Statement. State Forests of New South Wales, Sydney, Australia, 1994.

Van Deusen, P. C., Multiple solution harvest scheduling, *Silva Fennica*, 33(3): 207-216, 1999.