Multilevel Planning in Forestry

Samuel Pittman

A dissertation submitted in partial fulfillment of the
requirements for the degree of

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examining committee have been made.

Chair of Supervisory Committee:

B. Bruce Bare

Reading Committee:

B. Bruce Bare

David Briggs

Bruce Lippke

Date: Aug 7, 2003

University of Washington

Abstract

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Samuel Pittman

Chair of the Supervisory Committee

Dean B. Bruce Bare
College of Forest Resources

This dissertation is a study of multilevel planning in forestry. Two models are investigated, the holistic model and the compromise model. A sample problem is formulated to demonstrate each model. The holistic model formulates the harvest scheduling problem of maximizing net present value with harvest flow and adjacency constraints. The compromise model, using a hierarchical optimization model, formulates the allocation of volume in a large diversified forest products firm. Numerical results are only presented for the holistic case, since it appears to be the currently more relevant problem studied within the hierarchical approach to forest management. These results appear to be favorable, considering the complexity of the addressed problem. The role of the model within the hierarchal approach is also discussed. The derived interpretation of the holistic model, with the contrast of the compromise model suggests new strategies and stricter formulations for multilevel planning models appearing in forestry.

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Chapter 1: Introduction

Driven by a changing set of societal values and technological improvements, forest planning models have undergone dramatic evolution over the past century. Influencing the current method of forest land allocation and scheduling are complex issues of multiple use, sustainable forestry, land use ethics and traditional utilitarian economics. Researchers have spent substantial effort defining the qualitative nature and conceptuality of values attached to forest use and also incorporating them into forest planning models. However, because these values posses many facets, the richness of definition is nearly always reduced when the concepts are transformed to elements within a planning model. Nevertheless, without a quantitative method multiple use, sustainable forestry, land use ethics and traditional utilitarian economics can only obliquely influence the application of forestry. It is therefore imperative that planning models continue to improve so that decision-makers are aided by quantitative methods.

Currently many foresters and those interested in forestry believe that practicing sustainable forestry will allow society to arrive at the balance in resource use needed. This, however, will require the consideration of the ownership of the forests and these owners' objectives. Society desires both wood products as well as intact forests to satisfy ecosystem and recreation values. Currently, the USDA Forest Service has changed its emphasis from multiple-use to pure ecosystem management (Morrison 1994). It is possible that in the future as societal demands change, the

Forest Service will once again engage in timber management, but for now one must look at the future of the wood supply without its substantial involvement. Forest industry on the other hand, is primarily interested in providing wood products to the marketplace. Whether sustainability is part of their approach is not clear. In the long run, the sustenance of the wood supply by industry is extremely important to satisfying the overall demand for forest products.

Objectives

The intent of this dissertation is to examine multilevel forest planning from two angles. First, the conventional approach of managing the forest as an entity separate from the managing organization is considered. Second, a model of corporate rationing, which might be employed by a large corporation producing forest products from its own natural resources is developed. Each of these models advances the science of organizational management. In the future, these models will likely be merged, to provide a model which integrates the management of the firm and its resources simultaneously. However, at present this seems too large of a step to take, given current understanding of each problem separately. Therefore this dissertation focuses on further defining the problems, through derivations and applications that by themselves provide new insights into formulating planning models of hierarchical entities, and methods for solving them. *The objective of this thesis is to provide better understanding of multilevel planning models inherent in forestry applications.* More specifically, however, past models, in the development of the hierarchical approach to forest management have not recognized two distinct multilevel planning model formulations, the holistic and compromise models, in their approaches. Identifying these two models, with appropriate use, seems, from an organizational and theoretical viewpoint, extremely important. Therefore, Chapters 2, 3 and 4, comprising the body of this dissertation, are written as stand alone sections with objectives related to refining multilevel planning models in forestry. Chapters 2 and 3 address the holistic model. The forest planning problem which considers harvest flow restrictions and adjacency constraints in maximizing net present value is considered in each Chapter (this problem is defined in the section titled: The Forest Planning Problem with Harvest Flow and Adjacency Constraints).

The objective of Chapter 2 is to demonstrate the use of price directed decomposition as a tool for solving large, spatial integer forest planning problems with block angular structure.

The objective of Chapter 3 is to derive error bounds in the use of aggregation/ disaggregation techniques applied to large, spatial integer forest planning problems with block angular structure, while still using the same model formulation and decomposition technique as in Chapter 2.

A large donated data set generated several sample problems used to facilitate results for each of these Chapters. Chapter 4 looks at the business aspect of forest planning from the position of a large diversified forest products corporation utilizing its own natural resources for production. Chapter 4 is theoretical in nature, as it proposes a model, which extends the mean-variance formulation portfolio selection (Markowitz 1959) to capital rationing using equilibrium constraints.

The objective of Chapter 4 is to formulate the risk diversified forestry corporation capital rationing problem as a hierarchical optimization problem, and to discuss solution techniques for this formulation.

While this model serves as an advance in the theory of capital rationing, it also demonstrates the second type of multilevel planning model considered here, the compromise model. Understanding each of these models in use, and in theory directly advances the study of multilevel planning in forestry. Moreover, the numerical results derived from using the extended, large-scale optimization techniques to solve the holistic forest planning problem proclaims significant advance in computational experience, as measured by the results in this dissertation with comparison to other published results. As applied scientists, we must not forget the link between theory and application. Successful application is dependent upon a strong theoretical foundation. This dissertation emphasizes this in the topic of multi-level forest planning.

Literature Review: The History of American Forest Planning

The focus in this literature review is on public forest planning due to the lack of publication on private methodologies. Early American forest planning adopted many of the techniques applied in German forestry (Alston 1983). Planning in the early part of the 20th century was primarily focused on "biological sustainability", which at the time was perceived to be non declining flow of volume. Planning with the objective of sustainability required foresters to rely on an evolving suite of methods used to determine the "allowable cut" in a manner which regulated the yield per year. Determining the allowable cut was generally done via area control, volume control or an area and volume check method. Using an area control method allows an equal number of acres to be harvested each year. Yield is "sustained" by this method if the number of acres of each age class is the same and the number of age classes is equal to the rotation length plus the regeneration time. This of course, assumes the effect of site differences is controlled. Due to the unregulated forest structure in the U.S. at the time, this method could not be used in isolation to produce "sustained" volume (Iverson and Alston 1986). The method of volume control harvests the amount of volume growth accumulated each year. If the forest is regulated this will sustain the yield. However, the forest in the U.S. has never been regulated; there has always been acres held past the rotation age. The slow growth rate of old growth forests poses a significant cost in timber under this method. The Hanzlik formula (Davis 1966) was one formula used to account for production possibilities in the absence of a regulated forest, when even volume flow and forest regulation were desired. Interestingly, area volume check was more of a paradigm than an algorithm for combining the two methods (Leuschner 1990). This heuristic method is a compromise between area control and volume control when the forest is not regulated.

As a result of post World War II increased timber demands, methods of more efficient analysis than the previous by hand calculated formulas were required (Johnson and Tedder 1983). With the availability of computers, foresters developed binary search techniques to find sustainable maximum flows. Among the first models was ARVOL which calculated the allowable cut using the area volume check method (Chappelle 1966). SORAC, which followed ARVOL, additionally, simulated how intensive management of regenerated stands affects the current allowable cut. SIMAC (Sassaman et al. 1972) was another binary search model capable of assessing management regimes and their effect on the allowable cut. Johnson and Tedder (1983), in their review of several binary search models demonstrated the methodology of binary search using TREES as an example. This seems to be the most complex of these types of models developed at this time since it can emulate the linear programming (LP) formulations, Model I or Model II, proposed in Johnson and Scheurman (1977).

Linear Program representations of forest planning models followed binary search methods. Today they are still the primary tools used in long-range forest planning. The two landmark LP models used in federal U.S. forest management were/are Timber RAM (Navon 1971) and FORPLAN (Johnson and Crim 1986). Before discussing the use of LP and its employment in forest management models it is useful to digress and examine some of the laws and acts which have shaped the development of current forest planning. Gifford Pinchot introduced the concept of multiple use when he became the Chief of the Division of Forestry in 1898. However, the concept was not intensively understood until the demand on forest resources significantly increased following World War II (Alston 1972). The five primary enactment's which forest planning models have repeatedly been measured against are (see for example (Iverson and Alston 1986 and also Chappelle et al.1976):

1. The 1960 Multiple Use Sustained Yield Act
2. The National Environmental Policy Act of 1969 (NEPA)
3. The Endangered Species Act of 1973
4. The 1974 Forest and Rangeland Renewable Resources Planning Act (RPA)
5. The National Forest Management Act of 1976 (NFMA)

Planning in the presence of these acts required forest planners to look beyond sustained yield timber management. A major modeling paradigm known as multi-objective programming was used and enhanced, so that multiple resource planning involved more than just constraining the allowable cut to meet minimum requirements on other objectives. Timber Ram (Navon et al. 1971) and FORPLAN (Johnson and Crim 1986) are great examples of just how hard forest planners worked to incorporate these acts into forest planning, but they are also examples of how quickly these acts changed the requirements placed on forest planning models.

Timber RAM, developed in the Pacific Southwest Forest Range and Experimentation Station by Navon and others in 1971, was the first linear programming model used for U.S. National Forest planning. It was designed to optimize stumpage prices in the presence of various harvest flow constraints. Using a Model I (Johnson and Scheurman 1977) approach it addressed the current understanding of "biological sustainability" in calculating the allowable cut. The input to the model was silviculture regimes constructed by the user, flow restrictions, the value to maximize in the objective function and the number of periods with period length for which the forest plan extended. Forest inventory was generally aggregated so that the model size was solvable using the simplex method (Dantzig 1963).

Timber RAM was used for National Forest planning for most of the 1970's. However, the model's bias towards timber management, inability to address multiple forest product production, lack of understanding of the model by the majority of its users and the need for a better multiple use planning model lead to many criticisms and eventually its replacement by MUSYC (Johnson and Jones 1979). Chappelle et al. (1976) provided the following evaluative criteria a model should contain in order to solve the multi-product production on a sustained yield basis:

1. The model should be capable of accepting data as inputs for physical, biological, economic and social variables that bear most importantly on the problem;
2. The model, even if constructed for a single-resource functional analysis, should be capable of linkage with a comprehensive multiple-use planning model;
3. The model should be capable of handling both the temporal and spatial dimensions of resource production and management;
4. Outputs of the model should be presented in a format that can provide ready guidelines to planners and managers; and
5. The computer program should be efficient (i.e. compute model outputs at least cost), be transferable to computer centers with a variety of machinery, and be documented to the extent that it can be readily modified by a skilled computer programmer employed outside of the group responsible for development of the program.

Appealing to the above criteria, Chappelle et al. (1976) found Timber RAM to be limited in the following four categories: 1) silvicultural and management considerations, 2) economic and social considerations, 3) spatial considerations and 4) computational considerations.

The silvicultural limitations discussed by Chapelle et al. (1976) are: inadequate data description, a static scenario space and non flexibility of the model. It is also mentioned that the volume yield tables used by the model are not specific enough to meet biological objectives. Chappelle et al.(1976) suggest making growth functions an internal part of the model so that yield may be described in detail. A static scenario space refers to the limited set of management alternatives for each timber class LP optimizes. This critique is actually a critique of the matrix generation method used. Overcoming this requires an exhaustion of all alternatives. Flexibility limitations commented on include the lack of effect of pre-thinning management options implemented in the same decade as the final harvest. Managerial options for regenerated stands lack a specified planting window and a treatment regime for the stand. Yet, perhaps the largest limitation of Timber RAM, at least with current concerns, is the inability to specify cutting block size.

Economic and social considerations discussed are mainly aimed at the linear programming (LP) formulation of forest planning and its inability to model multiple objectives. The authors attach the following limitations to LP modeling as well as Timber RAM. Chappelle et al. (1976) point out that, while Timber RAM is marketed as a long range planning model, it is an LP model with a fixed technology matrix, thus, theoretically it is not a long range planning model. The authors also conclude that multiple use is another false advertisement and that non-timber objectives are only considered as constraints. Furthermore, the authors feel that LP cannot be used as a multi-objective planning method. Finally, the authors' find the model does not link well to regional constraints nor the structure of the over all forest products market.

Chappelle et al. (1976) discuss spatial and transportation considerations which accompany any forest plan that allocates resources efficiently. The aggregation of stands into timber classes imposes an undetermined cost on extracting the allowable cut, partly because the proximity of roads were not present in the model. Roading is a substantial consideration to ignore, since the costs may dominate the profitability of a forest plan. Currently, adjacency constraints and other habitat preserving objectives also require a spatial component. As the authors might have guessed at the time, spatial planning has become the most taxing element in forest planning.

The final category commented on by the authors' is what they have referred to as computational considerations. For several reasons the complexity of the computer package: Timber RAM is a barrier to use. The documentation is described as vague and lacking interpretation of inputs and outputs of the model despite the glossary supplied. Users of the model typically only use the simplest options provided. The authors attribute this to not only "vague" documentation but also to the lack of technical support supplied by the supporting agency. In fairness to the model it should be noted that complex problems require complex models which require adequately trained users in the use of LP if that is the planning method chosen.

Along the way to FORPLAN from Timber RAM the Multiple Use Sustained Yield Calculation Technique (MUSYC) was developed by Johnson and Jones (1979) to address some of the problems present in Timber RAM. MUSYC overcame some of the limitations of Timber RAM, but still did not satisfy the requirements of multiple use planning. MUSYC could implement either Model I or Model II (Johnson and Scheurman 1977). Constraints that reflected social and ecological variables were enhanced but still social and ecological considerations were not treated as objectives. Information could be aggregated within and across timber classes, something Timber RAM was incapable of. However, MUSYC, like Timber RAM, still used strata-based variables which proved to be a poor reflection of the problem when geographical variables were needed. Like Timber RAM, roading and other spatial issues were poorly addressed by MUSYC. Recognizing the improvements incorporated in MUSYC, the need for a more sincere treatment of multiple use and a more geographically explicit planning model lead to the development of FORPLAN (Johnson and Crim 1986).

The model FORPLAN is actually a sequence of two models: version 1 and version 2. Version 2 is treated as an appendage to version 1, supplementing its current options. The two models will, therefore, be discussed concurrently with delineation's inserted where appropriate. FORPLAN became available in 1979, replacing MUSYC; each model was designed by Norman Johnson and others. FORPLAN is differentiated from the past timber scheduling models by incorporating decision variables that track resources other than timber through time, its ability to implement hierarchical emphases and its treatment of resource allocation and resource scheduling as two possible entities.

In FORPLAN desired forest outputs could be aggregated, so that management considerations could be directed to the desired output. Desired outputs could be defined spatially or strata-based; in both cases they are termed "aggregate emphases" in version 1 (Iverson and Alston 1986). This feature of FORPLAN allowed personnel to assert their expertise in designing management prescriptions for acres or land units within an aggregate emphasis. This type of scheme allowed constraints across desired outputs as well as forest wide constraints. Additionally, model output could be separated according to aggregate emphases or aggregated as in past models. FORPLAN version 2 not only uses aggregate emphases to further refine the resolution of the planning problem, but also allows users to define strata-based analysis areas with spatially based zones. This required more user input into the model which lead to more spatially feasible harvest schedules, but also required larger matrices that taxed existing LP solvers.

FORPLAN was constructed to address the combined management goals of 154 National Forests. FORPLAN in its basic components was a matrix generator linked to an LP solver. Its objective was to guide forest management in compliance with the natural resource acts passed by Congress, in particular NFMA (Beuter and Iverson 1986). Such an endeavor obviously required a top-down approach. Forest wide objectives such as budgeting, allowable cut and net social benefit were required; however, regional and local objectives that required on the ground feasibility and considerations relevant only at the local level were also required. FORPLAN attempted to address both the allocation problem at the forest level and the scheduling problem at the local level (Bare and Field 1986). This made the model so large that several problems were encountered. Among them were: solvability of the model, understanding of the solution, on the ground infeasibility and required sensitivity analysis that was too costly.

While FORPLAN marked a vast improvement over past harvest scheduling models with its multiple objective framework, its multi-layered constraint capabilities and its ability to link to roading models, experts still questioned its usefulness in forest planning due to the previously listed problems and others. An entire conference: FORPLAN: An Evaluation of a Forest Planning Tool, employing experts from different disciplines interested in National Forest planning, was devoted to its evaluation as a forest planning model. Many of the papers presented questioned whether linear programming was the correct mathematical model to use, and even more broadly, whether mathematical programming was a reliable method to use in forest planning. However, the analysis went much deeper than this. The major criticisms fell on the role that mathematical programming took in forest planning and its opaqueness to those involved in the planning process who were not skilled in the art. Although the papers presented at the conference were written with the intent of evaluating FORPLAN with current and future objectives in mind, much more came from this conference. The following three forest planning concepts were common to many of the papers presented. They are important because they are derived from mistakes learned from using FORPLAN.

1) The role of the forest planning model in forest management.
2) The relationship between the model, the analysts running the model and the decision maker.
3) Future of mathematical programming in forestry.

The planning model was designed to seek information for the decision-maker with the goal of optimizing net public benefit (Bare and Field 1986). Instead, many times the model itself was being used as the decision maker (Johnson 1986), thus putting the technocrats running the model in the position to decide. This was seen as a clear structural defect in the decision model. Additionally, since National Forests are public land, a model that integrated public opinion into it was also necessary. However, the complex representation FORPLAN gave the problem generally disengaged the public from the plan and the actual decision. Johnson (1986) notes that FORPLAN was used as a shield by the U.S. Forest Service from the public in defending their actions. Considering the objectives, FORPLAN did not model the decision making process well. As one might imagine, these results lead to the investigation of the internal structure of FORPLAN: linear programming.

Linear programming has been employed by foresters to solve both the engineering problem of technical efficiency and the economic problem of allocation (Hof 1986). Since no explicit production function exists for the forest planning problem one is assembled by creating many scenarios to choose from. Thus, for economic efficiency to be achieved through LP, the optimal solution must be a linear combination of the scenarios generated. Although this aspect of LP has been critiqued in the review of FORPLAN, this method has been used since the inception of LP (see Dorfman et al 1958). Obviously, enumerating more scenarios brings the solution closer to economic efficiency (if that is a desired objective), but it also makes the matrix larger and therefore increases the cost of solving the problem. If the allocation problem were the only problem being solved by FORPLAN this may have been a feasible task, but FORPLAN was also solving the scheduling problem. The schedules produced by FORPLAN were often not feasible in terms of implementation. One reason for this was that LP does not produce integer solutions, except in rare cases (Bare and Field 1986). The outcome of this in the forest plan is that acres are not spatially identified except in aggregate form. This left a gap between the models solution and that which could be implemented. An infeasible solution produced surely means a problem was solved which does not represent the actual problem. Although the actual problem will seldom be completely described by the model, measures can be taken to ensure feasibility. Perhaps if FORPLAN set out to solve only the allocation problem LP may have not been challenged as a weak link in the planning process. Additionally, feasibility would have been less of an issue.

The linearity assumption between inputs and outputs has challenged applications of mathematical programming in forest planning, especially when integer variables are needed. This is really another divergence of the model and reality. No mathematical function will yield a perfect reflection of the true problem. However an integer formulation of the planning problem was needed. Bare and Field (1986) point out that non-linearities such as yield forecasts are easily handled, but that integer constraints are not. Much work has gone into the development of heuristics to tackle large integer programs (IP). The adjacency problem and the road construction problem have probably seen the largest application of such heuristics. Simulated annealing, Brach and bound, Tabu search, evolutionary programming and random search are just some of the methods used to solve IP in forestry.

Mathematical programming has been challenged to justify its existence in forest planning, yet it is not well understood by most (other than analysts) involved in the planning process. Attesting to this are many of the comments found in the previous critiques. Forest planning problems proposed in the 1980's taxed the solution methods to the point that the usefulness of mathematical programming in forestry was questioned. Bare and Field (1986) conclude that forest planning problems may have taken linear programming to its level of incompetence. However, the incompetence could not have been with linear programming, it has worked well in a variety of applications and is still a preferred planning tool by many operational researchers. Mathematical programming, as represented in FORPLAN, has produced solutions which are not feasible, and solutions which cannot be explained. In hindsight, it is easy to see the formulation of the problem foresters desired to solve was not present in FORPLAN. FORPLAN implemented a top-down approach. Johnson (1986) notes that the top-down approach FORPLAN took was counterintuitive to how many viewed forest planning. FORPLAN was modeling so many things in one monolithic problem that a large gap existed between the solution and reality. One might say that the resolution or representation of reality was sacrificed to consider more objectives. Many researchers at the time were looking toward a multilevel planning model to replace FORPLAN, one which considers a strategic-scale, tactical-scale and operational-scale plan.

With the dismissal of FORPLAN and the top down approach in public forest planning, two other strategies emerged. The bottom-up approach and the hierarchical approach (Gunn 1991), a method which blends the top-down approach with the bottom-up approach, were proposed as alternative methods to planning at the FORPLAN conference. The bottom-up approach solves the scheduling problem at the tactical level and then aggregates the schedules to produce an allocation: the strategic part of the solution. The bottom up approach can be easily criticized on its inability to represent forest-wide objectives and forest-wide constraints. While the hierarchical model has the ability to consider both forest-wide and lower level constraints and objectives it has been more difficult to specify and solve. The hierarchical approach attempts to optimize at all scales of planning simultaneously. If the hierarchical model is reasonably solvable, and can provide decisions which yield the same resolution as the bottom up approach, then the hierarchical model can be seen as superior due to its ability to simultaneously consider objectives and constraints at multiple scales.

Foresters started discussing the use of hierarchical planning models following the introduction and use of FORPLAN (Johnson and Crim 1986). Some examples of hierarchical forest planning models have been conceptual in nature (see for example Gunn 1991) while others have been more mathematical (see for example Weintraub and Cholaky 1991). Researchers have characterized the nature of the decision making process during forest planning as strategic, tactical and operational (Gunn 1991). This has helped to categorize decisions by scope so that the entire planning problem is not considered simultaneously. Furthermore, hierarchical planning models have used the concepts of strategic, tactical and operational to promote a multi-level structure. Separate models, one proposed for each decision type, linked by an algorithm to allow information to flow vertically through the models appears to be the current state, as depicted in the hierarchical forest planning literature.

Researchers have proposed mathematical models of the forest hierarchical planning process recognizing different viewpoints of the hierarchical approach. A common theme in many of the planning models is that strategic decisions derive from aggregate strata-based data (usually at the forest-level) while tactical decisions address spatial issues (usually at the sub-forest level). Further, a framework has been adopted wherein strategic solutions set guidelines for tactical planning which follows. And, recognizing the need for an iterative scheme in which these decisions could be adjusted, some researchers have proposed feedback and feed-forward mechanisms to connect levels that are considered to be modeling different aspects of the plan (Gunn 1991). The model of Weintraub and Cholaky (1991) utilizes this type of iterative scheme. Sub-forest or lower level spatial problems are solved to meet volume flows specified by a forest level strategic problem. If feasible solutions at the lower level cannot be found, then the upper level problem is solved again specifying new volume flow targets until feasible tactical solutions are found to be within some tolerance from the target. Bare and Lierman (1994) presented a similar model structure, which is spatially decomposed and utilizes similar aggregation procedures. Hof and Pickens (1987) presented a two-tiered model in which several spatially explicit tactical plans are proposed for each landscape. The upper level problem then selects a plan from those proposed for each landscape. Davis and Martell (1992) designed a model, SilviPlan, which solves both strategic and tactical problems. Their model uses aggregate time periods of 10 years in the strategic model and 1-year periods in the tactical model. The tactical model works within the guidelines produced in the first 10 years of the strategic model. However, the strategic and tactical models are not linked by any type of feedback mechanism. Nelson and Errico (1993) present a descriptive hierarchical process carried out using simulation. They divide the forest into management zones that form spatial sub-problems. Feasible spatial alternatives are constructed heuristically using the four-color theorem. Forest wide objectives and constraints are indirectly composed of aspatial data aggregated from the spatial sub-problems. Global objectives in this approach are satisfied using simulation, rather than explicitly targeted.

Evident in the models presented above is the consideration of localized, spatial sub-problems that are connected to a global, forest level problem. This type of relationship between a subsystem and the entire system is common in many application problems. An important characterization of multi-level models is the relationship of the objective and constraint sets of the two levels considered. In the case where only the forest is considered, conflicting objective and constraint sets seem unlikely-- therefore, implying a holistic model. However, in the case where different management levels of an organization are responsible for managing the forest, the possibility of conflicting and interdependent objective and constraint sets seems plausible -- therefore, implying a compromise model. Examining the formulations of holistic and compromise models, with an example of each, will further the understanding of relationships being considered in multi-level forest planning models.

Hierarchical and Decentralized Planning Models Overview

Often planning proceeds within a developed hierarchical system. Hierarchical structures are designed to promote efficient organization of systems which are too large to be managed as a whole. Although the large company with several divisions is the classic example drawn upon in much of the literature, one may also structure a hierarchy over other entities, such as time or spatial entities. In any case, explicitly formulating the decision model with specific objectives for each layer in the organization, with their interdependence declared, is a paramount step in the modeling process. Therefore the derived optimization problem, representing the decision model specifies the organizational structure.

The two general types of hierarchical models are termed holistic and compromise. These terms indicate whether the sought objectives of the different levels in the hierarchy are the same or different. The model is holistic if the objectives at all the levels are the same. In this case, either the model is derived from a single level optimization problem through some decomposition strategy or the model can usually be written as a single level optimization problem. It is not clear whether this model should be referred to as hierarchical, since its hierarchical properties are encountered in the solution strategy and are not necessary to specify the problem (see Bialas and Karwan 1984). Hierarchical planning models in the forestry literature are of this type. Although some of these planning models may address multiple objectives, this does not seem to distinguish the different levels. When different objectives exist at the different levels, the model is referred to as a compromise model. Compromise models imply the use of equilibrium constraints; in this context, optimization problems that are constrained by other optimization problems. This type of model can occur in many situations. A descriptive example occurs when there are multiple landowners in a geographic region, of which collective objectives are desired, but with the collective objective differing from the individual landowners'. For example, a regional objective of the public might be to minimize sediment deposition from harvesting in a watershed, while the objectives of the different landowners in the watershed might be maximization of net present value. Clearly, these two objectives are conflicting if the landowners' value is fulfilled from harvesting. If the entity responsible for the collective management has policy directives at their disposal, then a compromise model fits this situation nicely. Using the proper model to formulate the problem will have a direct impact on the quality of the solution; the model needs to accurately portray the situation.

In forestry, the inability to accurately solve large-scale planning problems lead to the hierarchical model. Many of the forest hierarchical planning models presented are similar to the holistic allocation models presented by economists, which are derived from the ideas of Dantzig-Wolfe (1961) and Benders (1962) decomposition. In theory, the hierarchical approach to forest planning differs from the simple resource allocation model due to the consideration of multiple time scales and the use of aggregation techniques that transform spatial data to strata-based data; however, it has not been demonstrated that this aggregation would change the model from holistic form. While decomposition will likely play a fundamental role in solving large-scale planning problems, a contribution to the theory of hierarchical forest planning models will occur when the problem to be modeled is formulated independent of the algorithm used to solve it, since it is the structure of the model that allows it to be classified and not the solution technique.

Decentralized planning in hierarchical organizations (holistic planning), also known as multilevel planning, was introduced by Dantzig and Wolfe (1961) through decomposition methods applicable to linear programming. When the higher level decision-maker does not have complete information of the lower level decision-maker's technology set, the process is said to behave according to imperfect information at the center. Two different algorithmic mechanisms have been presented by economists that solve the holistic formulation of a decentralized decision making model: price guided and budget or resource guided mechanisms. The allocation mechanisms are derived from price directed decomposition, first discussed by Dantzig and Wolfe (1961) and resource directed decomposition first discussed by Benders (1962). Dantzig and Wolfe were able to derive an alternative formulation of a block angular model through decomposition, which allowed them to attach an animated decision making scheme to their decomposition algorithm. An animated interpretation of resource directed decomposition has also been proposed (Heal

1969). However, it seems that Dantzig-Wolfe decomposition has been more popular among applied scientists. In contrast, Benders decomposition has been extensively used in integer programming (Nemhauser and Wolsey 1988).

Price allocating mechanisms and resource allocating mechanisms were developed by economists to solve large-scale planning problems likely to occur in a socialist economy. If the problem size is reasonable, the methods become unnecessary, since the original LP or mixed integer program MIP can be solved in original form and exactly. In these models, a central authority passes either resource prices or quantities to lower level agents. The agents then solve a profit maximization problem subject to their own constraints, passing the results of their plan back to the central authority so that they may determine another set of decisions. This process is iterated until a desired criterion is met. Due to the large size of forest planning problems, these solution strategies and resembling strategies have been considered in forestry (Weintraub and Cholaky 1991, Parades 1995).

In forestry, hierarchical planning is traditionally presented with three decision making levels, commonly called: strategic, tactical and operational. Gunn (1991) states that the strategic decision is usually one of resource allocation, the tactical decision is one which makes the most efficient use of these decisions and the operational decision involves planning for detailed operations. Generally, the levels are associated with different time scales and resolution of data. Data is usually aggregated as grander scope is considered. Although three different levels of planning are nearly always considered, forest researchers have only presented models which link strategic and tactical decisions (see, for example Weintraub and Cholaky 1991, Hoff and Pickens 1992, Davis and Martel 1992 and Nelson and Errico 1993). These applications have extended the frontier of decentralized thinking in forestry; foresters, like economists, have worked out methods that decompose the original problem into sub-problems that are easier to understand and compute.

The holistic model is presented as a single level optimization problem, with block angular structure [1.1]. It derives its name from the objective function being the sum of the objectives of the (n) subsystems present.

[1.1]

$$
\begin{array}{llllllll}
\max & c_1x_1 + & c_2x_2 + & \ldots & + c_{n-1}x_{n-1} + & c_nx_n & & \\
st. & & & & & & & \\
 & A_1x_1 + & A_2x_2 + & \ldots & + A_{n-1}x_{n-1} & A_nx_n & \leq & b \\
 & B_1x_1 & & & & & \leq & d_1 \\
 & & B_2x_2 & & & & \leq & d_2 \\
 & & & . & & & & . \\
 & & & & B_{n-1}x_{n-1} & & \leq & d_{n-1} \\
 & & & & & B_nx_n & \leq & d_n
\end{array}
$$

The interesting feature of this formulation is that if it were not for the (first constraint) joining constraint, this problem reduces to n individual planning/ optimization problems. It is this feature, with the application of decomposition to [1.1] that has stimulated the use of this formulation with bilevel structures. When operational researchers, economists, and other planners speak of resource prices or quantities, they are referring to prices/ allocations of the resources represented in the first constraint. The remaining constraints in [1.1] are partitioned into subsystems. Hence, upon choosing an allocation or resource prices for the scarce resources each of the individual subsystems can be maximized separately. This, in layman's terms, is the essence of decomposition. This model appears to have extensive merit in advancing the forest planning philosophy. Therefore, an application of this model to a forest planning problem is studied in Chapters 2 and 3 of this dissertation.

Bard (1983) presented a different type of multilevel planning model for decentralized decision-making, a compromise model. This model type, classified as a mathematical program with equilibrium constraints (MPEC), is formulated with optimization problems as constraints. This model is applied when the objectives of the different levels are not the same. The bilevel program [1.2], a special case of the multilevel program, which again is a special case of an MPEC, was first introduced by Bracken and McGill (1974). Bard (1983) has modeled the resource allocation problem as a bilevel program [1.2], following similar ideas of Burton and Obel (1977), where the separate divisions within the firm compete for joint scarce resources. Bialas and Karwan (1984) discuss several relevant problems which require the hierarchical optimization model. Moreover, several algorithms are presented which can be used to solve the program. Anandalingam and Friesz (1992) give several other examples of hierarchical optimization problems.

The compromise model is generally written as a multilevel optimization problem. The bilevel program, a specific case of the multilevel optimization problem, in general form appears as [1.2].

[1.2]

$$\begin{aligned} \max \quad & F(x, y_1, y_2, \ldots, y_n) \\ s.t. \quad & \\ & x \in X \\ & (x, y_1, y_2, \ldots, y_n) \in Z \\ & y_i \in \arg\max \{ f_i(x, y_i) : y_i \in Y_i; y_i \in S_i(x) \} \end{aligned}$$

In this formulation the variable x is associated with the upper level decision space and the variable y is associated with the lower level's. If the problem is one of planning, then one can think of a solution procedure sequentially. The upper level decision-maker supplies the lower level agent(s) with a decision x; x is then treated as a parameter in the lower level problem(s) that influences the agent(s) decisions. Upon the agent(s) making decisions, a y is fixed, in the upper level problem, for which the upper level decision-maker must take into account in making its next decision. As can be seen, in the general case the upper level and lower level constraints and objectives are interdependent. This interdependency makes the problem very interesting, amenable to many complex situations, but also, by current standards, difficult to solve.

There are several important characteristics to highlight when comparing and contrasting the holistic [1.1] and compromise [1.2] models. A major difference, which, of course, has implications, is that the compromise model contains an optimization problem as a constraint, while the holistic model does not. Moreover, within this constraint, the upper level's variable x becomes a parameter in the solution of the lower level problem. In contrast, the holistic model is not constrained by an optimization problem. Its bilevel interpretation is a property derived through decomposition, which is possible due to the constraints being composed of individual subsystems and a joining constraint which connects these subsystems together. Conceptually, the compromise model implies that the lower level problem acts autonomously in carrying out its objective, but must consider the upper level's decision, whereas in the holistic model, the lower level problems are guided to a solution which is optimal for the entire system. Under the interpretation of decomposition of the holistic model, the subsystems must make a decision which benefits the single objective. In contrast, in the compromise model, the lower level, in making its decision, in reaction to the upper level's decision, may detract from the upper level's objective. Hence, the property of interdependency is realized. The solution obtained by both the upper and lower level is a compromise of their objectives—hence the name compromise model. The compromise model discussed, is therefore remarkably similar to the famous Stackelberg game (see Luo et al. 1996).

The Forest Planning Problem with Harvest Flow and Adjacency Constraints

The problem of assigning forest management units to silviculture regimes under the presence of harvest flow restrictions has been a mainstay of forest planning problems (see Johnson and Scheurman 1977 and Garcia 1990). In the 1980's spatial concerns became an important added component to the planning problem. Among the various spatial concerns that have surfaced, adjacency constraints have received much attention. Significant research, discussed below, has been directed towards solving problems with adjacency constraints. Moreover, the study of hierarchical planning in forestry has proposed how these local adjacency problems fit into the global planning problem of also maintaining harvest flow restrictions. The model formulations of this problem have not been entirely clear or rigorous, in many cases, due to the algorithm being part of the formulation. The problem of forest scheduling with adjacency constraints has been presented, using what appears to be a compromise model, although it seems evident that it is a holistic model.

A small example of the spatial structure of a harvest scheduling problem is displayed in figure [1.1].

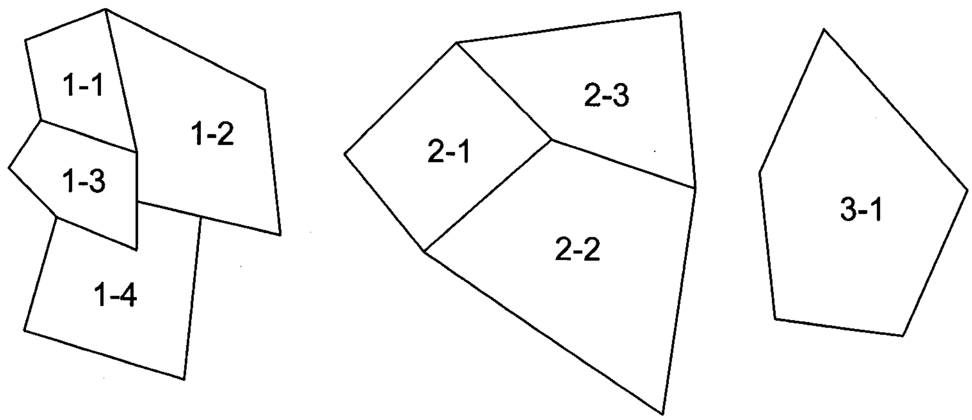


Figure 1.1

Polygons represent forest management units in 3 different contiguous land bases.

Consider an existing forest organized as in figure [1.1], with the planning problem specified as maximizing the net present value over all management options considered for each harvest unit, with adjacency constraints and harvest flow constraints present. While harvest flow restrictions are considered jointly over all land bases, adjacency constraints restrict harvest patterns over land bases independently. For example, if the exclusion time for harvesting adjacent units is one period, then the restriction on land base 2, is that at most one of the stands can be harvested per period. This, of course, has no implications with respect to adjacency restrictions for land bases 1 and 3. The larger the land bases, with respect to the number of management units, the more difficult the problem is to solve. It therefore makes absolute sense to only consider adjacency constraints over a single contiguous land base, in order to ease the problem solving effort. However, to accomplish this, the joining harvest flow constraints which cover all land bases together must be considered. One possibility, which is sub optimal, is to enforce the harvest flow restrictions over each land base separately, so that planning can be decentralized, and each contiguous land base can plan separately. Note that this is much more restrictive, than enforcing flow restrictions over all land bases together. An approach that has been proposed by many forest planners is to solve a global continuous, aggregate problem over all land bases, which specifies harvest flow for each land base, so that the amount of volume extracted from each land base is specified by period. The objective placed on each of the land bases is to achieve the volume goals set, considering the adjacency constraints. There are several items to ponder with this method. First, the original problem, a single objective problem of maximizing net present value, has now been partitioned by objectives with introduced levels. There is an upper level problem controlling harvest flow, maximizing NPV, and there are lower level problems (one for each contiguous land base) with the objective to meet volume targets specified by the upper level. The original holistic problem has been recast as a compromise/ hierarchical optimization problem. Concerns with this approach are that hierarchical optimization problems are much more difficult to solve than holistic problems, due thought has not been given to the resulting new problem formulation of compromising bilevel structure, rigor has been lost in problem formulation, since the formulation seems to include the algorithm, and optimality conditions for the bilevel compromise model have not been presented in forestry.

Moreover, there is not a known unified decomposition approach to deal with these problems as there is with the holistic case, which seems to be the reason for proposing the bilevel problem formulation. The likely reason this has occurred is insufficient problem formulation (see Pittman and Bare IN PRESS).

Another important issue related to solving forest planning problems with adjacency constraints is the method used to solve the resulting integer problem and/ or integer sub-problems if the problem is decomposed. It is widely recognized in forestry that heuristics such as simulated annealing, Tabu search, Monte Carlo simulation and genetic algorithms are necessary to solve these integer problems in reasonable time. Many heuristic methods have been proposed to allocate forest resources under adjacency constraints (Haight 2000). Nelson and Brodie (1990) compared Monte Carlo simulation to the traditional MIP method proposed by Kirby et al. (1986) to prescribe harvest schedules which constrain maximum clear-cut size and optimize road networks. Their work showed that Monte Carlo simulation could easily produce schedules with best values within 10% of the optimal value reached by MIP but never achieved values within 3% of optimality. Lockwood and Moore (1993) used simulated annealing to address the adjacency problem. While their method solved large problems, there was no comparison with an upper bound on optimality. Yoshimoto et al. (1994) developed a heuristic (SSMART) combining random search, and a decomposition method, so that the problem size was reduced and feasibility maintained throughout all periods. The authors reported objectives consistently within 2% of the branch and bound value for problems which the branch and bound method converged. Solution times were reported in hours for the scheduling of a 137 unit forest over multiple time periods. Snyder and ReVelle (1997) formulated the adjacency problem using a grid system, so that the corresponding graph problem is a planar network. This allowed them to solve the problem optimally with (SHARe) a model which employs a conventional network flow algorithm. They reported a solution time of 2.5 hrs. to solve a 441 harvest unit test problem on a "super computer". Hoganson and Borges (1998) used dynamic programming to solve the adjacency problem. Their method has found near optimal solutions for problems with 1000 stands. Bettinger et al. (1999) "intensify" tabu search by using 1-opt and 2-opt moves to better the resulting random feasible solution. The authors report reasonable CPU times for a 40 stand and 700 stand problem, scheduling over 5 periods. Additionally, their conclusion was that incorporating the 1-opt and 2-opt options in the tabu routine improved the heuristic. Comparisons between various algorithms have also been made, for instance, Boston and Bettinger (1999) compared Monte Carlo random search, simulated annealing and tabu search with results showing that simulated annealing and tabu search are superior to Monte Carlo random search. Haight's (2000) survey of heuristics eluded that dynamic programming (Borges et al. 1998 and Hoganson and Borges 1998) should be pursued as the most beneficial method. The most recent heuristic introduced to the adjacency problem is evolutionary programming (Lu and Eriksson 2000 and Falcao and Borges

2001). Although no comparison's using evolutionary programming and other methods were found, one must be weary of such comparisons. There are many different variational operators used in genetic algorithms (Michalewicz and Fogel 2000), which could confound such comparisons. While all of these heuristics are fascinating and clever in their approach, they are unnecessary if the integer problems can be solved optimally with similar or less CPU time. McDill and Braze (2000) indicate that CPLEX has substantially improved the branch and bound method, which is known to provide optimal solutions.

Since this exact problem (discussed above) has been studied extensively in the forest planning literature it is an excellent problem to study the large-scale optimization methods proposed in Chapters 2 and 3. Some researchers have moved on to more integrated models, which also include, for example, road options (see Weintraub and Cholaky 1991). This certainly seems to be the correct direction to move. However, large problems in the form of Figure 1.1 still exist, for example, in the southern part of the United States where road networks have been established. Moreover, adding additional decisions to the holistic model, such as road decisions can be accomplished within the holistic formulation. Hence, the large-scale methods of Chapters 1 and 2 will remain tenable.

Chapter 2: Hierarchical Production Planning in Forestry Using Price Directed Decomposition

Introduction

The hierarchical production planning (HPP) model has been advanced as a mechanism for modeling large decision-making ventures. It allows the decision making process to be decentralized so that different aspects of a decision are considered in relevant scope and detail. The HPP model has been studied extensively by several groups. Economists have used HPP to examine resource allocation in socialist economies (see Hurwicz 1973). Operational researchers have used HPP to integrate the objectives and constraints occurring at different layers of an organization to accomplish an overall planning strategy (Burton and Obel 1977). And, foresters have looked at several ways of implementing HPP in order to tackle large-scale forest planning problems (see Weintraub and Bare 1996). The model provides both computational benefits and implementation appeal.

The most fundamental concept within the HPP model is decomposition. The theory to drive the HPP model came shortly after the introduction of decomposition to block angular linear programming problems by (Dantzig and Wolfe 1961). Dantzig (1963) discussed an animated process of price directed decomposition (Dantzig-Wolfe decomposition, also known as column generation), in which the corporate headquarters directs the production of the different divisions to optimality for the corporation as a whole by charging the divisions for their use of shared resources. Shortly after Dantzig and Wolfe introduced price directed decomposition Benders (1962) published the dual method of resource directed decomposition, also known as decomposition by right hand sides. In the animated process, instead of headquarters charging the divisions for shared resources used, the amount of scarce resources allotted to each division is specified. Each of these methods of decomposition have formed the basis of differing decomposition algorithms used to solve large-scale optimization problems, including those derived from decentralized planning problems. Berck and Bible (1984) have discussed the benefits of using decomposition to solve large-scale linear forest planning problems.

Economists provide a substantial background to the study of decentralized planning and the use of decomposition. They have given considerable treatment to both linear and nonlinear economies, to conflicting and holistic objective problems and to both resource and price directed allocation mechanisms (see Arrow and Hurwicz 1977, Heal 1973 and Hurwicz 1973 for comprehensive reviews). Much of their work confirms that, in absence of convexity, decomposition methods are heuristic in nature and do not provide convergence to optima, in general. However, due to the presence of non-convex realities these heuristic methods may be indispensable in practice.

Operational researchers are still actively studying multi-level planning methods, due to the prevalence of hierarchically structured organizational models employed. The most general model is one of a corporate headquarters and several divisions which together make up a firm. Each of the divisions is considered to plan independently. The role of headquarters is to guide the independently functioning divisions towards a plan that optimizes the firm's objective as a whole (see Burton and Obel 1977 and Schneeweiβ 1995). In some organizational models the objectives of the headquarters and the divisions may be conflicting. Hence, the objective of the firm is not the maximization of the sum of all divisions (the holistic model). The bilevel program provides a model that represents this conflicting situation (see Bard 1983). This type of model, referred to as a compromise model, falling under the more general class of problems known as mathematical programs with equilibrium constraints is much more difficult to solve (see Luo et al. 1997) than the holistic model. However, it appears that these types of organizational models are becoming more prevalent, especially with large influential corporations owning significant stock in several smaller corporations (see Goedhart and Spronk 1995). Planning becomes more complex in this model due to the objectives and constraints at different levels being interdependent, verses the corporate objective being the sum of the divisions. This type of model is not considered further in this Chapter.

Many of the HPP ideas developed by the economists and operational researchers can be extended to the forestry planning model. While there is likely a hierarchical nature to the organization which manages a forest, the forest itself possesses what might be considered a hierarchical structure, or it can be organized into such for management. Due to the complexity of forest planning, the forest plan is often considered isolated from the products' market it feeds, except for parameters which enter the model. In order to carry out the HPP model, forestry planning problems have been decomposed spatially and temporally. Both the models' of Hoff and Pickens (1987) and Weintraub and Cholaky (1991) decompose the problem spatially. This is often done in forestry, since the spatial aspects of forest planning seem to be the most taxing. Moreover, spatial considerations such as adjacency constraints and road construction reside within localized subsystems that are linked to the entire planning model through non-spatial, joining constraints. Since spatial planning is now viewed as the current paradigm, it is likely that forest planning models will become spatially more complex in the future.

Much of the research on hierarchical production planning in forestry has focused on the qualitative aspects of the plan rather than the technical. Considerable research has gone into classifying the various scopes of the plan into the categories of strategic, tactical and operational (see Gunn 1992, Parades 1995 and Weintraub and Bare 1996). Some (see Weintraub and Bare 1996) believe that these three components of the plan are what define the coordinating levels; however, others (Parades 1995) believe that all levels will rely on strategic, tactical and operational concepts. The focus here is to analyze a method which allows general integer forest planning problems to be decomposed and not per se on the theoretical components of planning.

The decomposition methods discussed above, in general are not easily extendible to integer programming problems. Although methods exist which make use of Dantzig-Wolfe decomposition to solve integer programming problems such as branch and price (Barnhart et al. 1998, Vanderbeck 1998 and Martin 1999), substantial additional work is required beyond what is required for linear and convex programming problems. A forestry application of a heuristic close in nature to branch and price applied to a problem with "green-up" constraints is discussed by Weintraub et al. (1994). The spirit of the HPP model is somewhat lost when the divisional variables are no longer completely chosen by the division, as is the case in branch and price.

Often the model represented by the planning problem is considered a guide for decision-makers (Bare and Field 1986). In this representation, some constraints in the problem may be considered "soft" (Depta 1984 and Rockafellar 1999), so that slight violations may be acceptable. Lagrangian relaxation is one method for deriving this representation. The harvest-scheduling problem involving harvest flow and "green-up" (adjacency) constraints is prevalent in forestry. Several heuristic methods have been proposed to solve this NP hard (NP hard—no known polynomial time algorithm) mixed integer programming problem (Haight 2000). However, none have considered Lagrangian relaxation as a method to decompose the planning problem. This Chapter studies the effects of "relaxing" joining harvest flow constraints in a problem with "green-up" (adjacency) constraints so that standard Dantzig-Wolfe decomposition can be used. This methodology promotes the HPP modeling framework.

The objective of Chapter 2 is to demonstrate the use of price directed decomposition as a tool for solving large, spatial integer forest planning problems with block angular structure.

Methods

Many large-scale forest planning problems are of block angular structure. A general type of planning problem similar to Model I (Johnson and Scheurman 1977), but with recognition of management units, is presented to show the derivation of the forestry HPP model. Upon breaking from the general case problem, randomly generated planning problems with harvest flow and adjacency constraints are used to analyze the solution behavior of solving the problems with joining constraints treated as soft.

Given a holistic planning model with block angular structure, coupling constraints, such as harvest flow can be relaxed in order to arrive at what has been called the hierarchical production planning model. Consider problem [2.P1].

[2.P1]

$$\max imize \quad \sum_{i=1}^{n} c_i x_i$$

subject to

1) $$\sum_{i=1}^{n} A_i x_i \le \beta$$

2) $$B_i x_i \le b_i \qquad i = 1,2,\ldots,n$$

3) $$x_i \in \{0,1\}$$

First, note that c_i and A_i are linear, making this model a linear integer programming problem. (x_i) is a binary vector representing the possible management alternatives for each management unit in land base (group) i. Hence, (x_i) is composed of m (the number of management units in resource base i) vectors, where each of these m vectors has length k_m, equal to the number of management options considered for the particular unit. Thus, (c_i) gives the associated net present value of decision (x_i). Constraint [1] embodies all constraints which relate the individual resource groups (subsystems) to the entire planning problem such as allowable harvest flow deviation, habitat constraints which are considered over all subsystems, and possible desired acres in age class constraints. These constraints will be relaxed in the sequel. Constraint [2] represents the decision space specific to each of the groups (subsystems). If the overall problem is decomposed spatially, then these may represent contiguous harvest units such as tree farms, which possibly due to "green-up" restrictions, cannot be considered independently. These groupings could also delineate counties, districts, cities and other organizational constructs.

Using Lagrangian relaxation to obtain [2.P2], constraints [1] are moved to the objective function with price (y) paid for violation. The motivation for this is to obtain a decentralized formulation of [2.P1].

[2.P2]

$$\begin{array}{ll} \max imize & \sum_{i=1}^{n} c_i x_i + y\ (\beta - \sum_{i=1}^{n} A_i x_i) = \sum_{i=1}^{n} [c_i x_i - y\ A_i x_i] - y\ \beta \\ subject\ to: & \\ 2) & B_i x_i \le b_i \quad i = 1,2,\dots,n \\ 3) & x_i \in \{0,1\} \end{array}$$

[2.P3] is an equivalent problem to [2.P2], obtained with a slight amount of algebra.

[2.P3]

$$\begin{array}{ll} \max imize & \sum_{i=1}^{n} (c_i x_i + y A_i x_i) \\ subject\ to: & \\ 2) & B_i x_i \le b_i \quad i = 1,2,\dots,n \\ 3) & x_i \in \{0,1\} \end{array}$$

It is apparent from [2.P3] that y represents the price paid for joint, scarce resources as they are used by the groups (subsystems). If these joining constraints are harvest flow, then y represents the cost of volume flow restrictions. For a fixed y, it is immediately seen that [2.P3] can be solved by simply solving (n) smaller optimization problems of the form [2.P4] and assembling the solution.

[2.P4]

$$
\begin{array}{ll}
\max imize & c_i x_i + yA_i x_i \\
subject\ to: & \\
2) & B_i x_i \le b_i \\
3) & x_i \in \{0,1\}
\end{array}
$$

Hence, each group, given the appropriate price of joint resources, can plan separately. However, unfortunately, due to the integer constraint [3], solving [2.P3] does not exactly solve [2.P1]; the lack of equivalence between [2.P1] and [2.P3] is what is under investigation.

Planning agencies at the outset do not normally know the correct prices (y) for resources. This would presume they already knew the solution to the planning problem since these prices are the optimal dual variables. Column generation (see Dantzig 1963) provides a mechanism for iterative price determination in response to plans generated by the groups. The prices are determined in a master problem [2.P5], which uses a minimal generated basis to provide a piecewise linear approximation to the original problem [2.P1]; the resource prices are the dual variables associated with the joint constraints in [2.P5]. The basis is determined iteratively. At the kth iteration the master problem appears as [2.P5] and produces dual variables y^k.

[2.P5]

$$\begin{array}{ll} \max imize & \sum_i (\sum_{j=0}^{k-1} z^j (c_i x_i (y^j))) \\ subject\ to: & \\ 1) & \sum_i (\sum_{j=0}^{k-1} z^j (A_i x_i (y^j))) \leq \beta \\ 2) & \sum_{j=0}^{k-1} z^j = 1 \\ 3) & z^j \geq 0 \qquad j = 1,2,...k-1 \end{array}$$

The Lagrange multipliers associated with constraint [1] give the kth approximation to the resource prices; these are used by the groups to solve [2.P4]. Notice that z is the variable in this linear program and that the fixed x_i determined at the kth iteration is dependent upon the kth approximation of the resource prices, as denoted in [2.P5]. In actuality, the master problem does not directly need x_i. It only requires the aggregate objective coefficients $\langle c_i, x_i \rangle$ (the dot product) and the columns $A_i x_i$ if there is a change in resource use by the subsystems, to determine the next approximation of the resource prices. Most mathematical programming software allows the dual variables to be retrieved, so y can be ascertained by solving [2.P5]. Alternatively, one can solve the cutting plane problem, the dual of [2.P5] in order to find y. In this case, a constraint is added at iteration k instead of a column.

When the objective function value of [2.P5] and [2.P2] is within some preset tolerance (equal if x were continuous), the iteration scheme is halted. Upon termination, if x were a continuous variable instead of integer, the convex combination [2.1]:

$$[2.1] \qquad x_i = \sum_{j=0}^{k} z^j x_i^j (y^j)$$

yields the optimal solution to the problem. However, due to the integer requirement this convex combination is not a binary (0 – 1, integer) vector. Since z is clearly not constrained to be integer, this solution, in general does not solve [2.P1]. However, there is still some promising information determined from this approach. First, since the sub-problems [2.P4] are solved with the requirement of integrality, this is a tighter relaxation of [2.P1] then obtained by simply relaxing the integrality constraints [3] in [2.P1]. Thus, a tighter bound is obtained on the objective value of [2.P1] than produced using the linear programming relaxation. Moreover, a good approximation of the resource prices is determined.

The utility of these approximate prices, measured in terms of objective fulfillment and joint constraint violation under decentralized planning is of great importance in carrying out the forestry HPP model used in the hierarchical approach to forest planning, due to its inherent integer nature. To evaluate the effect of using approximate prices, several randomly assembled planning problems are generated, arriving at [2.P3]. These problems are decomposed according to the methodology discussed above. The master problem [2.P5] and the sub-problems [2.P4] are each solved using the default LP and MILP methods provided in ILOG CPLEX 8.1 respectively. Each planning problem consists of a random number of groups which themselves are randomly generated from smaller contiguous landscapes. Hence, necessary "green-up" restrictions are preserved. Each non-separable contiguous land base forms a micro-group. A macro-group consists of at least one micro-group. The randomly generated macro-groups, formed from smaller contiguous micro-groups, are assembled to portray plausible management organizational considerations.

Decomposing the planning problem over the macro-group relations versus the micro-groups may alter the planning effort and/ or the computational effort required. For example, it may require more iterations of the planning effort to compute usable resource prices using larger groups. To evaluate this, each planning problem is solved using the same data, but with the decomposition performed using the two different group representations. In practice, this would require the manager of each macro-group to manage possibly several smaller groups instead of one large one. Computationally, this investigates the effects of having to solve more, but smaller problems.

Since the planning problems are assembled in a random fashion, the statistical description of the generated problems is presented in the results section with the post solution information. The population used to construct the planning problems with the selection procedures used is detailed below. Seventy-five planning problems composed of a random number of macro-groups (between 6 and 20; the number selected with equal probability) are used to generate simulation statistics. The macro-groups are drawn randomly with replacement from a population of 237. Contiguous groups with more than 150 management units are omitted from the population due to the large number of planning problems being solved. On average, each macro-group is composed of 10.04 contiguous micro-groups. The mean number of management units in a micro-group is 3.52, giving an average of 35.99 management units in each macro-group. Hence, the expected number of planning units per planning problem is 485.87. The largest problem generated had 806 management units and the smallest problem solved had 187 management units.

Each planning problem is of the same type. There are eight, five-year planning periods. The allowable harvested volume deviation among consecutive periods is constrained to be within 10%. This is represented in constraint [1] in [2.P1]. Adjacent management units are precluded from harvest within the same five-year period and one period before and after. Other considerations, such as roads and habitat targets are not represented in the example, however, the general formulation allows for their inclusion. Only one rotation is considered. Including additional rotations will not change the block angular structure or the presentation above; however, additional rotations will increase the size of the planning problem; particularly, the number of columns. The management options in this demonstration are formed from weighted aggregations of more detailed management options. There is an average of 5.45 aggregated management options (columns) per management unit. Therefore, a column in one of the A_i matrices represents the volume extracted from the associated management unit under the aggregated management option. The related objective function coefficient in the vector c_i gives the net present value of the aggregated management option for the unit discounted at 8%. While this example problem may not be as complex as some planning problems, it includes enough detail to evaluate the approximate pricing methodology discussed.

Results

There are several important results produced from the simulation study to be discussed in this section. An array composed of various metrics was recorded for each solved planning problem during the simulations to facilitate examination of the results. The metrics recorded for each solved planning problem in component wise order are:

m_1 = matrix generation time

m_2 = time to find solution (includes all CPLEX calls)

m_3 = the master objective function value

m_4 = the sum of the objective function values for all the sub-problems solved using the prices approximated by the optimal dual variables pertaining to the master problem's joint constraints

$m_5 =$ the number of iterations needed to compute the resource prices

$m_6 =$ the total amount of volume over all periods by which the joint (harvest volume flow) constraints are violated

$m_7 =$ the sum of volume harvested in excess (positive) and below (negative) the allowable volume flow for all periods

$m_8 =$ the total volume scheduled for harvest

$m_9 =$ the number of (macro or micro-groups) comprising the problem

$m_{10} =$ the total number of management units represented in the problem

$m_{11} =$ the total number of management units assigned to a harvest management option

$m_{12} =$ the total acres assigned to be harvested in the planning problem

$m_{13} = (m_3 - m_4)/ m_3 =$ the percent difference in the master problem optimal value and the optimal value obtained using the final iterate solution

$m_{14} = m_6/ m_8 =$ the total volume flow deviation relative to the total volume scheduled

The components of the metric vector are related to objectives in this study. Therefore, relevant components are extracted as needed. The mean results are displayed in Table 2.1. The interdependence of the components can be examined in the correlation matrices (Tables 2.2 and 2.3). Seventy-five planning problems were solved to produce the mean and correlation results. In each solved planning problem the maximum number of planning iterations allowed to elapse was 85. If iteration 85 is reached, the algorithm terminates with the approximate prices and the corresponding solution. This happened 15 times in the macro-group formulation and 12 times in the micro-group formulation. This accounts for the slight deviations in some of the statistics that are expected to be consistent. Figure 2.1 gives a pictorial description in acres of the distribution of problem sizes that were considered.

The assessment of implementing the HPP model should be considered in light of the organization's structure. Two plausible methods of employing an HPP model are considered here. In method one, managers in charge of the macro-groups compute relevant alternatives for each of the management units along with a table indicating the spatial structure of their land base. The format of this data could be as extensive as the actual matrices required to solve the problem on a computer. Headquarters then uses this information to determine a plan for each of the land bases represented by a macro-group. Alternatively, using method two, software is given to each of the management groups which allows them to compute a plan for their land base as a function of the resource prices they are given from headquarters. In this setting, it may be desirable to develop a procedure which provides "in the ballpark" resource prices prior to the planning evolution in order to reduce the number of planning iterations. The organization's management style will likely dictate the approach used; the only difference between the methods is where the divisional plan is solved.

Obviously, since this study is being implemented as a research effort, the planning style is similar to one in which headquarters does all the problem solving.

Under this planning style, it is useful to know whether there are benefits to formulating the problem in its most decomposable form as opposed to using the organizational composition to perform the decomposition. Since the time to solve NP hard problems grows exponentially with the size of the problem, there is certainly an advantage to breaking the problem up, even if sub-problems must be solved many times. In this study, two levels of decomposition are considered to evaluate the number of planning iterations needed to converge on an acceptable plan (in this Chapter acceptable is defined $m_4 - m_3 < .00000001$). The mean number of iterations required for the macro-group and micro-group formulation is 36.6 and 26.4 respectively. The relation of these metrics to others can be found in Tables 2.2 and 2.3. The formulation using the most decomposable form requires fewer planning iterations (m_5), as might be expected and has a slightly higher attained mean NPV (m_4). The computed NPV (m_4) among these formulations differs because of the somewhat heuristic nature of treating the joint constraints as soft. The number of planning iterations is expected to be less for the more decomposed formulation because fewer columns are required per sub-problem in the master to generate the bases, due to the smaller sub-problem size. In the sequel, results are displayed in pairs, with the first number indicating the result using the macro-group decomposition and the second using the micro-group decomposition.

The primary objective of this study is to assess and display results derived from treating joining constraints as soft. The objective function of the master problem, the sum of the objective functions for all of the sub-problems solved using the approximate resource prices and the violation of the joint constraints are relevant measures for examining the proposed relaxation procedure. The objective function of the master problem is an upper bound on the NPV for the planning problem with all constraints satisfied (see formulation [2.P1]; i.e. the NPV sum over all sub-problems with joint constraints enforced is less than or equal to the master problem's NPV (optimal value)). However, since the joint constraints are treated as soft the relation of these two values is not certain. The relationship between the computed NPV (m_4) and the master problem NPV (m_3), and the relative violation of joint constraints can be depicted by two measures in the metric vector: m_{13} and m_{14}. The first number (m_{13}) gives the relative difference in the objective function values of the master and computed NPV. The second number (m_{14}) gives the amount of volume scheduled for harvest over all periods that is in violation of the joint constraints relative to the total volume scheduled in the plan. The mean of m_{13} is [-.00033, -.00022] with standard deviation [.0037, 0036] and the mean of m_{14} is [.00030, .00031] with standard deviation [.00025, .00022]. The results imply that, on average, higher NPV solutions are being found than allowable in the more restrictive formulation [2.P1], but that this comes with at a slight violation in the harvest flow constraints (see Figure 2.2). While both m_{13} and m_{14} are near zero with extremely small standard deviations, the violations may still be too large. If constraints are extremely rigid, for example harvest flow must not deviate more that 10% among periods, perhaps for legal reasons, then a method is necessary to eliminate violations. One option would be to manually adjust the harvest plan without re-running the model. Another option would be to re-run the model using a number slightly less than 10%, like 9.99%, so that the calculated flow is within 10% when the solution is found. Indeed, these are important issues to examine when solving a relaxed problem.

Due to the difficulty of solving integer programming problems, the computing time required to solve the model is also a required measure. A computing machine with a 756 MH processor and 384 MB of RAM was used for all computations. The solution times are factored into two components: matrix generation time (m_1) and solution time (m_2). Although much of the past literature has focused on developing heuristic methods for solving spatial planning problems due to slow performance of exact methods like branch and bound, it appears that matrix generation time is also considerable. In fact, in the macro-group formulation, matrix generation time is more than twice the solution time, on average. However, it is expected that this relationship would change if the matrix generation routine were programmed in a compiled language, instead of MATLAB. The cost of matrix generation is unavoidable whether exact methods or heuristics are used since an upper bound to the planning problem should always be found. In comparing the results of this study with past efforts in the literature, finding solutions using this relaxed method may be much faster than using heuristic methods to solve large integer planning problems of this type. Figure 2.3 shows the matrix generation and solution times plotted against problem size, measured by number of planning units. Some have proposed that the age structure of the forest may have an effect on the solution times. Figure 2.4 indicates that mean age and the variation in ages of the management units in a problem does not significantly impact the solution time. However, the problems seem to be very similar in age, with the mean age being fairly young. Age effects may be seen if the variation of age in the planning problems or if data with older aged stands were considered, which were not available at this time. Figure 2.5 shows the effect of having, within a planning problem large (measured by number of management units) contiguous groups. As can be seen, large contiguous groups and matrix generation times seem to be more correlated than the solution time; however, it is noted that the longest solution times had the largest micro-groups. This is an expected outcome, since solution times are known to grow exponentially for NP hard integer programming problems. This is why decomposition is such an attractive technique for solving problems, in which the integer problems can be parsed.

Discussion and Conclusion

In order to carry out the forestry HPP model using a price directed mechanism, joint constraints are treated as soft instead of hard. This allows the resulting planning problem to be solved using Dantzig-Wolfe decomposition. To investigate the impact of this in terms of objectives being met and constraints being violated, a simulation study was constructed. Randomly generated planning problems sampled from a large forestry data set were solved using the proposed price directed method. The simulation aspect of the study provides a more robust analysis of the proposed method. The results suggest that there is little sacrifice in joint constraint violation and that objectives are achieved.

There are two primary benefits to decentralization. The computation of very difficult planning problems becomes tractable and implementation of the plan becomes easier. These were the two major concerns regarding FORPLAN, a planning model capable of solving large-scale forest planning problems developed by the USDA Forest Service (see Bare and Field 1986, Iverson and Alston 1986 and Johnson 1986). Following FORPLAN, there has been an emphasis on planning from the bottom up, which also improves tractability and implementation. However, the bottom-up approach does not recognize the importance of coupling (joining) constraints. Often, meeting joint constraints when planning from the bottom up comes at a huge cost in terms of the objective, due to the rule based heuristics that must be applied in the solution finding procedure. As can be seen in the results, decentralized planning, using resource prices accomplishes the same task as planning from the bottom up, but without loss in optimality. Price directed decomposition promotes interaction and resonance of the model, the decision-making panel and the implementers of the plan.

Another important technique used in the HPP model is aggregation and dissection techniques (see Rogers et al 1991 and Weintraub 1995). The data in this study is at the highest level of aggregation. Combining decentralization with aggregation and dissection is an obvious direction to proceed towards advancing the HPP forestry model.

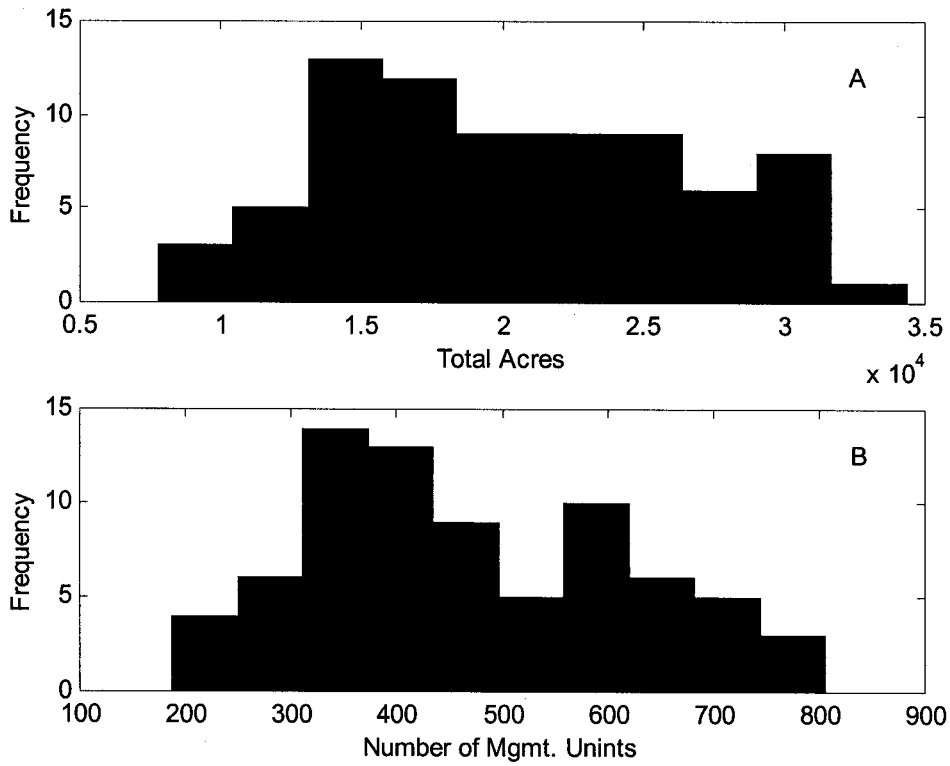


Figure 2.1
Histograms of total acres (A) and number of management units (B) contained in the randomly generated planning problems solved.

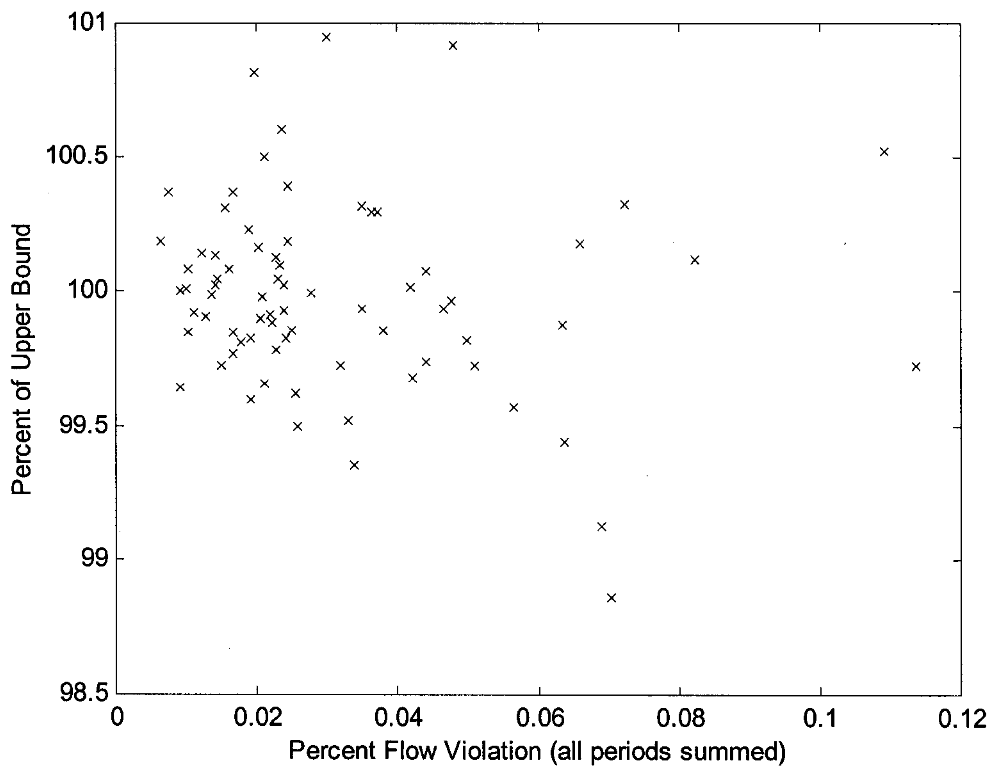


Figure 2.2
Percent of the upper bound (m_3) attained plotted against the percent of harvest flow violation m_{14} (micro-group formulation).

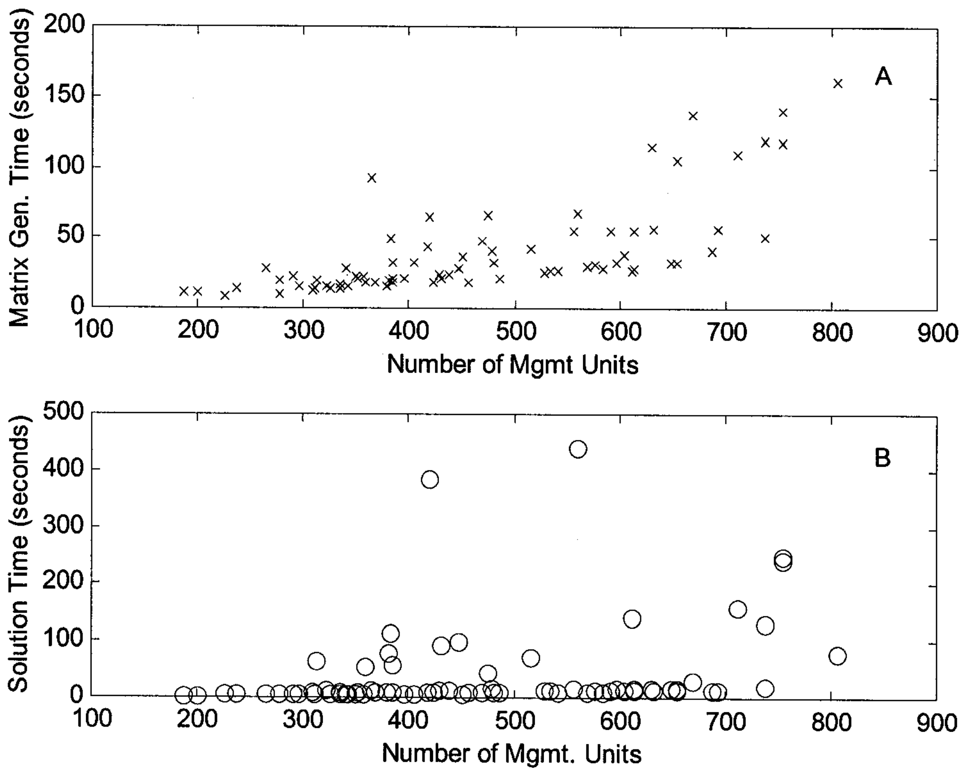


Figure 2.3
Matrix generation time (A) and Solution time (B) for each randomly generated problem (micro-group formulation) plotted against the number of management units in the problem.

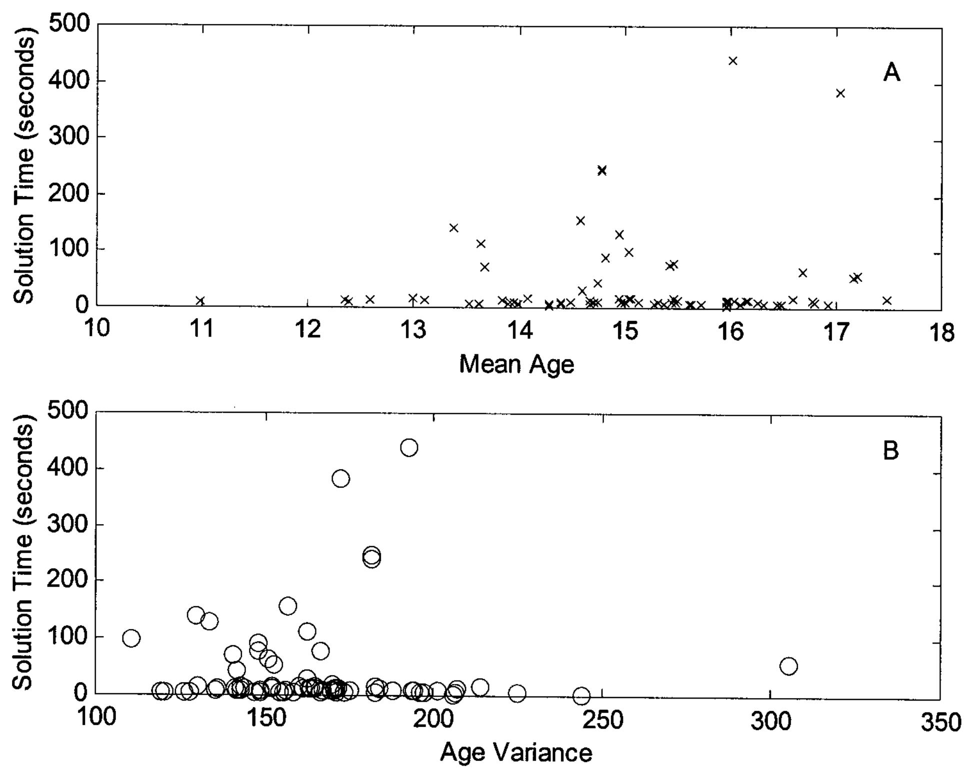
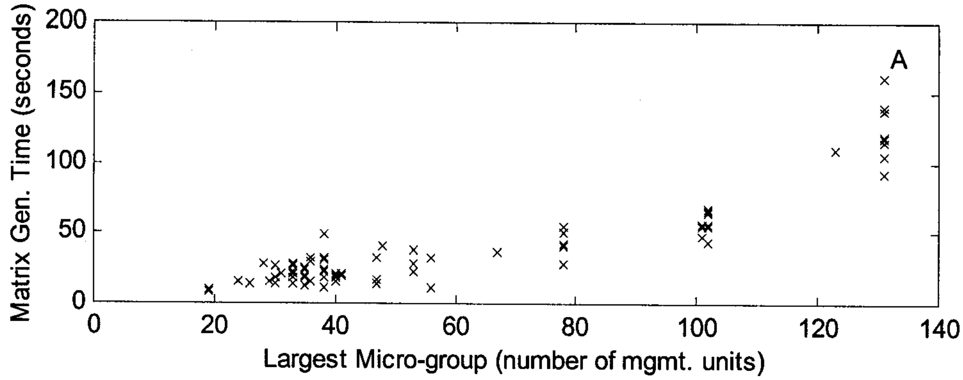


Figure 2.4
(A) Solution time plotted against mean stand age of all units within each planning randomly generated planning problem (micro-group formulation).
(B) Solution time plotted against the variance in stand ages for each randomly generated planning problem (micro-group formulation).



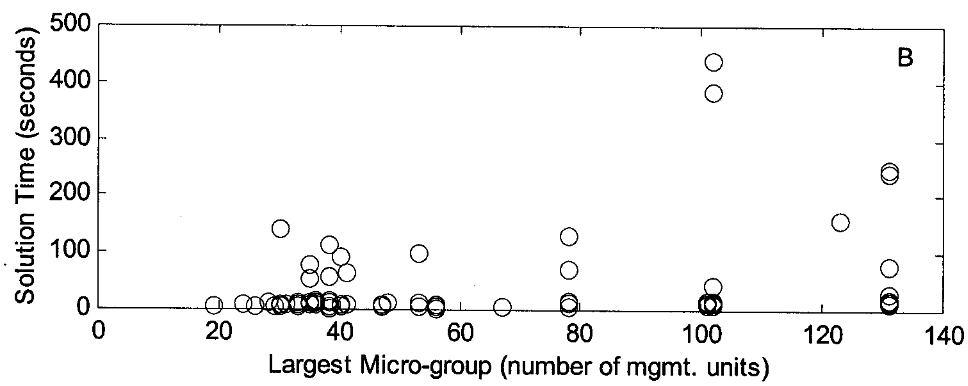


Figure 2.5
(A) Largest contiguous micro-group plotted against matrix generation time.
(B) Largest contiguous micro-group plotted against solution time.

Table 2.1 Means for recorded metrics

		Macro-Group	Micro-Group
mat gen time (seconds)	m_1	58.520093	40.14512
sol time (seconds)	m_2	22.2338	42.496693
master NPV ($)	m_3	76135815	76219096
usable NPV ($)	m_4	76158480	76239760
num planning iter	m_5	32.613333	26.373333
const violation (vol ft^3)	m_6	21132.451	22285.445
net violation (vol ft3)	m_7	-135113.91	-135750.13
total vol sched (vol ft3)	m_8	77524463	77656106
num groups	m_9	13.346667	131.98667
num of units in problem	m_{10}	468.02667	468.02667
num of units sched	m_{11}	388.22667	389.05333
total acres sched	m_{12}	18769.413	18794.213
$(m_3-m_4)/m_3$	m_{13}	-0.000329812	-0.00021617
m_6/m_8	m_{14}	0.000301936	0.000312785

Table 2.2 Correlation matrix for macro-group simulation

		m_1	m_2	m_3	m_4	m_5	m_6	m_7
mat gen time (seconds)	m_1	1.00	0.28	0.72	0.72	-0.03	-0.11	-0.74
sol time (seconds)	m_2	0.28	1.00	0.30	0.30	0.40	0.05	-0.31
master NPV ($)	m_3	0.72	0.30	1.00	1.00	0.19	-0.05	-0.99
usable NPV ($)	m_4	0.72	0.30	1.00	1.00	0.19	-0.05	-0.99
num planning iter	m_5	-0.03	0.40	0.19	0.19	1.00	-0.07	-0.19
const violation (vol ft^3)	m_6	-0.11	0.05	-0.05	-0.05	-0.07	1.00	0.05
net violation (vol ft3)	m_7	-0.74	-0.31	-0.99	-0.99	-0.19	0.05	1.00
total vol sched (vol ft3)	m_8	0.74	0.30	1.00	1.00	0.19	-0.05	-1.00
num groups	m_9	0.63	0.19	0.91	0.91	0.20	0.01	-0.91
num of units in problem	m_{10}	0.80	0.23	0.95	0.95	0.17	-0.05	-0.95
num of units sched	m_{11}	0.72	0.22	0.95	0.95	0.20	-0.04	-0.95
total acres sched	m_{12}	0.75	0.30	0.99	0.99	0.19	-0.03	-0.99
$(m_3-m_4)/m_3$	m_{13}	-0.03	0.11	0.03	0.02	0.05	-0.34	-0.04
m_6/m_8	m_{14}	-0.34	-0.08	-0.39	-0.38	-0.14	0.91	0.39

		m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}
mat gen time (seconds)	m_1	0.74	0.63	0.80	0.72	0.75	-0.03	-0.34
sol time (seconds)	m_2	0.30	0.19	0.23	0.22	0.30	0.11	-0.08
master NPV ($)	m_3	1.00	0.91	0.95	0.95	0.99	0.03	-0.39
usable NPV ($)	m_4	1.00	0.91	0.95	0.95	0.99	0.02	-0.38
num planning iter	m_5	0.19	0.20	0.17	0.20	0.19	0.05	-0.14
const violation (vol ft^3)	m_6	-0.05	0.01	-0.05	-0.04	-0.03	-0.34	0.91
net violation (vol ft3)	m_7	-1.00	-0.91	-0.95	-0.95	-0.99	-0.04	0.39
total vol sched (vol ft3)	m_8	1.00	0.92	0.96	0.96	0.99	0.04	-0.39
num groups	m_9	0.92	1.00	0.96	0.97	0.93	0.01	-0.31
num of units in problem	m_{10}	0.96	0.96	1.00	0.99	0.96	0.00	-0.38
num of units sched	m_{11}	0.96	0.97	0.99	1.00	0.96	0.04	-0.37
total acres sched	m_{12}	0.99	0.93	0.96	0.96	1.00	0.04	-0.37
$(m_3-m_4)/m_3$	m_{13}	0.04	0.01	0.00	0.04	0.04	1.00	-0.32
m_6/m_8	m_{14}	-0.39	-0.31	-0.38	-0.37	-0.37	-0.32	1.00

Table 2.3 Correlation matrix for micro-group simulation

		m_1	m_2	m_3	m_4	m_5	m_6	m_7
mat gen time (seconds)	m_1	1.00	0.40	0.63	0.63	0.20	0.06	-0.64
sol time (seconds)	m_2	0.40	1.00	0.34	0.34	0.75	0.24	-0.33
master NPV ($)	m_3	0.63	0.34	1.00	1.00	0.20	0.10	-1.00
usable NPV ($)	m_4	0.63	0.34	1.00	1.00	0.20	0.10	-1.00
num planning iter	m_5	0.20	0.75	0.20	0.20	1.00	0.06	-0.19
const violation (vol ft^3)	m_6	0.06	0.24	0.10	0.10	0.06	1.00	-0.09
net violation (vol ft3)	m_7	-0.64	-0.33	-1.00	-1.00	-0.19	-0.09	1.00
total vol sched (vol ft3)	m_8	0.65	0.33	1.00	1.00	0.19	0.10	-1.00
num groups	m_9	0.33	0.16	0.77	0.77	0.12	0.17	-0.77
num of units in problem	m_{10}	0.71	0.29	0.95	0.95	0.17	0.07	-0.95
num of units sched	m_{11}	0.62	0.29	0.95	0.95	0.18	0.08	-0.95
total acres sched	m_{12}	0.66	0.34	0.99	0.99	0.20	0.12	-0.99
$(m_3-m_4)/m_3$	m_{13}	-0.08	-0.08	-0.05	-0.06	0.16	-0.23	0.04
m_6/m_8	m_{14}	-0.24	0.02	-0.38	-0.38	-0.07	0.81	0.39

		m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}
mat gen time (seconds)	m_1	0.65	0.33	0.71	0.62	0.66	-0.08	-0.24
sol time (seconds)	m_2	0.33	0.16	0.29	0.29	0.34	-0.08	0.02
master NPV ($)	m_3	1.00	0.77	0.95	0.95	0.99	-0.05	-0.38
usable NPV ($)	m_4	1.00	0.77	0.95	0.95	0.99	-0.06	-0.38
num planning iter	m_5	0.19	0.12	0.17	0.18	0.20	0.16	-0.07
const violation (vol ft^3)	m_6	0.10	0.17	0.07	0.08	0.12	-0.23	0.81
net violation (vol ft3)	m_7	-1.00	-0.77	-0.95	-0.95	-0.99	0.04	0.39
total vol sched (vol ft3)	m_8	1.00	0.77	0.96	0.96	0.99	-0.04	-0.39
num groups	m_9	0.77	1.00	0.81	0.87	0.79	-0.08	-0.24
num of units in problem	m_{10}	0.96	0.81	1.00	0.99	0.96	-0.06	-0.39
num of units sched	m_{11}	0.96	0.87	0.99	1.00	0.96	-0.05	-0.38
total acres sched	m_{12}	0.99	0.79	0.96	0.96	1.00	-0.04	-0.37
$(m_3-m_4)/m_3$	m_{13}	-0.04	-0.08	-0.06	-0.05	-0.04	1.00	-0.14
m_6/m_8	m_{14}	-0.39	-0.24	-0.39	-0.38	-0.37	-0.14	1.00

Chapter 3: A Developed Aggregation and Disaggregation Technique Relevant for Integer Forestry Hierarchical Production Planning Problems

Introduction

Although computing power is ever increasing, allowing operational researchers to solve larger and larger decision models, problems are still routinely encountered which are beyond current technology. In order to consider large-scale models with significant detail, aggregation/ disaggregation methods are employed (Rogers et al. 1991). Moreover, the hierarchical production planning (HPP) model is often utilized to model large decision making ventures in structured organizations, in which aggregation techniques play a key role. Aggregation and disaggregation methods are often used to normalize the data relative to the decision. This study explores a formal aggregation/ disaggregation (A/D) method within the HPP model in order to forward current forest planning efforts.

A/D methods, like decomposition methods, are indispensable in carrying out the HPP model. In large-scale planning problems, decisions can often be related to hierarchical levels within organizations or to a particular time horizon. Often the terms strategic, tactical and operational are used to delineate the major three components of a decision. In making strategic decisions, for example, the detail of data, the detail of solution and the planning horizon is not the same as operational decisions. Aggregation/ disaggregation techniques can be used to manage this, keeping problem data at a minimum, so large, otherwise intractable problems can be solved, but without the loss of necessary detail and optimality.

Aggregation has been used extensively in forest planning. Each of the early forest planing models: Timber RAM (Navon 1971), MUSYC (Johnson and Jones 1979) and FORPLAN (Johnson and Crim1986), based on the models discussed in Johnson and Scheurman (1977), implicitly assume strata-based aggregation, also called modal by Weintraub (1995). In fact, the major improvements in the evolution of FORPLAN were based on aggregation flexibility (Iverson and Alston 1986). What eventually lead to FORPLAN's dismissal by many was its lack of disaggregation to spatially feasible solutions. The difficulty of disaggregating strata-based forest plans stimulated the use of two different approaches to solving the planning problem: the bottom up approach and the HPP model. Planning from the bottom up does not attempt to reduce the burden of a huge data set. Instead, this model employs heuristics, often rule based, to solve the resulting huge planning problem. This model does not find optimal solutions but focuses on finding feasible solutions. The HPP model reduces the data complexity where it is unnecessary and considers detailed data when necessary by using A/D methods and decomposition. The superiority of the HPP model is derived from its ability to address both global objectives and constraints and local (those occurring on only a smaller subset of the data) objectives and constraints simultaneously, whereas the bottom up model satisfies global constraints through rule based heuristics and considers global objectives in reduced priority. Additionally, the HPP model addresses problem optimality directly, whereas the bottom up approach has no method to do so. A major concern with the bottom-up approach is that it does not contain a formulation of the problem it attempts to solve independent of the algorithm used to solve it.

Several researchers, realizing the importance of optimality at both the global and local levels, have sought to develop the forestry HPP model using A/ D techniques. Hof and Pickens (1987) use a two tiered model, where entire tactical plans are aggregated into 0 – 1 variables at the upper level. The upper level in their model, for each landscape (sub-problem) chooses among the several plans presented for each landscape. Weintraub and Cholaky (1991) also present a two-tiered model in which aggregation is proposed. Road planning, which is detailed at the tactical level, is bundled into 0 – 1 proxy variables at the strategic level. A variable taking the value "1" indicates, for example, a road layout plan implemented on a specific area in a given time frame; this is similar to the aggregation approach used by Hof and Pickens (1987). Additionally Weintraub and Cholaky (1991) aggregate similar stands from the same management zone (modal aggregation) into single macro-stands at the strategic level. Davis and Martell (1992) designed a model which solves both strategic and tactical problems. The model uses aggregate time periods of 10 years in the strategic level model and uses 1 year periods in the tactical model. The tactical model makes up the first 10 years of the strategic model. In this case, solutions are not disaggregated; instead, the data is scoped to meet the level of detail where necessary. The strategic and tactical models are not linked by any type of feedback mechanism. Nelson and Errico (1993) present a descriptive hierarchical process carried out using simulation. They divide the forest into management zones that form spatial sub-problems. Feasible spatial alternatives are constructed heuristically using the four color theorem. Forest wide objectives and constraints are indirectly composed of aspatial data aggregated from the spatial sub-problems. This heuristic method is clearly a bottom up strategy, in which upper level objectives and constraints are explored through simulation rather than met. Bare and Liebermann (1994) present an HPP model very similar to Weintraub and Cholaky's. Their model aggregates both by time and space as one moves between the three tiers discussed: strategic, tactical and operational. The model allows for feedback if necessary (for example, if a higher level plan cannot be disaggregated feasibly at a lower level), but attempts to rectify inconsistencies within the tier using heuristics first. While aggregation is a consistent theme in these papers, the methodology is often less formal than presented in the operations research literature. Often the presentation of an unreduced model is lacking. This severely inhibits the study of the disaggregation process and the error analysis incurred from aggregation. A formal modeling procedure of the A/G process can strengthen the HPP forest planning model.

It appears that aggregation has been used since the mid 1960's and A/D methods supported with error bounds have been under study since Geoffrion's work

(1970 a, b, c). In linear programming, it is possible to aggregate columns, rows or both with error bounds (Zipkin 1980a, b). A clustering algorithm is generally used to find like rows and/ or columns to aggregate. Upon defining the clusters, a method of combing the elements into a single entity is used. Fixed-weight combination, often used, combines elements relative to their influence on the objective function. Using this method, a weighting vector (g) is used to transform the original components into a singe aggregate component. This same vector can also be used for disaggregation, upon solving the aggregate problem. Alternatively, optimal disaggregation can also be used to disaggregate the solution (Zipkin 1980). Taking [3.P1] as a primal problem example, given J columns determined to be similar enough for aggregation a single column (A_J) is formed from the J similar columns as in [3.1].

[3.P1]

$$\begin{aligned} &\max imize \quad cx \\ &subject\ to: \\ &\qquad Ax \leq b \\ &\qquad x \geq 0 \end{aligned}$$

[3.1] $$A_J = \sum_{j=1}^{J} A_j g_j$$

[3.2] $$g_j = \frac{c_j}{\sum_{j=1}^{J} c_j}$$

[3.3] $$c_J = \sum_{j=1}^{J} c_j g_j$$

g is referred to as the weighting vector. The aggregate column produced therefore emphasizes higher valued options. In linear programming, upon solving an aggregated problem, the solution can easily be disaggregated to a solution in terms of the original variables using the vector g. Hence, [3.4] yields the solution in its original, disaggregate form.

[3.4] $x_j = g_j x_J$

Under the assumption of a linear or general convex problem, it is noted that the disaggregate solution will be feasible if fixed weight aggregation and disaggregation are used (Zipkin 1980b), since the aggregate problem is a restriction of the original problem. Optimal disaggregation can also be used when fixed weight aggregation is employed to yield a feasible and improvement in the disaggregate solution (Zipkin 1980b). In this case, a sub-problem of the form shown in 3.P2 is solved for each of the clusters to disaggregate the aggregate solution.

(3.P2)

$$
\begin{aligned}
&\max imize \quad c_J x_J \\
&subject\, to: \\
&\qquad A_j x_j \le g_J A_J^T x_J \\
&\qquad x_j \ge 0 \qquad j = 1,2,\ldots J
\end{aligned}
$$

Unfortunately, extending many of the rigorous techniques of aggregation and disaggregation to integer programming is not possible. Forestry has experienced this in trying to disaggregate macro-stand (a strata-based aggregate column representing multiple spatially distinct stands, with similar inventories) solutions to individual stands. Constraint aggregation, however, has played a fundamental role in integer programming (Nemhaeuser and Wolsey 1988). Significant computational gain is generally noticed when multiple constraints are aggregated into one "covering" constraint. In fact, the default in commercial software such as CPLEX, preprocesses the constraint matrix in order to reduce the number of constraints. On the other hand, column aggregation with the intent of post-solution disaggregation has not generated such usable results. The disaggregation process results in multiplying a fraction within the weight vector g by the aggregated solution, which generally produces a non-integer. Hallefjord and Storoy (1990) provide improved bounds for 0 – 1 integer problems using a relaxation technique to carry out Zipkin's (1980c) bounding method used for LP.

Bounding the difference between the LP disaggregate and LP optimal value was derived by Zipkin 1980b and was also refined by Medelsshon 1980, Taylor 1983 and Frolik 1986. A-priori bounds are assigned upon forming the aggregate model, but before solving the model. A-posteriori bounds are placed on the model after the aggregate model has been solved. These bounds are tighter than the former. Using a simulation analysis similar to this study, Norman et al. (1999), demonstrate a-posteriori error bounds have significant correlation with actual error, but that a-priori error bounds are not significantly correlated with actual error. However, a-priori error bounds were reported to be significantly correlated to a-posteriori error bounds. Iterative aggregation/ disaggregation (IAD) methods have also been proposed as an improvement to strengthen error bounds. These methods use information from the dual variables corresponding to the reduced problem in order to update the weighting vector g. Dudkin, Rabinovich and Vakhutinsky (1987) discuss the convergence to optimal solutions of these methods. Jornsten and Leisten (1995) discuss the similarities of IAD and decomposition, as they apply to decentralized planning in organizations modeled using block angular linear programs. Unfortunately, none of these analytical error bounding methods extend easily to integer programs. It is therefore necessary to facilitate a different method of error analysis to examine aggregation and disaggregation applied to the forest planning problem, which is inherently integer.

In most cases forest planning problems are large enough to require aggregation in order to solve them. In the sequel, an aggregation/ disaggregation scheme is proposed for block angular forest planning problems. Instead of aggregating stands into macro-stands which is often done, for example Model I and II (Johnson and Scheurman), investments (forest management options) for each stand are aggregated based on similarity. Decomposition is used address the large number of management units. Groups of spatially contiguous units are planned independently using a modified Dantzig-Wolfe pricing scheme.

The objective of Chapter 3 is to derive error bounds in the use of aggregation/ disaggregation techniques applied to large, spatial integer forest planning problems with block angular structure, while still using the same model formulation and decomposition technique as in Chapter 2

Methods

The output of a planning model prescribes a guideline of current actions to take in order to meet objectives and constraints defined over the entire planning horizon. The level of detail necessary from the model depends upon its use. It has been noted by forest operational researchers that planning models have several uses. For instance, the model can be used to make strategic, tactical and operational decisions. Each of these decisions require different scope and detail; it is therefore unnecessary for the model to provide the same level of detail and scope over the entire planning horizon to satisfy informational requirements. On the other hand, it is necessary that information drawn from the model in these different states be commensurate. This demands a linked approach relying on systems analysis as it pertains to large-scale optimization problems. To this end, an aggregation/ disaggregation method using decomposition is proposed.

The model representing the planning problem should always be formulated in complete detail, before applying aggregation. The model describes, in the language of mathematics the desires and necessities of the planning effort. The formulation serves as a blueprint for the planning process. In this study, we seek to maximize the net present worth of the forest using a discount rate of 8% in the presence of flow (+ or – 10% among periods) and "green-up" restrictions (preclusion of adjacent unit harvests in the same period and adjacent periods). The outcome of an optimal plan is an assignment of all management units to a management option defined in terms of the 5 year periods that is optimal for the forest as a whole in the presence of the constraints considered. The unreduced, original model in this study appears in [3.P3].

[3.P3]

$$\max imize \quad \sum_{i=1}^{n} c_i x_i$$

subject to

1) $$\sum_{i=1}^{n} A_i x_i \leq \beta$$

2) $$B_i x_i \leq b_i \qquad i = 1,2,\ldots,n$$

3) $$x_i \in \{0,1\}$$

First note, that c_i and A_i are linear, making this model a linear integer programming problem. (x_i) is a binary vector representing the possible management alternatives before aggregation for each management unit in land base (group) i. Hence, (x_i) is composed of m (the number of management units in resource base i) vectors, where each of these m vectors has length k_m, equal to the number of management options considered for the particular unit. Thus, (c_i) gives the associated net present value of decision (x_i). Constraints [1] embody all constraints which relate the spatially distinct resource groups. In this case allowable harvest flow deviation. These constraints are treated as soft as in Chapter 2. Constraint [2] represents the decision space specific to each of the groups. In this case, the groups are composed of one or more spatially contiguous sets of harvest units which are inseparable due to the adjacency constraints (constraints 2).

This study uses two levels of aggregation to reduce the size of the problem. Fixed weight aggregation is used for all aggregation. Management options for units are first aggregated by management option type and harvest year, producing an intermediate aggregate problem, and then management option types are aggregated for each harvest year, producing the most aggregate problem. The difference between two management options with the same management option type is the timing of the silvilculture actions. For example, one management option may be thin in periods 2 and 5 and harvest in period 7, and another might be thin in periods 2 and 4 and harvest in period 6. However, these options would not be in the same aggregation group because the harvest period differs. A formal clustering method is not used since natural groupings exist. However, if a formal clustering method could be used, care would need to be taken to preserve the adjacency constraints. At all levels of aggregation, management units are preserved, so that spatial feasibility is preserved throughout the process. Upon solving the most aggregate model, specifying a harvest period for each management unit, the solution is disaggregated using a special form of optimal disaggregation, discussed in the sequel. The most aggregate model provides the harvest year for all management units in the presence of the harvest flow and adjacency constraints. Therefore, dissagregation to find the management option type can ignore adjacency constraints. Management option type for each unit is determined by solving the intermediate aggregate model with data corresponding to the possible harvest periods previously determined, in the presence of harvest flow restrictions. Upon solving this problem, a solution is found which contains harvest year, determined from the first problem and management option type. Therefore, at this point the only unknown is the management option within the management option type and harvest period specified. The final optimal disaggregation problem solves for the optimal management option for each unit given the solutions of the previous aggregate problems. Again, harvest flow is constrained during this disaggregation. As does the most aggregate problem, the intermediate problem "filters" the data to be considered in the most disaggregate problem. The aggregation and disaggregation process uses fixed weightings to filter out low valued decisions and then finds the highest valued decision among those remaining.

It is useful to analyze the affect of applying two levels of aggregation as opposed to one. The first important property of the bilevel aggregation is that it is also a single level aggregation, with a different weighting vector. Consider the problem of aggregating x into two clusters of y (the intermediate variable).

[3.5] $$y_1 = x_1 g_1 + x_2 g_2; \quad g_1 + g_2 = 1$$
$$y_2 = x_3 g_3 + x_4 g_4; \quad g_3 + g_4 = 1$$

Next, consider the problem of aggregating y into one cluster of z (the most aggregate variable).

[3.6] $$z = y_1 \hat{g}_1 + y_2 \hat{g}_2; \qquad \hat{g}_1 + \hat{g}_2 = 1$$

Therefore, we verified that:

[3.7] $$z = (x_1 g_1 + x_2 g_2)\hat{g}_1 + (x_3 g_3 + x_4 g_4)\hat{g}_2$$
$$= x_1 g_1 \hat{g}_1 + x_2 g_2 \hat{g}_1 + x_3 g_3 \hat{g}_2 + x_4 g_4 \hat{g}_2$$

It is easily seen that:

[3.8] $$g_1 \hat{g}_1 + g_2 \hat{g}_1 + g_3 \hat{g}_2 + g_4 \hat{g}_2 = 1$$

Upon defining the weighting vector as in [3.9], we see that the bilevel aggregation is a single fixed weight aggregation, but with different weights.

[3.9] $$\tilde{g} = (g_1 \hat{g}_1, g_2 \hat{g}_1, g_3 \hat{g}_2, g_4 \hat{g}_2)$$

It can be verified that the weighting vector in [3.9] is, generally, not the same weighting vector that would be obtained if fixed weight aggregation is used to aggregate all the management options by harvest period, excluding the consideration of management option type. [3.9] is the weighting vector obtained under the distinction of an intermediate clustering.

Although it would be very interesting to compare the use of different weighting vectors, it is outside of the scope of this study. The size of the sample problems solved would need to be reduced to a carry out this objective; it is therefore considered a topic for future research. Seventy-five planning problems are solved using the described A/D method and solved using an unreduced model for comparison. Due to the size of the resulting problems in full disaggregate form, it is not computationally feasible to analyze the error of the entire process. Instead, the error introduced in the transition from the most aggregate problem to the intermediate aggregate problem is analyzed. Therefore, along with the entire A/D procedure, the intermediate tier model is solved without aggregation. Hence, this single optimization problem solves for the treatment regime type and harvest period simultaneously in order to generate comparative results for the A/D approach. Using the most aggregate and intermediate aggregate forms allows the error analysis to proceed in the presence of adjacency and harvest flow constraints. Furthermore, this transition is representative of the problem encountered when an intermediate level is not acknowledged. The management option types, which are aggregated by harvest period could be alleviated. In doing this, all management options pertaining to a harvest period for a given unit would be aggregated. The only relevant difference of aggregating all the option types by harvest period versus all the options by harvest period is the number of members in each cluster. Of course, there would be far greater options aggregated per harvest period as opposed to option types. The presented error results are relevant for either case, so long as the number of members per aggregate variable are in the neighborhood as those in this study (discussed next). Unfortunately, it is difficult to estimate the error incurred upon reaching the final solution. It is also difficult to determine whether including the intermediate level problem reduces or increases the error incurred or equivalently, whether the alternative weighting vector [3.9] is better than using the standard fixed weight vector. However, including the intermediate problem appears to be necessary with regards to computational considerations.

The data set in this study consists of multiple simulated management options for each management unit. The data is specified by five-year periods. Each management unit is forecasted under an average of 101 management options with a maximum of 303, minimum of 1 and standard deviation of 73.8. The average number of harvest period options per management unit is 5.47 with a maximum of 8, a minimum of 1 and a standard deviation of 1.55. The mean number of management option types per harvest period is 3.5 with a maximum of 5, a minimum of 1 and a standard deviation of 1.62. Each unit is identified to a spatially contiguous group of units called a micro-group. A macro-group is composed of one or more micro-groups. Rogers et al. (1991) and others have suggested solving multiple randomly generated problems for gaining aggregation error information. Planning problems are randomly generated based on the group structure. Seventy-five planning problems composed of a random number of macro-groups (between 6 and 20 selected with equal probability) are used to generate simulation statistics. The macro-groups are drawn randomly with replacement from a population of 237. Contiguous groups with more than 150 management units are omitted from the population due to the large number of planning problems being solved. On average, each macro-group is composed of 10.04 contiguous micro-groups. The mean number of management units in a micro-group is 3.52, giving an average of 35.99 management units in each macro-group. Hence, the mean number of planning units per planning problem is 485.87. The largest problem generated had 806 management units and the smallest problem solved had 187 management units.

Model [3.P3], an integer program with block angular structure is representative of the planning problems solved at all levels of aggregation. Therefore, the same decomposition strategy discussed in Chapter 1 is used to solve the model at all levels of aggregation. The decomposition of the planning problem is done with respect to the macro-groups in this Chapter.

Results

The results are organized around the following four problems and their interrelation: the most aggregate problem (specifies harvest period for each unit), the intermediate aggregate problem (specifies management option type for each unit), the final disaggregation problem (specifies management option) and the unreduced intermediate level problem (specifies harvest period and management option type for each unit simultaneously). To give a sense of the entire problem and A/D process and to provide objective function value differences among the different levels of aggregation, solution results of the entire process are presented. The expected error of using the proposed A/D process is derived using the transition from the most aggregate problem to the intermediate results (a specification of harvest period and management option type).

The error introduced from using A/D is measured in terms of the objective function value (Rogers et al 1991). A bound on the error incurred from using aggregation provides the maximum distance one will be from the true optimal value of the problem given the proposed A/D procedure. In the case of integer programming, recall that these bounds must be derived by relaxing the integer constraints, in order to use the LP bound to approximate this error (see Hallefjord and Storoy 1991). Alternatively, the aggregation process may be studied through simulation using small enough sample problems, which can be solved in unreduced form, as is done in Norman et al. (1999).

Much of the time A/D is used to ease computational burden. However, in forest management, the level of aggregation can also represent the nature of the decision (Gunn 1992). For example, strategic decisions may only need to use the most aggregate problem's solution, while tactical and/ or operational decisions may need the solution of the most disaggregate solution. Of interest, is the difference in the objective values of the problems at different levels of aggregation. The differences will measure the value of the A/D procedure in terms of implementation. If these separate, but linked problems are used to model decision-making at different organizational levels, large deviations in these values will surely lead to a poorly managed enterprise. Figure 3.1 displays the percent deviation of NPV for the different levels of aggregate solutions. Category one shows the percent difference in the most aggregate and the intermediate objective function values, category two shows the percent difference between the intermediate and the most disaggregate problems' objective function values and category three displays the sum of the percent errors just listed. The total deviation of all transitions gives a measure of the overall consistency of the different level plans. The outlying data point in each category is caused by a planning problem which, in solving the intermediate problem, did not converge to the optimal solution given the maximum number of allowed planning iterations. This was determined by looking at the problem solution log. This mishap also could have been identified by comparing the disaggregate solution objective value to the aggregate objective value, which are largely different. The percent error of the outlier's most aggregate solution relative to the unreduced intermediate problem is 11.4%, which is clearly different from the 55% found at the intermediate level. Due to the mechanics of the A/D process the final disaggregate problem will be adversely affected by the intermediate solution. Its percent error relative to the unreduced intermediate problem is 67%. The results displayed in Figure 3.1 demonstrate that the A/G methodology produces consistent solutions in terms of NPV among the different levels of aggregation. Casting aside the outlier, the maximum total percent error encountered for the entire process (category 3) is 10.1%, the mean percent error 6.4% and standard deviation 1.1%.

While the previous discussion validates the consistency of NPV among different levels of aggregation, it does not provide a measure of loss in optimality; this is addressed using the most aggregate and intermediate aggregate problems. Two important aspects to surface in analyzing the error made from transitioning to the intermediate aggregate problem from the most aggregate problem are the magnitude of error and the dependence relation of the error and the problem size. The optimal solution to the problem of determining harvest period and management option type is given by the unreduced problem. Therefore, the optimal value of this problem provides the least upper bound (LUB) to the intermediate aggregate solution, specifying harvest period and management option type. Taking the ratio of the objective function value of the intermediate aggregate problem to this LUB, multiplied by 100 yields percent attainment. 100 minus this value gives percent error.

Figure 3.2 displays a plot of this percent error against the total volume scheduled in the planning problem, where total volume scheduled is used to measure the size of the problem. In viewing Figure 3.2, it appears that the percent error and the total volume scheduled are unrelated, as can be seen from the non increasing nature of the percent error data with respect to total volume scheduled. Moreover, with the outlier removed, the standard deviation (2.1%) about the mean error (7.9%) appears to be constant. Since the most disaggregate problem was too large to solve in unreduced form, the error of paramount interest, the difference in the optimal values of the entire unreduced problem, specifying harvest year and management option for each unit, and the aggregate problem could not be found. The produced results, presented as an estimation of possible error in carrying out the proposed A/G process, are intended to provide guidelines and stimulate further thinking in A/G error estimation procedures for the forestry planning problem that is inherently integer. Recall that if there are only a small number of management options being considered, and these options are aggregated by harvest period, then the error results relate to that problem. There is no mathematical difference in aggregating option types and options by harvest period, except in this problem the number of each type. Consult the data description for more information on the number of options and management options encountered in this study.

Discussion and Conclusion

The forest planning problem can often be represented using block angular form. This formulation recognizes two types of constraints: global and local. Forest planning problems are generally made up of several contiguous groups of land or land bases delineated by organizational constructs. These land bases are related to each other through global constraints in the planning problem. Decomposition allows decentralization of the plan with respect to these groups. However, in the case of most forest planning problems, the sub-problems encountered for each group are still too large to be solved exactly. Aggregation can be used without substantial loss in optimality to handle this cumbering affect. Moreover, if detailed solutions are unnecessary, the sub-problems can be modeled in aggregate form to eliminate significant computation and provide courser scale information that is commensurate with finer scale solutions.

The results in this study, using a non-analytical method to address the loss in optimality shows that A/D techniques can be used to solve large-scale forest planning problems which are inherently integer, finding feasible solutions without substantial loss in optimality. Although we were unable to find the complete loss in optimality of using two disaggregations (or the revised weighting vector (see [3.9]) which reflects the hierarchical grouping structure), the results suggest the proposed A/D functions without significant loss in optimality. The A/D method becomes more attractive when it is compared against past and some current practices, which make no attempt to bound the loss in optimality incurred from disaggregation.

The models presented in Johnson and Scheurman (1977) are used by many forestry organizations to plan forest management activities. These models, implemented in FORPLAN are representative of the so-called monolithic model. One of the major issues with Model I and II are the problems encountered in disaggregating solutions. These models suggest the proportion of acres of a macro-stand to be managed under a certain management option. There is no recognition of where in space these proportions are located. Often, this leads to splitting the management units or simply rounding the solution in order to implement the plan. The unreduced model from which Model I and II are derived is rarely mentioned. Therefore, the disaggregation to finer scale solutions happens in absence of any quantitative method, without bounds on the error incurred from diasagregation. Many have questioned the application of mathematical programming to forest planning problems because of the inability to disaggregate to feasible solutions (see Bare and Field 1986). It seems obvious that the aggregate model was not defined to make this aggregation easy. The proper process of model formulation followed by solution was never followed. Hence, the solution tool (mathematical programming) was blamed for the poor results, instead of the user's inexperience or lack of knowledge of the tool. Those developing the bottom-up approach to forest planning have ventured further from addressing the fundamental issue of problem formulation. This methodology offers no rigorous formulation to provide an error analysis.

The proper formulation of a planning model starts with a written mathematical description of the problem. If this formulation is seen to be unsolvable with current technology, then methods of aggregation, relaxation and decomposition are considered. Without a correctly written mathematical model, there is no way to assess the solution in terms of optimality of the original problem. The blueprint used throughout engineering, like the mathematical formulation of a problem, represents a well thought out plan written in a formalized planning language. One of the essential properties of a blueprint is it specifies the conceptual design independent of the actual development. A proper model formulation has a similar property: the specification of the model is independent of the algorithm used to solve it. Many of the formulations presented to solve forest planning problems do not have this property.

Often the first 5-10 years of a harvest plan demands a finer level of detail than considered in this Chapter, with possibly different or additional constraints and objectives. There are several ways of coping with this in a model which is based on a finer scale. Davis and Martel (1993) suggest representing the first 10 years of the plan in yearly periods, as opposed to 10 year periods representing the rest of the planning horizon. This is a nice approach so long as the objectives in these first few years are the same as those throughout the rest of the planning horizon. If this expansion in the number of time periods presents a computational burden, then aggregation could be performed on these periods. This should be done with a complete formulation of the unreduced model, so that a formal A/G method can be used, so that feasibility and optimality are addressed. If the near term objectives and constraints are different from the rest of the planning problem, for example, if they are linked to market forecasts, work force requirements and mill capabilities, then a different type of model may be necessary. The headquarters of the managing enterprise may be responsible for supplying raw resources to its divisions, for product conversion. If these divisions are producing different products and supplying different markets then there will be a vector of projected rates of return with a corresponding correlation matrix describing the interdependence of these rates. In this scenario it is desirable for headquarters to consider the profit maximization, risk adjusted rate of return. This model type represents a situation with conflicting objectives between the divisions and the headquarters. Hence, a compromise model must be employed. Chapters 2 and 3 have thoroughly considered the hierarchical production planning model, which is termed holistic because the objective of the planning problem is the sum of the divisions or geographical units' objectives. Chapter 4 will address the model with conflicting objectives: the hierarchical optimization problem (see Luo et al. 1996).

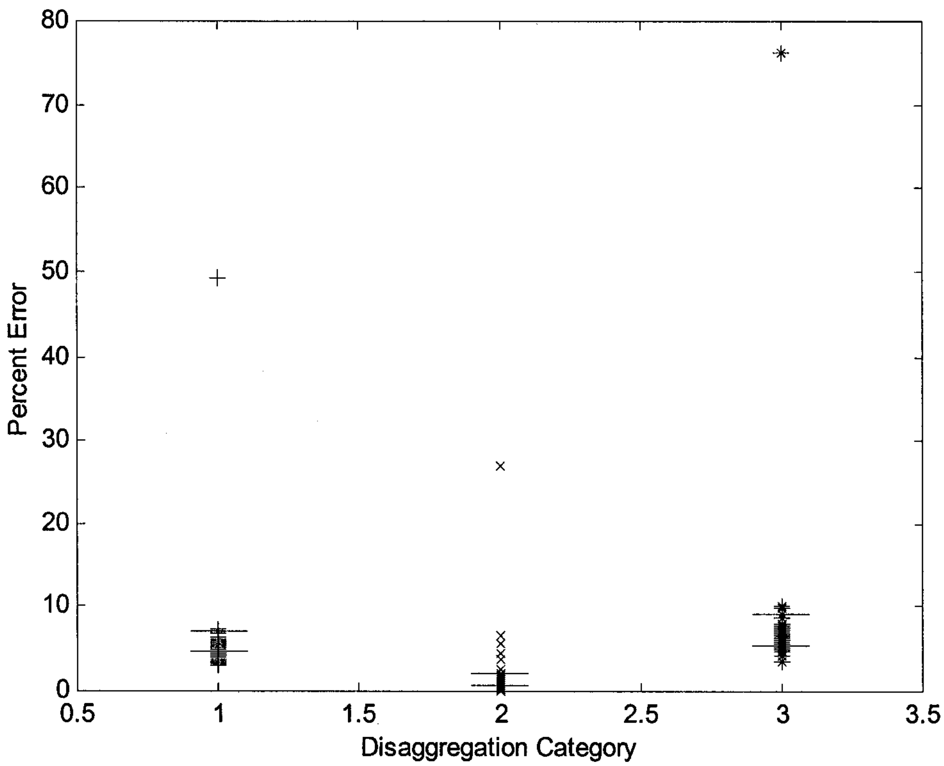


Figure 3.1
Percent difference of net present value for different aggregation levels. Error bars indicate 95% confidence of the mean. Category 1 shows the percent difference of the objective function values for the aggregate and intermediate problems, category two shows the percent difference of the objective function for the intermediate and most disaggregate problems and category 3 displays the absolute sum deviation of problems.

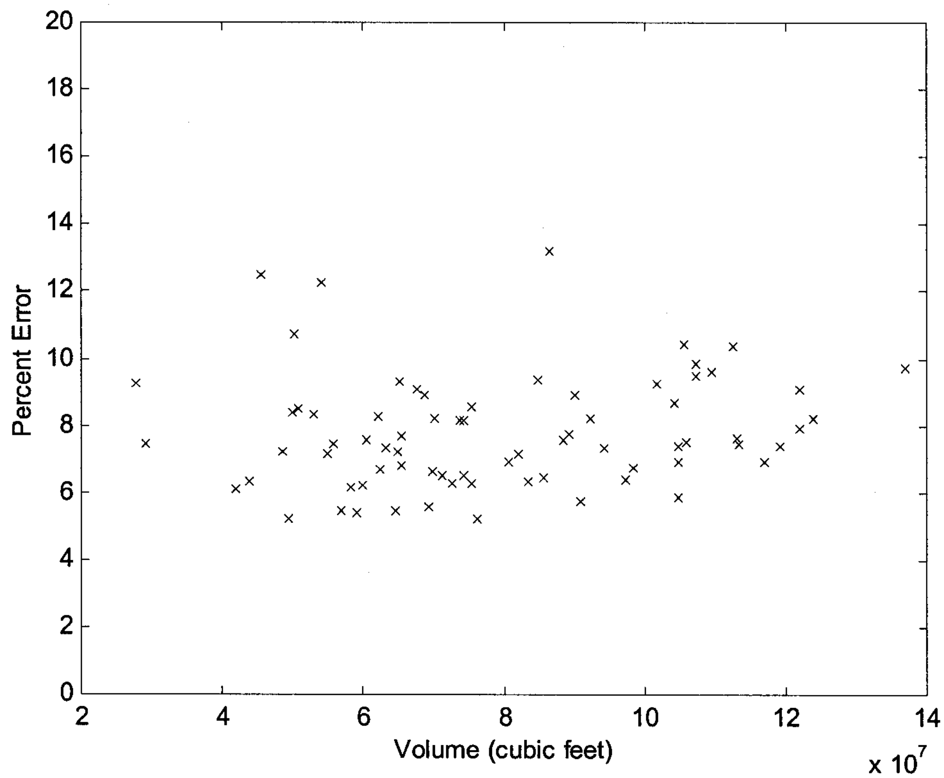


Figure 3.2
Percent error (= 100* (1-disaggregate NPV/ unreduced NPV)) incurred from problem aggregation plotted with total volume scheduled in the unreduced problem.

Chapter 4: A Bilevel, Mean-Variance Capital Rationing Model, Applied to the Product Diversified Forestry Corporation

Introduction

Often, large businesses decentralize management in order to reduce the effects of diminishing returns of scale. A typical infrastructure is a headquarters with multiple divisions (Burton and Obel 1977). A common objective for the headquarters is maximization of the rate of return or the value of the firm (Goedhard and Spronk 1995). The headquarters is responsible for steering the business in the right direction given forecasted market conditions. On the other hand, the leader(s) of each division is (are) responsible for acting in the best interest of that division. This leads to a divisional objective of maximizing the value of the division given the resources that headquarters allocates to it and whatever other resources it can obtain. With these two levels of management each pursuing interdependent objectives, an operational model that links them together is necessary.

The theory of quantitative portfolio management, pioneered by Markowitz (1959, 1987), has taken a central role in modern finance theory. Its extension to resource allocation simply requires the resources of the firm to be viewed as wealth to be invested in the different divisions of the firm. Hence, each division can be viewed as a security providing a rate of return with an associated risk. Likewise, the scarce resources of the firm can be viewed as wealth to be invested in the firm in order to control the rate of return and associated risk.

The integrated forest products/ timber producing firm contains an infrastructure that is amenable to risk diversification through resource allocation to its different divisions. Although there has been a clear shift in the ownership structure of forest resources held for timber production to companies which are not holding product conversion facilities, some companies still own large amounts of timberland and product conversion facilities. These companies, selling timber on the open market and producing forest products can shield themselves from risk by capital rationing using a model which extends the principles developed in portfolio selection theory. Viewing the capital rationing decision as a portfolio selection decision requires a substantial modeling overhaul. Consider a forestry firm that rations its timber resources to its different market sectors, for example engineered wood products, paper, solid wood products and timber sales on the open market. Each market sector can be considered a different investment with possibly different price and demand trends. Moreover, the harvested volume and/ or planned harvest can be considered as wealth to be invested into each of the market sectors. Hence, each division, producing in different markets is treated as an investment by the headquarters, while the harvest and other possible cash flows are considered wealth to be invested in each of these divisions. Since the productivity of each division is dependent upon the resources allocated to it by headquarters, the assumption of independence between the investment and the wealth invested in it, held by the mean variance model of Markowitz (1959) no longer holds.

The objective of Chapter 4 is to formulate the risk diversified forestry corporation capital rationing problem as a hierarchical optimization problem, and to discuss solution techniques for this formulation.

The Mean-Variance Model

Several formulations of the portfolio optimization problem have been given in the literature, see Markowitz (1987), Michaud (1998), Elton and Gruber (1999) and Allen (2000). An optimal portfolio can be described in terms of the expected rate of return and the associated risk of the portfolio. Under the mean – variance formulation (Markowitz 1959) the variance in the rate of return measures the risk of the investment. Therefore, there are efficient rates of return – risk combinations that make a portfolio optimal. Such a specification allows one to find an optimal investment strategy given a risk preference. A general formulation of the mean – variance formulation is given by [4.P1].

[4.P1]

$$\begin{aligned} &\max imize \quad (1-\lambda)Rx - \lambda(x'\Sigma x) \\ &subject\ to: \\ &\qquad x' \cdot 1 \leq 1 \\ &\qquad x \geq 0 \end{aligned}$$

x- is a n – dimensional decision variable representing the proportion of wealth invested in each investment.

R- is an n – dimensional vector giving the expected rate of return for each of the n investments.

Σ- is the covariance matrix, describing the variance in the expected rates of return for each of the n investments.

λ- indicates the risk preference of the investor.

Problem [4.P1] can also be thought of as a function of λ; in this case, problem [4.P1] would be repeatedly solved varying the parameter λ to develop the efficient portfolio frontier. The parameter λ allows the selected portfolio to depend on the investors personal feeling about risk.

The Model

The Hierarchical Mean Variance Model

Extending the mean variance model to allow interdependence between the investment and the wealth invested in it, such as the case in capital rationing requires the use of equilibrium constraints, in general. This, of course, assumes that the investment or division in the case of capital rationing does not have the same objective as the headquarters, which is the case when the division has some level of autonomy. Consider the forestry firm acting to maximize risk-adjusted returns in its rationing process of harvested volume. [4.P2] gives an abstract formulation of the problem.

[4.P2]

$$\max \quad (1-\lambda)\sum_{k=1}^{K} E_{\omega}[r_k(x_k, y_k, \omega_k)]x_k - \lambda x' \Sigma_{\omega}(r(x,y,\omega))x$$

$$st \quad \sum_{k=1}^{K} x_k \le V$$

$$y_k \in \arg\max\{E[r_k(x_k, y_k, \omega_k)] : y_k \in C_k(x_k); y_k \in Y_k(\omega_k)\} \qquad k = 1,2,\ldots K$$

k is the number of divisions.

x is a vector made up of each of the x_k vectors, pertaining to the headquarters' decision.

y is a vector made up of each of the y_k vectors, pertaining to the decision of each division.

ω is a random vector made up of each of the ω_k vectors, describing the uncertain unfolding of future events; market demand and product prices in this case.

r is the function giving the rate of return of a decision x, y, with the underlying random variable ω.

E_ω is the expectation function with respect to ω.

Σ_ω is the covariance matrix of the rate of return vector r, with respect to ω.

V is the volume harvest that will be allocated to the different divisions.

$C_k(x_k,\omega_k)$ is the constraint set (decision space) for y_k dependent upon the decision made by the upper level and the uncertain future.

Y_k is the constraint set (decision space) for y_k not dependent upon the decision made by the upper level and the uncertain future.

In effort to promote solvability of problem [4.P2], the assumption that the support of ω is discrete or that it can be approximated by a discrete probability distribution is important. Therefore Q economic scenarios are considered, each having a varying affect on the outlook of the k divisions. The economic scenarios are representations of different exogenous effects on the firm. Each scenario represents a forecast which determines prices and demand trends for the different market sectors in which the divisions are engaged. These prices and demand trends are represented by the different cost coefficients and resource vectors of the lower level problems, which, are indexed by ν. An estimation of the probability of realizing each scenario is specified, and used to derive expectations. Upon carrying out the matrix multiplication in the objective function of [4.P2], [4.1] is obtained.

[4.1]

$$(1-\lambda)\sum_{k=1}^{K} E_{\omega}(r_k)x_k - \lambda\{\sum_{k=1}^{K}(E_{\omega}(r_k^2) - E_{\omega}(r_k)^2)x_k^2 - 2[\sum_{i<j} E_{\omega}(r_i r_j) - E_{\omega}(r_i)E_{\omega}(r_j)]x_i x_j\}$$

In considering Q discrete scenarios, with each scenario ν, occurring with probability p^{ν} [4.1] can be written as [4.2].

[4.2]

$$(1-\lambda)\sum_{k=1}^{K}(\sum_{\nu=1}^{Q} r_k^{\nu} p_k^{\nu})x_k - \lambda\sum_{k=1}^{K}[\sum_{\nu=1}^{Q}(r_k^{\nu})^2 p_k^{\nu} - (\sum_{\nu=1}^{Q} r_k^{\nu} p_k^{\nu})^2]x_k^2 -$$

$$2\lambda[\sum_{i<j}(\sum_{\nu=1}^{Q} r_i^{\nu} r_j^{\nu} p^{\nu} - (\sum_{\nu=1}^{Q} r_i^{\nu} p^{\nu})(\sum_{\nu=1}^{Q} r_j^{\nu} p^{\nu})]x_i x_j$$

The dependence of r, the rate of return on the decisions x and y, has been suppressed in the derivations above. Since the rate of return for each different scenario is controlled by the decision x of the upper level and then autonomously by y, it is necessary to specify a lower level reaction for each scenario and each division. Although it is more direct to extract the rate of return directly from the lower level instead of the decision y, since r is the only element used by the upper level, this creates a non-convex constraint within the lower level see [4.3]. [4.3]

$$r_k^{\nu} = \arg\max\{c_k^{\nu} y_k^{\nu} : 0 = \sum_{l=1}^{P} e^{-r_k^{\nu}} \bar{c}_k^{\nu} y_k^{\nu}; A_k^{\nu} y_k^{\nu} \le b_k^{\nu}; B_k^{\nu} y_k^{\nu} \le x_k^{\nu}\}$$

The theoretical implication of this is that the convergence to an optimal solution of the Karush-Kuhn-Tucker formulation may not satisfy the original problem. This is remedied in the sequel. This expression states that under scenario ν division k will maximize its net present value, which will determine a rate of return (the first constraint), will have to adhere to its production constraints independent of the decision made by the upper level (the second constraint), and will also have to adhere to the constraint imposed by the allocation of volume at the upper level (the third constraint). Putting the components of this problem together one obtains [4.P3].

[4.P3]

$$\max \quad (1-\lambda)\sum_{k=1}^{K}(\sum_{v=1}^{Q} r_k^v p_k^v)x_k - \lambda\sum_{k=1}^{K}[\sum_{v=1}^{Q}(r_k^v)^2 p_k^v - (\sum_{v=1}^{Q} r_k^v p_k^v)^2]x_k^2 - 2\lambda[\sum_{i<j}(\sum_{v=1}^{Q} r_i^v r_j^v p^v - (\sum_{v=1}^{Q} r_i^v p^v)(\sum_{v=1}^{Q} r_j^v p^v)]x_i x_j$$

st

$$\sum_{k=1}^{K} x_k \le V$$

$$0 = \sum_{l=1}^{P} e^{-r_k^v l}\bar{c}_k^v y_k^v \qquad \forall k,v$$

$$y_k^v = \arg\max\{c_k^v y_k^v : A_k^v y_k^v \le b_k^v ; B_k^v y_k^v \le x_k\} \qquad \forall k,v$$

Notice that in [4.P3] the constraint specifying the rate of return has been moved to the upper level. As can be seen, this makes the lower level problem a linear programming problem. This appears to be important in deriving optimality conditions and solving the problem.

It is instructive to briefly analyze the model specifying for the firm's resource allocation problem and just how it might be used. Somewhere at the headquarters level in a corporation, market forecasts are made for each of the markets in which it invests. These forecasts are likely linked to some economic indicator, such as the interest rate. As a function of this indicator, a demand and price scenario is estimated. In [4.P3] these different scenarios are indexed by ν. Thus, for example, Q values for the future economic indicator are estimated, with probability p of realization. For each scenario ν, the lower levels problem data is specified; each division is constrained to produce less than demanded and must sell at a price that is set by the market, as estimated a-priori by headquarters, under that economic scenario. For each scenario ν, each division reacts with a decision y specifying a rate of return. Upon inspecting the ν rate of returns for each of the divisions the correlation of the rates for each division and the weighted expected rate of return for the corporation as a whole can be computed (this is the upper level objective). The upper level, in ascertaining the reaction of its divisions to all the scenarios simultaneously, is able to make a resource allocation decision, which maximizes the expected rate of return and mitigate risk at its preference level λ. The parameter λ, measures the risk preference of the firm. Therefore, even if λ were 0, the firm still maximizes the expected rate of return. The interpretation of $\lambda = 0$ is a firm which is indifferent about risk. On the other hand, if $\lambda = 1$ the upper level is only concerned about mitigating risk. In a sense, inasmuch as λ measures the risk preference of the firm, it also measures the similarity of the objectives between the upper and lower levels. When $\lambda = 0$ the problem could be modeled as holistic since the objectives of the two levels directly coincide. As might be noted, the problem only specifies a decision x and not really y, since y is dependent upon ω, which has not yet been realized.

Solution Methods

Several solution techniques have been proposed for the bilevel program, such as [4.P3]. Most of these make use of a reformulation of the problem to a non-linear programming problem. In general, bilevel programs and the resulting reformulation are non-convex programming problems (Anandalingam and Friesz 1992, Bard and Edmunds 1992 and Luo et al. 1996). This can be seen by reformulating the bilevel program in its Kurush Kuhn Tucker (KKT) formulation, as discussed in Luo et al. (1996). In this approach, the interpretation that the lower level decisions are chosen by the upper level is discussed in Bard and Edmunds (1992). The (KKT) form of [4.P3] is shown in [4.P4].

[4.P4]

$$\max \quad \begin{array}{l}(1-\lambda)\sum_{k=1}^{K}(\sum_{v=1}^{Q}r_k^v p_k^v)x_k - \lambda\sum_{k=1}^{K}[\sum_{v=1}^{Q}(r_k^v)^2 p_k^v - (\sum_{v=1}^{Q}r_k^v p_k^v)^2]x_k^2 - \\ 2\lambda[\sum_{i<j}(\sum_{v=1}^{Q}r_i^v r_j^v p^v - (\sum_{v=1}^{Q}r_i^v p^v)(\sum_{v=1}^{Q}r_j^v p^v)]x_i x_j\end{array}$$

$s.t.$

$$\sum_{k=1}^{K}x_k \le V$$

$$0 = \sum_{l=1}^{P}e^{-r_k^v l}\bar{c}_k^v y_k^v$$

$$\nabla_y c_k^v y_k^v + \sum_{i=1}^{m_1}\lambda_i \nabla_y (A_{k\,i}^v y_{k\,i}^v - b_{k\,i}^v) + \sum_{j=1}^{m_2}\lambda_i \nabla_y (B_k^v y_k^v - x_k) = 0 \qquad \forall k,v$$

$$A_k^v y_k^v - b_k^v \le 0 \qquad \forall k,v$$

$$B_k^v y_k^v - x_k^v \le 0 \qquad \forall k,v$$

$$\lambda^T \begin{pmatrix} A_k^v y_k^v - b_k^v \\ B_k^v y_k^v - x_k \end{pmatrix} = 0 \qquad \forall k,v$$

The equivalence of [4.P3] and [4.P4] rests upon satisfying a sequentially bounded constraint qualification, convexity of the constraints at the lower level problems in the variable y and the existence and continuity of the third constraint, the KKT conditions for the lower level problem (the reader is referred to Luo et al 1996 for theoretical discussion) . Under the assumption of these conditions, if a triplet (λ,x,y) is a global minimizer of [4.P4], with the constraints satisfied, then (x,y) minimizes [4.P3]. Therefore, traditional nonlinear programming algorithms can be used to solve [4.P4], obtaining a solution to [4.P3]. Sequential Quadratic Programming (SQP) appears to be the most successful approach (Leiffer 2001), although much success has also been reported using other techniques. Nicholls (1995) uses a vertex search technique, similar to Bard's approach (1983) to solve a bilevel formulation of an aluminum smelter problem. Bard and Moore (1990) and Bard (1990) have worked out the branch and bound method for solving the bilevel program with linear or quadratic objectives and linear lower level constraints. Edmunds and Bard (1992) extend the branch and bound solution technique to also solve problems in which discrete variables are present in the upper level problem. Judice and Faustino (1994) compare their hybrid enumeration algorithm, to the branch and bound method of Bard and Moore (1990), indicating that their method consistently out-performed the branch and bound method. It appears that many of the methods being developed could be used to solve problem [4.P4].

Discussion

There are several interesting research questions that could be addressed in investigating model [4.P4]. Understanding the effect of the firms risk preference on the allocation of resources could be investigated by solving [4.P4] for different lambda. Another interesting study would be to investigate the utility of considering different economic scenarios, which accounts for future risk. This could be done by setting lambda to zero, generating several scenarios, solving the resulting model and comparing the output to the solution of the model when only the mean scenario is considered. Lambda should be set to zero since under the consideration of one scenario a variance has no meaning. Alternatively, the variance could be estimated a-priori, and lambda could be allowed to be greater than zero. This would measure the value of risk amelioration. The evaluation could be made using real data for a past situation, or the solutions of both models could be compared under several outcomes. Examining the mean value lost or gained with respect to different realized outcomes of each model (the one with several scenarios and the one with one mean scenario) would provide a good measure of the value of including uncertainty in the model. In order to evaluate the verity of the model, it would need to be compared to a current approach. If a forestry corporation was to divulge such information, and the model could be adapted to the firm's structure than this comparison could be done. All of these comparative methods could stimulate interesting results in future research.

These approaches were not followed at this time because of time constraints. The problem proposed in this Chapter is a dissertation topic in itself. The model is included in this dissertation as a comparative device to the holistic model. It seems clear that many of the models being presented within the hierarchical approach to forest management were contemplating, at least conceptually, both holistic and compromise models, without the exact theoretical knowledge and implications of compromise models, and the resulting hierarchical optimization problem. This Chapter has covered the general background of the compromise model with a detailed example to promote further thinking about model refinement within the hierarchical approach to forest management.

Chapter 5: Conclusion

As forest planning evolves, forest planning models must provide an accurate representation of new objectives and constraints as they appear in the forestry sector. The hierarchical approach to forest management has arrived, because it portrays the multilevel fashion in which decisions are made, and because the resulting planning problems appear to have multilevel structure, as well. This dissertation has shown the importance of precision in formulating these problems. The procedure for precise problem formulation followed by a properly derived solution technique of the holistic model provides a sound method for arriving at the hierarchical model often discussed in the forest planning literature. Deriving this interpretation from a rigorously formulated problem, instead of representing the problem with levels connected by an algorithm seems to contain significant theoretical implications for planning problems which can be decomposed spatially. Importantly, it identifies the problem considered as holistic in type.

Forest planners have and continue to define the role of the mathematical model in the multilevel approach to forest planning. This dissertation emphasizes the critical importance of model formulation as the first step in the construction of a model. The model formulation provides a mission statement of the planning effort, which accounts for the organizational structure of the planning entity and the entity being managed. The solution of the model is a subsequent step that provides a guide for decision-makers. Chapters 2 and 3 of this dissertation postulate that the holistic model resides within the hierarchical approach to forest management, and does not propose to model the decision making process itself, but instead supporting the decision with a quantitative method.

To further the discussion of model formulation, two different multilevel models were presented which are relevant for many forestry and also, more generally, natural resource applications. The two formulations are differentiated according to the objectives occurring at the different levels. The models can also be differentiated, in how the multilevel structure is realized. The holistic model, represented by the block angular program realizes multilevel structure upon decomposing the planning problem. The compromise model, on the other hand, realizes multilevel structure immediately in the formulation, due to the optimization problem (equilibrium) constraints. Interestingly, in solving large-scale block angular programs, decomposition is performed, and becomes part of the solution technique which also provides multilevel interpretation. In contrast, solving a bilevel program usually requires one to reformulate it as a single level, nonlinear optimization problem. Hence, in the solution techniques, the single level problem is transformed to a bilevel problem, and the bilevel program is transformed to a single level program. This should stimulate some thought, as to just how far one should proceed, when interpreting algorithmic features.

The large-scale optimization techniques used to solve and interpret the forest planning problem discussed in Chapters 2 and 3 present significant computational improvements. The results suggest that the integer forest planning problem of maximizing net present value with harvest flow and adjacency constraints can be solved efficiently, meeting objectives and constraints. By solving several problems instead of just one, confidence in the methods are displayed. The results displayed, suggest that foresters may no longer need to look to heuristic search methods which do not find optimal solutions to planning problems. Although the solution methods proposed here are also somewhat heuristic in nature, in that joint constraints are treated as soft, the techniques are derived from exact methods. Hence, the excellent numerical validation of these techniques, rest upon rigor and theory, which is evident in the derivation of the algorithms. In considering decomposition only (Chapter 2), all of the solutions found were within 1.5% (see Figure 2.2) of the upper bound on the optimal value.

Chapter 4, somewhat different from Chapters 2 and 3, formulates a stochastic compromise model, which serves two purposes in this dissertation. First, it provides a contrast to the holistic model, which seems to be the correct model type for the forest planning models discussed within the hierarchical approach in the forestry literature. Secondly, the stochastic compromise model formulates the corporate rationing problem faced by large timber companies which hold timber resources for conversion into forest products. Although there was not a dataset available to calibrate this model, its inclusion in this dissertation as an alternate formulation seems ostensible, since compromise models do not appear to have been presented in forestry. Among the many issues arising in natural resource management, are management scenarios with multiple players possessing different objectives and constraint sets. Public officials or organizations are often responsible for managing these different agents. The model of Chapter 4 provides the formulation and demonstrates the necessary transformations to solve hierarchical optimization problems. Therefore, this Chapter 4 provides the groundwork for future applications of these types of models in natural resource management.

Chapters 2-4 of this dissertation provide new insights and methods in the study of multilevel planning in forestry. Since management often proceeds across related disjoint geographies, within organizations that contain multilevel structure, and among organizations pursuing different objectives that can be influenced through policy directives, multilevel and decentralized planning seem to be at the forefront of natural resource management. This dissertation has added to the scientific understanding of multilevel planning in natural resource management in application, theory and algorithms.

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Vita

Sam Pittman is a resident and native of Seattle, Washington where he was born. While attending the University of Washington he has earned the following degrees: Bachelor of Science in Mathematics, Master of Science in Forest Biometrics and Master of Science in Applied Mathematics. In 2003 he completed his education at the University of Washington with a Doctorate of Philosophy in Forest Operations Research.

University of Washington
Graduate School

This is to certify that I have examined this copy of a doctoral by

Samuel Pittman

and found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
examining committee have been made.

Chair of Supervisory Committee:

B. Bruce Bare

Reading Committee:

B. Bruce Bare

David Briggs

Bruce Lippke

Date: Aug 7, 2003

University of Washington

Abstract

Multilevel Planning in Forestry

Samuel Pittman

Chair of the Supervisory Committee

Dean B. Bruce Bare
College of Forest Resources

This dissertation is a study of multilevel planning in forestry. Two models are investigated, the holistic model and the compromise model. A sample problem is formulated to demonstrate each model. The holistic model formulates the harvest scheduling problem of maximizing net present value with harvest flow and adjacency constraints. The compromise model, using a hierarchical optimization model, formulates the allocation of volume in a large diversified forest products firm. Numerical results are only presented for the holistic case, since it appears to be the currently more relevant problem studied within the hierarchical approach to forest management. These results appear to be favorable, considering the complexity of the addressed problem. The role of the model within the hierarchal approach is also discussed. The derived interpretation of the holistic model, with the contrast of the compromise model suggests new strategies and stricter formulations for multilevel planning models appearing in forestry.

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Chapter 1: Introduction

Driven by a changing set of societal values and technological improvements, forest planning models have undergone dramatic evolution over the past century. Influencing the current method of forest land allocation and scheduling are complex issues of multiple use, sustainable forestry, land use ethics and traditional utilitarian economics. Researchers have spent substantial effort defining the qualitative nature and conceptuality of values attached to forest use and also incorporating them into forest planning models. However, because these values posses many facets, the richness of definition is nearly always reduced when the concepts are transformed to elements within a planning model. Nevertheless, without a quantitative method multiple use, sustainable forestry, land use ethics and traditional utilitarian economics can only obliquely influence the application of forestry. It is therefore imperative that planning models continue to improve so that decision-makers are aided by quantitative methods.

Currently many foresters and those interested in forestry believe that practicing sustainable forestry will allow society to arrive at the balance in resource use needed. This, however, will require the consideration of the ownership of the forests and these owners' objectives. Society desires both wood products as well as intact forests to satisfy ecosystem and recreation values. Currently, the USDA Forest Service has changed its emphasis from multiple-use to pure ecosystem management (Morrison 1994). It is possible that in the future as societal demands change, the

Forest Service will once again engage in timber management, but for now one must look at the future of the wood supply without its substantial involvement. Forest industry on the other hand, is primarily interested in providing wood products to the marketplace. Whether sustainability is part of their approach is not clear. In the long run, the sustenance of the wood supply by industry is extremely important to satisfying the overall demand for forest products.

Objectives

The intent of this dissertation is to examine multilevel forest planning from two angles. First, the conventional approach of managing the forest as an entity separate from the managing organization is considered. Second, a model of corporate rationing, which might be employed by a large corporation producing forest products from its own natural resources is developed. Each of these models advances the science of organizational management. In the future, these models will likely be merged, to provide a model which integrates the management of the firm and its resources simultaneously. However, at present this seems too large of a step to take, given current understanding of each problem separately. Therefore this dissertation focuses on further defining the problems, through derivations and applications that by themselves provide new insights into formulating planning models of hierarchical entities, and methods for solving them. *The objective of this thesis is to provide better understanding of multilevel planning models inherent in forestry applications.* More specifically, however, past models, in the development of the hierarchical approach to forest management have not recognized two distinct multilevel planning model formulations, the holistic and compromise models, in their approaches. Identifying these two models, with appropriate use, seems, from an organizational and theoretical viewpoint, extremely important. Therefore, Chapters 2, 3 and 4, comprising the body of this dissertation, are written as stand alone sections with objectives related to refining multilevel planning models in forestry. Chapters 2 and 3 address the holistic model. The forest planning problem which considers harvest flow restrictions and adjacency constraints in maximizing net present value is considered in each Chapter (this problem is defined in the section titled: The Forest Planning Problem with Harvest Flow and Adjacency Constraints).

The objective of Chapter 2 is to demonstrate the use of price directed decomposition as a tool for solving large, spatial integer forest planning problems with block angular structure.

The objective of Chapter 3 is to derive error bounds in the use of aggregation/ disaggregation techniques applied to large, spatial integer forest planning problems with block angular structure, while still using the same model formulation and decomposition technique as in Chapter 2.

A large donated data set generated several sample problems used to facilitate results for each of these Chapters. Chapter 4 looks at the business aspect of forest planning from the position of a large diversified forest products corporation utilizing its own natural resources for production. Chapter 4 is theoretical in nature, as it proposes a model, which extends the mean-variance formulation portfolio selection (Markowitz 1959) to capital rationing using equilibrium constraints.

The objective of Chapter 4 is to formulate the risk diversified forestry corporation capital rationing problem as a hierarchical optimization problem, and to discuss solution techniques for this formulation.

While this model serves as an advance in the theory of capital rationing, it also demonstrates the second type of multilevel planning model considered here, the compromise model. Understanding each of these models in use, and in theory directly advances the study of multilevel planning in forestry. Moreover, the numerical results derived from using the extended, large-scale optimization techniques to solve the holistic forest planning problem proclaims significant advance in computational experience, as measured by the results in this dissertation with comparison to other published results. As applied scientists, we must not forget the link between theory and application. Successful application is dependent upon a strong theoretical foundation. This dissertation emphasizes this in the topic of multi-level forest planning.

Literature Review: The History of American Forest Planning

The focus in this literature review is on public forest planning due to the lack of publication on private methodologies. Early American forest planning adopted many of the techniques applied in German forestry (Alston 1983). Planning in the early part of the 20th century was primarily focused on "biological sustainability", which at the time was perceived to be non declining flow of volume. Planning with the objective of sustainability required foresters to rely on an evolving suite of methods used to determine the "allowable cut" in a manner which regulated the yield per year. Determining the allowable cut was generally done via area control, volume control or an area and volume check method. Using an area control method allows an equal number of acres to be harvested each year. Yield is "sustained" by this method if the number of acres of each age class is the same and the number of age classes is equal to the rotation length plus the regeneration time. This of course, assumes the effect of site differences is controlled. Due to the unregulated forest structure in the U.S. at the time, this method could not be used in isolation to produce "sustained" volume (Iverson and Alston 1986). The method of volume control harvests the amount of volume growth accumulated each year. If the forest is regulated this will sustain the yield. However, the forest in the U.S. has never been regulated; there has always been acres held past the rotation age. The slow growth rate of old growth forests poses a significant cost in timber under this method. The Hanzlik formula (Davis 1966) was one formula used to account for production possibilities in the absence of a regulated forest, when even volume flow and forest regulation were desired. Interestingly, area volume check was more of a paradigm than an algorithm for combining the two methods (Leuschner 1990). This heuristic method is a compromise between area control and volume control when the forest is not regulated.

As a result of post World War II increased timber demands, methods of more efficient analysis than the previous by hand calculated formulas were required (Johnson and Tedder 1983). With the availability of computers, foresters developed binary search techniques to find sustainable maximum flows. Among the first models was ARVOL which calculated the allowable cut using the area volume check method (Chappelle 1966). SORAC, which followed ARVOL, additionally, simulated how intensive management of regenerated stands affects the current allowable cut. SIMAC (Sassaman et al. 1972) was another binary search model capable of assessing management regimes and their effect on the allowable cut. Johnson and Tedder (1983), in their review of several binary search models demonstrated the methodology of binary search using TREES as an example. This seems to be the most complex of these types of models developed at this time since it can emulate the linear programming (LP) formulations, Model I or Model II, proposed in Johnson and Scheurman (1977).

Linear Program representations of forest planning models followed binary search methods. Today they are still the primary tools used in long-range forest planning. The two landmark LP models used in federal U.S. forest management were/are Timber RAM (Navon 1971) and FORPLAN (Johnson and Crim 1986). Before discussing the use of LP and its employment in forest management models it is useful to digress and examine some of the laws and acts which have shaped the development of current forest planning. Gifford Pinchot introduced the concept of multiple use when he became the Chief of the Division of Forestry in 1898. However, the concept was not intensively understood until the demand on forest resources significantly increased following World War II (Alston 1972). The five primary enactment's which forest planning models have repeatedly been measured against are (see for example (Iverson and Alston 1986 and also Chappelle et al.1976):

1. The 1960 Multiple Use Sustained Yield Act
2. The National Environmental Policy Act of 1969 (NEPA)
3. The Endangered Species Act of 1973
4. The 1974 Forest and Rangeland Renewable Resources Planning Act (RPA)
5. The National Forest Management Act of 1976 (NFMA)

Planning in the presence of these acts required forest planners to look beyond sustained yield timber management. A major modeling paradigm known as multi-objective programming was used and enhanced, so that multiple resource planning involved more than just constraining the allowable cut to meet minimum requirements on other objectives. Timber Ram (Navon et al. 1971) and FORPLAN (Johnson and Crim 1986) are great examples of just how hard forest planners worked to incorporate these acts into forest planning, but they are also examples of how quickly these acts changed the requirements placed on forest planning models.

Timber RAM, developed in the Pacific Southwest Forest Range and Experimentation Station by Navon and others in 1971, was the first linear programming model used for U.S. National Forest planning. It was designed to optimize stumpage prices in the presence of various harvest flow constraints. Using a Model I (Johnson and Scheurman 1977) approach it addressed the current understanding of "biological sustainability" in calculating the allowable cut. The input to the model was silviculture regimes constructed by the user, flow restrictions, the value to maximize in the objective function and the number of periods with period length for which the forest plan extended. Forest inventory was generally aggregated so that the model size was solvable using the simplex method (Dantzig 1963).

Timber RAM was used for National Forest planning for most of the 1970's. However, the model's bias towards timber management, inability to address multiple forest product production, lack of understanding of the model by the majority of its users and the need for a better multiple use planning model lead to many criticisms and eventually its replacement by MUSYC (Johnson and Jones 1979). Chappelle et al. (1976) provided the following evaluative criteria a model should contain in order to solve the multi-product production on a sustained yield basis:

1. The model should be capable of accepting data as inputs for physical, biological, economic and social variables that bear most importantly on the problem;
2. The model, even if constructed for a single-resource functional analysis, should be capable of linkage with a comprehensive multiple-use planning model;
3. The model should be capable of handling both the temporal and spatial dimensions of resource production and management;
4. Outputs of the model should be presented in a format that can provide ready guidelines to planners and managers; and
5. The computer program should be efficient (i.e. compute model outputs at least cost), be transferable to computer centers with a variety of machinery, and be documented to the extent that it can be readily modified by a skilled computer programmer employed outside of the group responsible for development of the program.

Appealing to the above criteria, Chappelle et al. (1976) found Timber RAM to be limited in the following four categories: 1) silvicultural and management considerations, 2) economic and social considerations, 3) spatial considerations and 4) computational considerations.

The silvicultural limitations discussed by Chapelle et al. (1976) are: inadequate data description, a static scenario space and non flexibility of the model. It is also mentioned that the volume yield tables used by the model are not specific enough to meet biological objectives. Chappelle et al.(1976) suggest making growth functions an internal part of the model so that yield may be described in detail. A static scenario space refers to the limited set of management alternatives for each timber class LP optimizes. This critique is actually a critique of the matrix generation method used. Overcoming this requires an exhaustion of all alternatives. Flexibility limitations commented on include the lack of effect of pre-thinning management options implemented in the same decade as the final harvest. Managerial options for regenerated stands lack a specified planting window and a treatment regime for the stand. Yet, perhaps the largest limitation of Timber RAM, at least with current concerns, is the inability to specify cutting block size.

Economic and social considerations discussed are mainly aimed at the linear programming (LP) formulation of forest planning and its inability to model multiple objectives. The authors attach the following limitations to LP modeling as well as Timber RAM. Chappelle et al. (1976) point out that, while Timber RAM is marketed as a long range planning model, it is an LP model with a fixed technology matrix, thus, theoretically it is not a long range planning model. The authors also conclude that multiple use is another false advertisement and that non-timber objectives are only considered as constraints. Furthermore, the authors feel that LP cannot be used as a multi-objective planning method. Finally, the authors' find the model does not link well to regional constraints nor the structure of the over all forest products market.

Chappelle et al. (1976) discuss spatial and transportation considerations which accompany any forest plan that allocates resources efficiently. The aggregation of stands into timber classes imposes an undetermined cost on extracting the allowable cut, partly because the proximity of roads were not present in the model. Roading is a substantial consideration to ignore, since the costs may dominate the profitability of a forest plan. Currently, adjacency constraints and other habitat preserving objectives also require a spatial component. As the authors might have guessed at the time, spatial planning has become the most taxing element in forest planning.

The final category commented on by the authors' is what they have referred to as computational considerations. For several reasons the complexity of the computer package: Timber RAM is a barrier to use. The documentation is described as vague and lacking interpretation of inputs and outputs of the model despite the glossary supplied. Users of the model typically only use the simplest options provided. The authors attribute this to not only "vague" documentation but also to the lack of technical support supplied by the supporting agency. In fairness to the model it should be noted that complex problems require complex models which require adequately trained users in the use of LP if that is the planning method chosen.

Along the way to FORPLAN from Timber RAM the Multiple Use Sustained Yield Calculation Technique (MUSYC) was developed by Johnson and Jones (1979) to address some of the problems present in Timber RAM. MUSYC overcame some of the limitations of Timber RAM, but still did not satisfy the requirements of multiple use planning. MUSYC could implement either Model I or Model II (Johnson and Scheurman 1977). Constraints that reflected social and ecological variables were enhanced but still social and ecological considerations were not treated as objectives. Information could be aggregated within and across timber classes, something Timber RAM was incapable of. However, MUSYC, like Timber RAM, still used strata-based variables which proved to be a poor reflection of the problem when geographical variables were needed. Like Timber RAM, roading and other spatial issues were poorly addressed by MUSYC. Recognizing the improvements incorporated in MUSYC, the need for a more sincere treatment of multiple use and a more geographically explicit planning model lead to the development of FORPLAN (Johnson and Crim 1986).

The model FORPLAN is actually a sequence of two models: version 1 and version 2. Version 2 is treated as an appendage to version 1, supplementing its current options. The two models will, therefore, be discussed concurrently with delineation's inserted where appropriate. FORPLAN became available in 1979, replacing MUSYC; each model was designed by Norman Johnson and others. FORPLAN is differentiated from the past timber scheduling models by incorporating decision variables that track resources other than timber through time, its ability to implement hierarchical emphases and its treatment of resource allocation and resource scheduling as two possible entities.

In FORPLAN desired forest outputs could be aggregated, so that management considerations could be directed to the desired output. Desired outputs could be defined spatially or strata-based; in both cases they are termed "aggregate emphases" in version 1 (Iverson and Alston 1986). This feature of FORPLAN allowed personnel to assert their expertise in designing management prescriptions for acres or land units within an aggregate emphasis. This type of scheme allowed constraints across desired outputs as well as forest wide constraints. Additionally, model output could be separated according to aggregate emphases or aggregated as in past models. FORPLAN version 2 not only uses aggregate emphases to further refine the resolution of the planning problem, but also allows users to define strata-based analysis areas with spatially based zones. This required more user input into the model which lead to more spatially feasible harvest schedules, but also required larger matrices that taxed existing LP solvers.

FORPLAN was constructed to address the combined management goals of 154 National Forests. FORPLAN in its basic components was a matrix generator linked to an LP solver. Its objective was to guide forest management in compliance with the natural resource acts passed by Congress, in particular NFMA (Beuter and Iverson 1986). Such an endeavor obviously required a top-down approach. Forest wide objectives such as budgeting, allowable cut and net social benefit were required; however, regional and local objectives that required on the ground feasibility and considerations relevant only at the local level were also required. FORPLAN attempted to address both the allocation problem at the forest level and the scheduling problem at the local level (Bare and Field 1986). This made the model so large that several problems were encountered. Among them were: solvability of the model, understanding of the solution, on the ground infeasibility and required sensitivity analysis that was too costly.

While FORPLAN marked a vast improvement over past harvest scheduling models with its multiple objective framework, its multi-layered constraint capabilities and its ability to link to roading models, experts still questioned its usefulness in forest planning due to the previously listed problems and others. An entire conference: FORPLAN: An Evaluation of a Forest Planning Tool, employing experts from different disciplines interested in National Forest planning, was devoted to its evaluation as a forest planning model. Many of the papers presented questioned whether linear programming was the correct mathematical model to use, and even more broadly, whether mathematical programming was a reliable method to use in forest planning. However, the analysis went much deeper than this. The major criticisms fell on the role that mathematical programming took in forest planning and its opaqueness to those involved in the planning process who were not skilled in the art. Although the papers presented at the conference were written with the intent of evaluating FORPLAN with current and future objectives in mind, much more came from this conference. The following three forest planning concepts were common to many of the papers presented. They are important because they are derived from mistakes learned from using FORPLAN.

1) The role of the forest planning model in forest management.
2) The relationship between the model, the analysts running the model and the decision maker.
3) Future of mathematical programming in forestry.

The planning model was designed to seek information for the decision-maker with the goal of optimizing net public benefit (Bare and Field 1986). Instead, many times the model itself was being used as the decision maker (Johnson 1986), thus putting the technocrats running the model in the position to decide. This was seen as a clear structural defect in the decision model. Additionally, since National Forests are public land, a model that integrated public opinion into it was also necessary. However, the complex representation FORPLAN gave the problem generally disengaged the public from the plan and the actual decision. Johnson (1986) notes that FORPLAN was used as a shield by the U.S. Forest Service from the public in defending their actions. Considering the objectives, FORPLAN did not model the decision making process well. As one might imagine, these results lead to the investigation of the internal structure of FORPLAN: linear programming.

Linear programming has been employed by foresters to solve both the engineering problem of technical efficiency and the economic problem of allocation (Hof 1986). Since no explicit production function exists for the forest planning problem one is assembled by creating many scenarios to choose from. Thus, for economic efficiency to be achieved through LP, the optimal solution must be a linear combination of the scenarios generated. Although this aspect of LP has been critiqued in the review of FORPLAN, this method has been used since the inception of LP (see Dorfman et al 1958). Obviously, enumerating more scenarios brings the solution closer to economic efficiency (if that is a desired objective), but it also makes the matrix larger and therefore increases the cost of solving the problem. If the allocation problem were the only problem being solved by FORPLAN this may have been a feasible task, but FORPLAN was also solving the scheduling problem. The schedules produced by FORPLAN were often not feasible in terms of implementation. One reason for this was that LP does not produce integer solutions, except in rare cases (Bare and Field 1986). The outcome of this in the forest plan is that acres are not spatially identified except in aggregate form. This left a gap between the models solution and that which could be implemented. An infeasible solution produced surely means a problem was solved which does not represent the actual problem. Although the actual problem will seldom be completely described by the model, measures can be taken to ensure feasibility. Perhaps if FORPLAN set out to solve only the allocation problem LP may have not been challenged as a weak link in the planning process. Additionally, feasibility would have been less of an issue.

The linearity assumption between inputs and outputs has challenged applications of mathematical programming in forest planning, especially when integer variables are needed. This is really another divergence of the model and reality. No mathematical function will yield a perfect reflection of the true problem. However an integer formulation of the planning problem was needed. Bare and Field (1986) point out that non-linearities such as yield forecasts are easily handled, but that integer constraints are not. Much work has gone into the development of heuristics to tackle large integer programs (IP). The adjacency problem and the road construction problem have probably seen the largest application of such heuristics. Simulated annealing, Brach and bound, Tabu search, evolutionary programming and random search are just some of the methods used to solve IP in forestry.

Mathematical programming has been challenged to justify its existence in forest planning, yet it is not well understood by most (other than analysts) involved in the planning process. Attesting to this are many of the comments found in the previous critiques. Forest planning problems proposed in the 1980's taxed the solution methods to the point that the usefulness of mathematical programming in forestry was questioned. Bare and Field (1986) conclude that forest planning problems may have taken linear programming to its level of incompetence. However, the incompetence could not have been with linear programming, it has worked well in a variety of applications and is still a preferred planning tool by many operational researchers. Mathematical programming, as represented in FORPLAN, has produced solutions which are not feasible, and solutions which cannot be explained. In hindsight, it is easy to see the formulation of the problem foresters desired to solve was not present in FORPLAN. FORPLAN implemented a top-down approach. Johnson (1986) notes that the top-down approach FORPLAN took was counterintuitive to how many viewed forest planning. FORPLAN was modeling so many things in one monolithic problem that a large gap existed between the solution and reality. One might say that the resolution or representation of reality was sacrificed to consider more objectives. Many researchers at the time were looking toward a multilevel planning model to replace FORPLAN, one which considers a strategic-scale, tactical-scale and operational-scale plan.

With the dismissal of FORPLAN and the top down approach in public forest planning, two other strategies emerged. The bottom-up approach and the hierarchical approach (Gunn 1991), a method which blends the top-down approach with the bottom-up approach, were proposed as alternative methods to planning at the FORPLAN conference. The bottom-up approach solves the scheduling problem at the tactical level and then aggregates the schedules to produce an allocation: the strategic part of the solution. The bottom up approach can be easily criticized on its inability to represent forest-wide objectives and forest-wide constraints. While the hierarchical model has the ability to consider both forest-wide and lower level constraints and objectives it has been more difficult to specify and solve. The hierarchical approach attempts to optimize at all scales of planning simultaneously. If the hierarchical model is reasonably solvable, and can provide decisions which yield the same resolution as the bottom up approach, then the hierarchical model can be seen as superior due to its ability to simultaneously consider objectives and constraints at multiple scales.

Foresters started discussing the use of hierarchical planning models following the introduction and use of FORPLAN (Johnson and Crim 1986). Some examples of hierarchical forest planning models have been conceptual in nature (see for example Gunn 1991) while others have been more mathematical (see for example Weintraub and Cholaky 1991). Researchers have characterized the nature of the decision making process during forest planning as strategic, tactical and operational (Gunn 1991). This has helped to categorize decisions by scope so that the entire planning problem is not considered simultaneously. Furthermore, hierarchical planning models have used the concepts of strategic, tactical and operational to promote a multi-level structure. Separate models, one proposed for each decision type, linked by an algorithm to allow information to flow vertically through the models appears to be the current state, as depicted in the hierarchical forest planning literature.

Researchers have proposed mathematical models of the forest hierarchical planning process recognizing different viewpoints of the hierarchical approach. A common theme in many of the planning models is that strategic decisions derive from aggregate strata-based data (usually at the forest-level) while tactical decisions address spatial issues (usually at the sub-forest level). Further, a framework has been adopted wherein strategic solutions set guidelines for tactical planning which follows. And, recognizing the need for an iterative scheme in which these decisions could be adjusted, some researchers have proposed feedback and feed-forward mechanisms to connect levels that are considered to be modeling different aspects of the plan (Gunn 1991). The model of Weintraub and Cholaky (1991) utilizes this type of iterative scheme. Sub-forest or lower level spatial problems are solved to meet volume flows specified by a forest level strategic problem. If feasible solutions at the lower level cannot be found, then the upper level problem is solved again specifying new volume flow targets until feasible tactical solutions are found to be within some tolerance from the target. Bare and Lierman (1994) presented a similar model structure, which is spatially decomposed and utilizes similar aggregation procedures. Hof and Pickens (1987) presented a two-tiered model in which several spatially explicit tactical plans are proposed for each landscape. The upper level problem then selects a plan from those proposed for each landscape. Davis and Martell (1992) designed a model, SilviPlan, which solves both strategic and tactical problems. Their model uses aggregate time periods of 10 years in the strategic model and 1-year periods in the tactical model. The tactical model works within the guidelines produced in the first 10 years of the strategic model. However, the strategic and tactical models are not linked by any type of feedback mechanism. Nelson and Errico (1993) present a descriptive hierarchical process carried out using simulation. They divide the forest into management zones that form spatial sub-problems. Feasible spatial alternatives are constructed heuristically using the four-color theorem. Forest wide objectives and constraints are indirectly composed of aspatial data aggregated from the spatial sub-problems. Global objectives in this approach are satisfied using simulation, rather than explicitly targeted.

Evident in the models presented above is the consideration of localized, spatial sub-problems that are connected to a global, forest level problem. This type of relationship between a subsystem and the entire system is common in many application problems. An important characterization of multi-level models is the relationship of the objective and constraint sets of the two levels considered. In the case where only the forest is considered, conflicting objective and constraint sets seem unlikely-- therefore, implying a holistic model. However, in the case where different management levels of an organization are responsible for managing the forest, the possibility of conflicting and interdependent objective and constraint sets seems plausible -- therefore, implying a compromise model. Examining the formulations of holistic and compromise models, with an example of each, will further the understanding of relationships being considered in multi-level forest planning models.

Hierarchical and Decentralized Planning Models Overview

Often planning proceeds within a developed hierarchical system. Hierarchical structures are designed to promote efficient organization of systems which are too large to be managed as a whole. Although the large company with several divisions is the classic example drawn upon in much of the literature, one may also structure a hierarchy over other entities, such as time or spatial entities. In any case, explicitly formulating the decision model with specific objectives for each layer in the organization, with their interdependence declared, is a paramount step in the modeling process. Therefore the derived optimization problem, representing the decision model specifies the organizational structure.

The two general types of hierarchical models are termed holistic and compromise. These terms indicate whether the sought objectives of the different levels in the hierarchy are the same or different. The model is holistic if the objectives at all the levels are the same. In this case, either the model is derived from a single level optimization problem through some decomposition strategy or the model can usually be written as a single level optimization problem. It is not clear whether this model should be referred to as hierarchical, since its hierarchical properties are encountered in the solution strategy and are not necessary to specify the problem (see Bialas and Karwan 1984). Hierarchical planning models in the forestry literature are of this type. Although some of these planning models may address multiple objectives, this does not seem to distinguish the different levels. When different objectives exist at the different levels, the model is referred to as a compromise model. Compromise models imply the use of equilibrium constraints; in this context, optimization problems that are constrained by other optimization problems. This type of model can occur in many situations. A descriptive example occurs when there are multiple landowners in a geographic region, of which collective objectives are desired, but with the collective objective differing from the individual landowners'. For example, a regional objective of the public might be to minimize sediment deposition from harvesting in a watershed, while the objectives of the different landowners in the watershed might be maximization of net present value. Clearly, these two objectives are conflicting if the landowners' value is fulfilled from harvesting. If the entity responsible for the collective management has policy directives at their disposal, then a compromise model fits this situation nicely. Using the proper model to formulate the problem will have a direct impact on the quality of the solution; the model needs to accurately portray the situation.

In forestry, the inability to accurately solve large-scale planning problems lead to the hierarchical model. Many of the forest hierarchical planning models presented are similar to the holistic allocation models presented by economists, which are derived from the ideas of Dantzig-Wolfe (1961) and Benders (1962) decomposition. In theory, the hierarchical approach to forest planning differs from the simple resource allocation model due to the consideration of multiple time scales and the use of aggregation techniques that transform spatial data to strata-based data; however, it has not been demonstrated that this aggregation would change the model from holistic form. While decomposition will likely play a fundamental role in solving large-scale planning problems, a contribution to the theory of hierarchical forest planning models will occur when the problem to be modeled is formulated independent of the algorithm used to solve it, since it is the structure of the model that allows it to be classified and not the solution technique.

Decentralized planning in hierarchical organizations (holistic planning), also known as multilevel planning, was introduced by Dantzig and Wolfe (1961) through decomposition methods applicable to linear programming. When the higher level decision-maker does not have complete information of the lower level decision-maker's technology set, the process is said to behave according to imperfect information at the center. Two different algorithmic mechanisms have been presented by economists that solve the holistic formulation of a decentralized decision making model: price guided and budget or resource guided mechanisms. The allocation mechanisms are derived from price directed decomposition, first discussed by Dantzig and Wolfe (1961) and resource directed decomposition first discussed by Benders (1962). Dantzig and Wolfe were able to derive an alternative formulation of a block angular model through decomposition, which allowed them to attach an animated decision making scheme to their decomposition algorithm. An animated interpretation of resource directed decomposition has also been proposed (Heal

1969). However, it seems that Dantzig-Wolfe decomposition has been more popular among applied scientists. In contrast, Benders decomposition has been extensively used in integer programming (Nemhauser and Wolsey 1988).

Price allocating mechanisms and resource allocating mechanisms were developed by economists to solve large-scale planning problems likely to occur in a socialist economy. If the problem size is reasonable, the methods become unnecessary, since the original LP or mixed integer program MIP can be solved in original form and exactly. In these models, a central authority passes either resource prices or quantities to lower level agents. The agents then solve a profit maximization problem subject to their own constraints, passing the results of their plan back to the central authority so that they may determine another set of decisions. This process is iterated until a desired criterion is met. Due to the large size of forest planning problems, these solution strategies and resembling strategies have been considered in forestry (Weintraub and Cholaky 1991, Parades 1995).

In forestry, hierarchical planning is traditionally presented with three decision making levels, commonly called: strategic, tactical and operational. Gunn (1991) states that the strategic decision is usually one of resource allocation, the tactical decision is one which makes the most efficient use of these decisions and the operational decision involves planning for detailed operations. Generally, the levels are associated with different time scales and resolution of data. Data is usually aggregated as grander scope is considered. Although three different levels of planning are nearly always considered, forest researchers have only presented models which link strategic and tactical decisions (see, for example Weintraub and Cholaky 1991, Hoff and Pickens 1992, Davis and Martel 1992 and Nelson and Errico 1993). These applications have extended the frontier of decentralized thinking in forestry; foresters, like economists, have worked out methods that decompose the original problem into sub-problems that are easier to understand and compute.

The holistic model is presented as a single level optimization problem, with block angular structure [1.1]. It derives its name from the objective function being the sum of the objectives of the (n) subsystems present.

[1.1]

$$
\begin{array}{llllllll}
\max & c_1x_1 + & c_2x_2 + & \ldots & + c_{n-1}x_{n-1} + & c_nx_n & & \\
st. & & & & & & & \\
 & A_1x_1 + & A_2x_2 + & \ldots & + A_{n-1}x_{n-1} & A_nx_n & \leq & b \\
 & B_1x_1 & & & & & \leq & d_1 \\
 & & B_2x_2 & & & & \leq & d_2 \\
 & & & \cdot & & & & \cdot \\
 & & & & B_{n-1}x_{n-1} & & \leq & d_{n-1} \\
 & & & & & B_nx_n & \leq & d_n
\end{array}
$$

The interesting feature of this formulation is that if it were not for the (first constraint) joining constraint, this problem reduces to n individual planning/ optimization problems. It is this feature, with the application of decomposition to [1.1] that has stimulated the use of this formulation with bilevel structures. When operational researchers, economists, and other planners speak of resource prices or quantities, they are referring to prices/ allocations of the resources represented in the first constraint. The remaining constraints in [1.1] are partitioned into subsystems. Hence, upon choosing an allocation or resource prices for the scarce resources each of the individual subsystems can be maximized separately. This, in layman's terms, is the essence of decomposition. This model appears to have extensive merit in advancing the forest planning philosophy. Therefore, an application of this model to a forest planning problem is studied in Chapters 2 and 3 of this dissertation.

Bard (1983) presented a different type of multilevel planning model for decentralized decision-making, a compromise model. This model type, classified as a mathematical program with equilibrium constraints (MPEC), is formulated with optimization problems as constraints. This model is applied when the objectives of the different levels are not the same. The bilevel program [1.2], a special case of the multilevel program, which again is a special case of an MPEC, was first introduced by Bracken and McGill (1974). Bard (1983) has modeled the resource allocation problem as a bilevel program [1.2], following similar ideas of Burton and Obel (1977), where the separate divisions within the firm compete for joint scarce resources. Bialas and Karwan (1984) discuss several relevant problems which require the hierarchical optimization model. Moreover, several algorithms are presented which can be used to solve the program. Anandalingam and Friesz (1992) give several other examples of hierarchical optimization problems.

The compromise model is generally written as a multilevel optimization problem. The bilevel program, a specific case of the multilevel optimization problem, in general form appears as [1.2].

[1.2]

$$\begin{aligned}
\max \quad & F(x, y_1, y_2, \ldots, y_n) \\
s.t. \quad & \\
& x \in X \\
& (x, y_1, y_2, \ldots, y_n) \in Z \\
& y_i \in \arg\max \{ f_i(x, y_i) : y_i \in Y_i ; y_i \in S_i(x) \}
\end{aligned}$$

In this formulation the variable x is associated with the upper level decision space and the variable y is associated with the lower level's. If the problem is one of planning, then one can think of a solution procedure sequentially. The upper level decision-maker supplies the lower level agent(s) with a decision x; x is then treated as a parameter in the lower level problem(s) that influences the agent(s) decisions. Upon the agent(s) making decisions, a y is fixed, in the upper level problem, for which the upper level decision-maker must take into account in making its next decision. As can be seen, in the general case the upper level and lower level constraints and objectives are interdependent. This interdependency makes the problem very interesting, amenable to many complex situations, but also, by current standards, difficult to solve.

There are several important characteristics to highlight when comparing and contrasting the holistic [1.1] and compromise [1.2] models. A major difference, which, of course, has implications, is that the compromise model contains an optimization problem as a constraint, while the holistic model does not. Moreover, within this constraint, the upper level's variable x becomes a parameter in the solution of the lower level problem. In contrast, the holistic model is not constrained by an optimization problem. Its bilevel interpretation is a property derived through decomposition, which is possible due to the constraints being composed of individual subsystems and a joining constraint which connects these subsystems together. Conceptually, the compromise model implies that the lower level problem acts autonomously in carrying out its objective, but must consider the upper level's decision, whereas in the holistic model, the lower level problems are guided to a solution which is optimal for the entire system. Under the interpretation of decomposition of the holistic model, the subsystems must make a decision which benefits the single objective. In contrast, in the compromise model, the lower level, in making its decision, in reaction to the upper level's decision, may detract from the upper level's objective. Hence, the property of interdependency is realized. The solution obtained by both the upper and lower level is a compromise of their objectives—hence the name compromise model. The compromise model discussed, is therefore remarkably similar to the famous Stackelberg game (see Luo et al. 1996).

The Forest Planning Problem with Harvest Flow and Adjacency Constraints

The problem of assigning forest management units to silviculture regimes under the presence of harvest flow restrictions has been a mainstay of forest planning problems (see Johnson and Scheurman 1977 and Garcia 1990). In the 1980's spatial concerns became an important added component to the planning problem. Among the various spatial concerns that have surfaced, adjacency constraints have received much attention. Significant research, discussed below, has been directed towards solving problems with adjacency constraints. Moreover, the study of hierarchical planning in forestry has proposed how these local adjacency problems fit into the global planning problem of also maintaining harvest flow restrictions. The model formulations of this problem have not been entirely clear or rigorous, in many cases, due to the algorithm being part of the formulation. The problem of forest scheduling with adjacency constraints has been presented, using what appears to be a compromise model, although it seems evident that it is a holistic model.

A small example of the spatial structure of a harvest scheduling problem is displayed in figure [1.1].

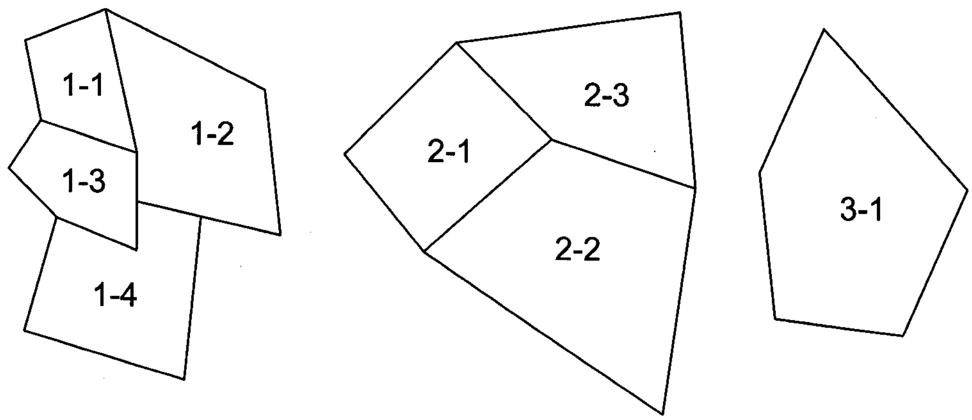

Figure 1.1

Polygons represent forest management units in 3 different contiguous land bases.

Consider an existing forest organized as in figure [1.1], with the planning problem specified as maximizing the net present value over all management options considered for each harvest unit, with adjacency constraints and harvest flow constraints present. While harvest flow restrictions are considered jointly over all land bases, adjacency constraints restrict harvest patterns over land bases independently. For example, if the exclusion time for harvesting adjacent units is one period, then the restriction on land base 2, is that at most one of the stands can be harvested per period. This, of course, has no implications with respect to adjacency restrictions for land bases 1 and 3. The larger the land bases, with respect to the number of management units, the more difficult the problem is to solve. It therefore makes absolute sense to only consider adjacency constraints over a single contiguous land base, in order to ease the problem solving effort. However, to accomplish this, the joining harvest flow constraints which cover all land bases together must be considered. One possibility, which is sub optimal, is to enforce the harvest flow restrictions over each land base separately, so that planning can be decentralized, and each contiguous land base can plan separately. Note that this is much more restrictive, than enforcing flow restrictions over all land bases together. An approach that has been proposed by many forest planners is to solve a global continuous, aggregate problem over all land bases, which specifies harvest flow for each land base, so that the amount of volume extracted from each land base is specified by period. The objective placed on each of the land bases is to achieve the volume goals set, considering the adjacency constraints. There are several items to ponder with this method. First, the original problem, a single objective problem of maximizing net present value, has now been partitioned by objectives with introduced levels. There is an upper level problem controlling harvest flow, maximizing NPV, and there are lower level problems (one for each contiguous land base) with the objective to meet volume targets specified by the upper level. The original holistic problem has been recast as a compromise/ hierarchical optimization problem. Concerns with this approach are that hierarchical optimization problems are much more difficult to solve than holistic problems, due thought has not been given to the resulting new problem formulation of compromising bilevel structure, rigor has been lost in problem formulation, since the formulation seems to include the algorithm, and optimality conditions for the bilevel compromise model have not been presented in forestry.

Moreover, there is not a known unified decomposition approach to deal with these problems as there is with the holistic case, which seems to be the reason for proposing the bilevel problem formulation. The likely reason this has occurred is insufficient problem formulation (see Pittman and Bare IN PRESS).

Another important issue related to solving forest planning problems with adjacency constraints is the method used to solve the resulting integer problem and/ or integer sub-problems if the problem is decomposed. It is widely recognized in forestry that heuristics such as simulated annealing, Tabu search, Monte Carlo simulation and genetic algorithms are necessary to solve these integer problems in reasonable time. Many heuristic methods have been proposed to allocate forest resources under adjacency constraints (Haight 2000). Nelson and Brodie (1990) compared Monte Carlo simulation to the traditional MIP method proposed by Kirby et al. (1986) to prescribe harvest schedules which constrain maximum clear-cut size and optimize road networks. Their work showed that Monte Carlo simulation could easily produce schedules with best values within 10% of the optimal value reached by MIP but never achieved values within 3% of optimality. Lockwood and Moore (1993) used simulated annealing to address the adjacency problem. While their method solved large problems, there was no comparison with an upper bound on optimality. Yoshimoto et al. (1994) developed a heuristic (SSMART) combining random search, and a decomposition method, so that the problem size was reduced and feasibility maintained throughout all periods. The authors reported objectives consistently within 2% of the branch and bound value for problems which the branch and bound method converged. Solution times were reported in hours for the scheduling of a 137 unit forest over multiple time periods. Snyder and ReVelle (1997) formulated the adjacency problem using a grid system, so that the corresponding graph problem is a planar network. This allowed them to solve the problem optimally with (SHARe) a model which employs a conventional network flow algorithm. They reported a solution time of 2.5 hrs. to solve a 441 harvest unit test problem on a "super computer". Hoganson and Borges (1998) used dynamic programming to solve the adjacency problem. Their method has found near optimal solutions for problems with 1000 stands. Bettinger et al. (1999) "intensify" tabu search by using 1-opt and 2-opt moves to better the resulting random feasible solution. The authors report reasonable CPU times for a 40 stand and 700 stand problem, scheduling over 5 periods. Additionally, their conclusion was that incorporating the 1-opt and 2-opt options in the tabu routine improved the heuristic. Comparisons between various algorithms have also been made, for instance, Boston and Bettinger (1999) compared Monte Carlo random search, simulated annealing and tabu search with results showing that simulated annealing and tabu search are superior to Monte Carlo random search. Haight's (2000) survey of heuristics eluded that dynamic programming (Borges et al. 1998 and Hoganson and Borges 1998) should be pursued as the most beneficial method. The most recent heuristic introduced to the adjacency problem is evolutionary programming (Lu and Eriksson 2000 and Falcao and Borges

2001). Although no comparison's using evolutionary programming and other methods were found, one must be weary of such comparisons. There are many different variational operators used in genetic algorithms (Michalewicz and Fogel 2000), which could confound such comparisons. While all of these heuristics are fascinating and clever in their approach, they are unnecessary if the integer problems can be solved optimally with similar or less CPU time. McDill and Braze (2000) indicate that CPLEX has substantially improved the branch and bound method, which is known to provide optimal solutions.

Since this exact problem (discussed above) has been studied extensively in the forest planning literature it is an excellent problem to study the large-scale optimization methods proposed in Chapters 2 and 3. Some researchers have moved on to more integrated models, which also include, for example, road options (see Weintraub and Cholaky 1991). This certainly seems to be the correct direction to move. However, large problems in the form of Figure 1.1 still exist, for example, in the southern part of the United States where road networks have been established. Moreover, adding additional decisions to the holistic model, such as road decisions can be accomplished within the holistic formulation. Hence, the large-scale methods of Chapters 1 and 2 will remain tenable.

Chapter 2: Hierarchical Production Planning in Forestry Using Price Directed Decomposition

Introduction

The hierarchical production planning (HPP) model has been advanced as a mechanism for modeling large decision-making ventures. It allows the decision making process to be decentralized so that different aspects of a decision are considered in relevant scope and detail. The HPP model has been studied extensively by several groups. Economists have used HPP to examine resource allocation in socialist economies (see Hurwicz 1973). Operational researchers have used HPP to integrate the objectives and constraints occurring at different layers of an organization to accomplish an overall planning strategy (Burton and Obel 1977). And, foresters have looked at several ways of implementing HPP in order to tackle large-scale forest planning problems (see Weintraub and Bare 1996). The model provides both computational benefits and implementation appeal.

The most fundamental concept within the HPP model is decomposition. The theory to drive the HPP model came shortly after the introduction of decomposition to block angular linear programming problems by (Dantzig and Wolfe 1961). Dantzig (1963) discussed an animated process of price directed decomposition (Dantzig-Wolfe decomposition, also known as column generation), in which the corporate headquarters directs the production of the different divisions to optimality for the corporation as a whole by charging the divisions for their use of shared resources. Shortly after Dantzig and Wolfe introduced price directed decomposition Benders (1962) published the dual method of resource directed decomposition, also known as decomposition by right hand sides. In the animated process, instead of headquarters charging the divisions for shared resources used, the amount of scarce resources allotted to each division is specified. Each of these methods of decomposition have formed the basis of differing decomposition algorithms used to solve large-scale optimization problems, including those derived from decentralized planning problems. Berck and Bible (1984) have discussed the benefits of using decomposition to solve large-scale linear forest planning problems.

Economists provide a substantial background to the study of decentralized planning and the use of decomposition. They have given considerable treatment to both linear and nonlinear economies, to conflicting and holistic objective problems and to both resource and price directed allocation mechanisms (see Arrow and Hurwicz 1977, Heal 1973 and Hurwicz 1973 for comprehensive reviews). Much of their work confirms that, in absence of convexity, decomposition methods are heuristic in nature and do not provide convergence to optima, in general. However, due to the presence of non-convex realities these heuristic methods may be indispensable in practice.

Operational researchers are still actively studying multi-level planning methods, due to the prevalence of hierarchically structured organizational models employed. The most general model is one of a corporate headquarters and several divisions which together make up a firm. Each of the divisions is considered to plan independently. The role of headquarters is to guide the independently functioning divisions towards a plan that optimizes the firm's objective as a whole (see Burton and Obel 1977 and Schneeweiß 1995). In some organizational models the objectives of the headquarters and the divisions may be conflicting. Hence, the objective of the firm is not the maximization of the sum of all divisions (the holistic model). The bilevel program provides a model that represents this conflicting situation (see Bard 1983). This type of model, referred to as a compromise model, falling under the more general class of problems known as mathematical programs with equilibrium constraints is much more difficult to solve (see Luo et al. 1997) than the holistic model. However, it appears that these types of organizational models are becoming more prevalent, especially with large influential corporations owning significant stock in several smaller corporations (see Goedhart and Spronk 1995). Planning becomes more complex in this model due to the objectives and constraints at different levels being interdependent, verses the corporate objective being the sum of the divisions. This type of model is not considered further in this Chapter.

Many of the HPP ideas developed by the economists and operational researchers can be extended to the forestry planning model. While there is likely a hierarchical nature to the organization which manages a forest, the forest itself possesses what might be considered a hierarchical structure, or it can be organized into such for management. Due to the complexity of forest planning, the forest plan is often considered isolated from the products' market it feeds, except for parameters which enter the model. In order to carry out the HPP model, forestry planning problems have been decomposed spatially and temporally. Both the models' of Hoff and Pickens (1987) and Weintraub and Cholaky (1991) decompose the problem spatially. This is often done in forestry, since the spatial aspects of forest planning seem to be the most taxing. Moreover, spatial considerations such as adjacency constraints and road construction reside within localized subsystems that are linked to the entire planning model through non-spatial, joining constraints. Since spatial planning is now viewed as the current paradigm, it is likely that forest planning models will become spatially more complex in the future.

Much of the research on hierarchical production planning in forestry has focused on the qualitative aspects of the plan rather than the technical. Considerable research has gone into classifying the various scopes of the plan into the categories of strategic, tactical and operational (see Gunn 1992, Parades 1995 and Weintraub and Bare 1996). Some (see Weintraub and Bare 1996) believe that these three components of the plan are what define the coordinating levels; however, others (Parades 1995) believe that all levels will rely on strategic, tactical and operational concepts. The focus here is to analyze a method which allows general integer forest planning problems to be decomposed and not per se on the theoretical components of planning.

The decomposition methods discussed above, in general are not easily extendible to integer programming problems. Although methods exist which make use of Dantzig-Wolfe decomposition to solve integer programming problems such as branch and price (Barnhart et al. 1998, Vanderbeck 1998 and Martin 1999), substantial additional work is required beyond what is required for linear and convex programming problems. A forestry application of a heuristic close in nature to branch and price applied to a problem with "green-up" constraints is discussed by Weintraub et al. (1994). The spirit of the HPP model is somewhat lost when the divisional variables are no longer completely chosen by the division, as is the case in branch and price.

Often the model represented by the planning problem is considered a guide for decision-makers (Bare and Field 1986). In this representation, some constraints in the problem may be considered "soft" (Depta 1984 and Rockafellar 1999), so that slight violations may be acceptable. Lagrangian relaxation is one method for deriving this representation. The harvest-scheduling problem involving harvest flow and "green-up" (adjacency) constraints is prevalent in forestry. Several heuristic methods have been proposed to solve this NP hard (NP hard—no known polynomial time algorithm) mixed integer programming problem (Haight 2000). However, none have considered Lagrangian relaxation as a method to decompose the planning problem. This Chapter studies the effects of "relaxing" joining harvest flow constraints in a problem with "green-up" (adjacency) constraints so that standard Dantzig-Wolfe decomposition can be used. This methodology promotes the HPP modeling framework.

The objective of Chapter 2 is to demonstrate the use of price directed decomposition as a tool for solving large, spatial integer forest planning problems with block angular structure.

Methods

Many large-scale forest planning problems are of block angular structure. A general type of planning problem similar to Model I (Johnson and Scheurman 1977), but with recognition of management units, is presented to show the derivation of the forestry HPP model. Upon breaking from the general case problem, randomly generated planning problems with harvest flow and adjacency constraints are used to analyze the solution behavior of solving the problems with joining constraints treated as soft.

Given a holistic planning model with block angular structure, coupling constraints, such as harvest flow can be relaxed in order to arrive at what has been called the hierarchical production planning model. Consider problem [2.P1].

[2.P1]

$$
\begin{array}{lll}
\max imize & \sum_{i=1}^{n} c_i x_i & \\
\textit{subject to} & & \\
1) & \sum_{i=1}^{n} A_i x_i \le \beta & \\
2) & B_i x_i \le b_i & i = 1,2,\ldots,n \\
3) & x_i \in \{0,1\} &
\end{array}
$$

First, note that c_i and A_i are linear, making this model a linear integer programming problem. (x_i) is a binary vector representing the possible management alternatives for each management unit in land base (group) i. Hence, (x_i) is composed of m (the number of management units in resource base i) vectors, where each of these m vectors has length k_m, equal to the number of management options considered for the particular unit. Thus, (c_i) gives the associated net present value of decision (x_i). Constraint [1] embodies all constraints which relate the individual resource groups (subsystems) to the entire planning problem such as allowable harvest flow deviation, habitat constraints which are considered over all subsystems, and possible desired acres in age class constraints. These constraints will be relaxed in the sequel. Constraint [2] represents the decision space specific to each of the groups (subsystems). If the overall problem is decomposed spatially, then these may represent contiguous harvest units such as tree farms, which possibly due to "green-up" restrictions, cannot be considered independently. These groupings could also delineate counties, districts, cities and other organizational constructs.

Using Lagrangian relaxation to obtain [2.P2], constraints [1] are moved to the objective function with price (y) paid for violation. The motivation for this is to obtain a decentralized formulation of [2.P1].

[2.P2]

$$\begin{array}{ll} \max imize & \sum_{i=1}^{n} c_i x_i + y\ (\beta - \sum_{i=1}^{n} A_i x_i) = \sum_{i=1}^{n} [c_i x_i - y\ A_i x_i] - y\ \beta \\ subject\ to: & \\ 2) & B_i x_i \le b_i \quad i = 1,2,\ldots,n \\ 3) & x_i \in \{0,1\} \end{array}$$

[2.P3] is an equivalent problem to [2.P2], obtained with a slight amount of algebra.

[2.P3]

$$\begin{array}{ll} \max imize & \sum_{i=1}^{n} (c_i x_i + y A_i x_i) \\ subject\ to: & \\ 2) & B_i x_i \le b_i \quad i = 1,2,\ldots,n \\ 3) & x_i \in \{0,1\} \end{array}$$

It is apparent from [2.P3] that y represents the price paid for joint, scarce resources as they are used by the groups (subsystems). If these joining constraints are harvest flow, then y represents the cost of volume flow restrictions. For a fixed y, it is immediately seen that [2.P3] can be solved by simply solving (n) smaller optimization problems of the form [2.P4] and assembling the solution.

[2.P4]

$$\begin{array}{ll} \max imize & c_i x_i + yA_i x_i \\ subject\ to: & \\ 2) & B_i x_i \leq b_i \\ 3) & x_i \in \{0,1\} \end{array}$$

Hence, each group, given the appropriate price of joint resources, can plan separately. However, unfortunately, due to the integer constraint [3], solving [2.P3] does not exactly solve [2.P1]; the lack of equivalence between [2.P1] and [2.P3] is what is under investigation.

Planning agencies at the outset do not normally know the correct prices (y) for resources. This would presume they already knew the solution to the planning problem since these prices are the optimal dual variables. Column generation (see Dantzig 1963) provides a mechanism for iterative price determination in response to plans generated by the groups. The prices are determined in a master problem [2.P5], which uses a minimal generated basis to provide a piecewise linear approximation to the original problem [2.P1]; the resource prices are the dual variables associated with the joint constraints in [2.P5]. The basis is determined iteratively. At the kth iteration the master problem appears as [2.P5] and produces dual variables y^k.

[2.P5]

$$\begin{array}{lll}
\max imize & \sum_i (\sum_{j=0}^{k-1} z^j (c_i x_i (y^j))) & \\
subject\,to: & & \\
1) & \sum_i (\sum_{j=0}^{k-1} z^j (A_i x_i (y^j))) \leq \beta & \\
2) & \sum_{j=0}^{k-1} z^j = 1 & \\
3) & z^j \geq 0 \qquad j = 1,2,...k-1 &
\end{array}$$

The Lagrange multipliers associated with constraint [1] give the kth approximation to the resource prices; these are used by the groups to solve [2.P4]. Notice that z is the variable in this linear program and that the fixed x_i determined at the kth iteration is dependent upon the kth approximation of the resource prices, as denoted in [2.P5]. In actuality, the master problem does not directly need x_i. It only requires the aggregate objective coefficients $<c_i, x_i>$ (the dot product) and the columns A_i x_i if there is a change in resource use by the subsystems, to determine the next approximation of the resource prices. Most mathematical programming software allows the dual variables to be retrieved, so y can be ascertained by solving [2.P5]. Alternatively, one can solve the cutting plane problem, the dual of [2.P5] in order to find y. In this case, a constraint is added at iteration k instead of a column.

When the objective function value of [2.P5] and [2.P2] is within some preset tolerance (equal if x were continuous), the iteration scheme is halted. Upon termination, if x were a continuous variable instead of integer, the convex combination [2.1]:

$$[2.1] \qquad x_i = \sum_{j=0}^{k} z^j x_i^j (y^j)$$

yields the optimal solution to the problem. However, due to the integer requirement this convex combination is not a binary (0 – 1, integer) vector. Since z is clearly not constrained to be integer, this solution, in general does not solve [2.P1]. However, there is still some promising information determined from this approach. First, since the sub-problems [2.P4] are solved with the requirement of integrality, this is a tighter relaxation of [2.P1] then obtained by simply relaxing the integrality constraints [3] in [2.P1]. Thus, a tighter bound is obtained on the objective value of [2.P1] than produced using the linear programming relaxation. Moreover, a good approximation of the resource prices is determined.

The utility of these approximate prices, measured in terms of objective fulfillment and joint constraint violation under decentralized planning is of great importance in carrying out the forestry HPP model used in the hierarchical approach to forest planning, due to its inherent integer nature. To evaluate the effect of using approximate prices, several randomly assembled planning problems are generated, arriving at [2.P3]. These problems are decomposed according to the methodology discussed above. The master problem [2.P5] and the sub-problems [2.P4] are each solved using the default LP and MILP methods provided in ILOG CPLEX 8.1 respectively. Each planning problem consists of a random number of groups which themselves are randomly generated from smaller contiguous landscapes. Hence, necessary "green-up" restrictions are preserved. Each non-separable contiguous land base forms a micro-group. A macro-group consists of at least one micro-group. The randomly generated macro-groups, formed from smaller contiguous micro-groups, are assembled to portray plausible management organizational considerations.

Decomposing the planning problem over the macro-group relations versus the micro-groups may alter the planning effort and/ or the computational effort required. For example, it may require more iterations of the planning effort to compute usable resource prices using larger groups. To evaluate this, each planning problem is solved using the same data, but with the decomposition performed using the two different group representations. In practice, this would require the manager of each macro-group to manage possibly several smaller groups instead of one large one. Computationally, this investigates the effects of having to solve more, but smaller problems.

Since the planning problems are assembled in a random fashion, the statistical description of the generated problems is presented in the results section with the post solution information. The population used to construct the planning problems with the selection procedures used is detailed below. Seventy-five planning problems composed of a random number of macro-groups (between 6 and 20; the number selected with equal probability) are used to generate simulation statistics. The macro-groups are drawn randomly with replacement from a population of 237. Contiguous groups with more than 150 management units are omitted from the population due to the large number of planning problems being solved. On average, each macro-group is composed of 10.04 contiguous micro-groups. The mean number of management units in a micro-group is 3.52, giving an average of 35.99 management units in each macro-group. Hence, the expected number of planning units per planning problem is 485.87. The largest problem generated had 806 management units and the smallest problem solved had 187 management units.

Each planning problem is of the same type. There are eight, five-year planning periods. The allowable harvested volume deviation among consecutive periods is constrained to be within 10%. This is represented in constraint [1] in [2.P1]. Adjacent management units are precluded from harvest within the same five-year period and one period before and after. Other considerations, such as roads and habitat targets are not represented in the example, however, the general formulation allows for their inclusion. Only one rotation is considered. Including additional rotations will not change the block angular structure or the presentation above; however, additional rotations will increase the size of the planning problem; particularly, the number of columns. The management options in this demonstration are formed from weighted aggregations of more detailed management options. There is an average of 5.45 aggregated management options (columns) per management unit. Therefore, a column in one of the A_i matrices represents the volume extracted from the associated management unit under the aggregated management option. The related objective function coefficient in the vector c_i gives the net present value of the aggregated management option for the unit discounted at 8%. While this example problem may not be as complex as some planning problems, it includes enough detail to evaluate the approximate pricing methodology discussed.

Results

There are several important results produced from the simulation study to be discussed in this section. An array composed of various metrics was recorded for each solved planning problem during the simulations to facilitate examination of the results. The metrics recorded for each solved planning problem in component wise order are:

m_1 = matrix generation time

m_2 = time to find solution (includes all CPLEX calls)

m_3 = the master objective function value

m_4 = the sum of the objective function values for all the sub-problems solved using the prices approximated by the optimal dual variables pertaining to the master problem's joint constraints

$m_5 =$ the number of iterations needed to compute the resource prices

$m_6 =$ the total amount of volume over all periods by which the joint (harvest volume flow) constraints are violated

$m_7 =$ the sum of volume harvested in excess (positive) and below (negative) the allowable volume flow for all periods

$m_8 =$ the total volume scheduled for harvest

$m_9 =$ the number of (macro or micro-groups) comprising the problem

$m_{10} =$ the total number of management units represented in the problem

$m_{11} =$ the total number of management units assigned to a harvest management option

$m_{12} =$ the total acres assigned to be harvested in the planning problem

$m_{13} = (m_3 - m_4)/ m_3 =$ the percent difference in the master problem optimal value and the optimal value obtained using the final iterate solution

$m_{14} = m_6/ m_8 =$ the total volume flow deviation relative to the total volume scheduled

The components of the metric vector are related to objectives in this study. Therefore, relevant components are extracted as needed. The mean results are displayed in Table 2.1. The interdependence of the components can be examined in the correlation matrices (Tables 2.2 and 2.3). Seventy-five planning problems were solved to produce the mean and correlation results. In each solved planning problem the maximum number of planning iterations allowed to elapse was 85. If iteration 85 is reached, the algorithm terminates with the approximate prices and the corresponding solution. This happened 15 times in the macro-group formulation and 12 times in the micro-group formulation. This accounts for the slight deviations in some of the statistics that are expected to be consistent. Figure 2.1 gives a pictorial description in acres of the distribution of problem sizes that were considered.

The assessment of implementing the HPP model should be considered in light of the organization's structure. Two plausible methods of employing an HPP model are considered here. In method one, managers in charge of the macro-groups compute relevant alternatives for each of the management units along with a table indicating the spatial structure of their land base. The format of this data could be as extensive as the actual matrices required to solve the problem on a computer. Headquarters then uses this information to determine a plan for each of the land bases represented by a macro-group. Alternatively, using method two, software is given to each of the management groups which allows them to compute a plan for their land base as a function of the resource prices they are given from headquarters. In this setting, it may be desirable to develop a procedure which provides "in the ballpark" resource prices prior to the planning evolution in order to reduce the number of planning iterations. The organization's management style will likely dictate the approach used; the only difference between the methods is where the divisional plan is solved.

Obviously, since this study is being implemented as a research effort, the planning style is similar to one in which headquarters does all the problem solving.

Under this planning style, it is useful to know whether there are benefits to formulating the problem in its most decomposable form as opposed to using the organizational composition to perform the decomposition. Since the time to solve NP hard problems grows exponentially with the size of the problem, there is certainly an advantage to breaking the problem up, even if sub-problems must be solved many times. In this study, two levels of decomposition are considered to evaluate the number of planning iterations needed to converge on an acceptable plan (in this Chapter acceptable is defined $m_4 - m_3 < .00000001$). The mean number of iterations required for the macro-group and micro-group formulation is 36.6 and 26.4 respectively. The relation of these metrics to others can be found in Tables 2.2 and 2.3. The formulation using the most decomposable form requires fewer planning iterations (m_5), as might be expected and has a slightly higher attained mean NPV (m_4). The computed NPV (m_4) among these formulations differs because of the somewhat heuristic nature of treating the joint constraints as soft. The number of planning iterations is expected to be less for the more decomposed formulation because fewer columns are required per sub-problem in the master to generate the bases, due to the smaller sub-problem size. In the sequel, results are displayed in pairs, with the first number indicating the result using the macro-group decomposition and the second using the micro-group decomposition.

The primary objective of this study is to assess and display results derived from treating joining constraints as soft. The objective function of the master problem, the sum of the objective functions for all of the sub-problems solved using the approximate resource prices and the violation of the joint constraints are relevant measures for examining the proposed relaxation procedure. The objective function of the master problem is an upper bound on the NPV for the planning problem with all constraints satisfied (see formulation [2.P1]; i.e. the NPV sum over all sub-problems with joint constraints enforced is less than or equal to the master problem's NPV (optimal value)). However, since the joint constraints are treated as soft the relation of these two values is not certain. The relationship between the computed NPV (m_4) and the master problem NPV (m_3), and the relative violation of joint constraints can be depicted by two measures in the metric vector: m_{13} and m_{14}. The first number (m_{13}) gives the relative difference in the objective function values of the master and computed NPV. The second number (m_{14}) gives the amount of volume scheduled for harvest over all periods that is in violation of the joint constraints relative to the total volume scheduled in the plan. The mean of m_{13} is [-.00033, -.00022] with standard deviation [.0037, 0036] and the mean of m_{14} is [.00030, .00031] with standard deviation [.00025, .00022]. The results imply that, on average, higher NPV solutions are being found than allowable in the more restrictive formulation [2.P1], but that this comes with at a slight violation in the harvest flow constraints (see Figure 2.2). While both m_{13} and m_{14} are near zero with extremely small standard deviations, the violations may still be too large. If constraints are extremely rigid, for example harvest flow must not deviate more that 10% among periods, perhaps for legal reasons, then a method is necessary to eliminate violations. One option would be to manually adjust the harvest plan without re-running the model. Another option would be to re-run the model using a number slightly less than 10%, like 9.99%, so that the calculated flow is within 10% when the solution is found. Indeed, these are important issues to examine when solving a relaxed problem.

Due to the difficulty of solving integer programming problems, the computing time required to solve the model is also a required measure. A computing machine with a 756 MH processor and 384 MB of RAM was used for all computations. The solution times are factored into two components: matrix generation time (m_1) and solution time (m_2). Although much of the past literature has focused on developing heuristic methods for solving spatial planning problems due to slow performance of exact methods like branch and bound, it appears that matrix generation time is also considerable. In fact, in the macro-group formulation, matrix generation time is more than twice the solution time, on average. However, it is expected that this relationship would change if the matrix generation routine were programmed in a compiled language, instead of MATLAB. The cost of matrix generation is unavoidable whether exact methods or heuristics are used since an upper bound to the planning problem should always be found. In comparing the results of this study with past efforts in the literature, finding solutions using this relaxed method may be much faster than using heuristic methods to solve large integer planning problems of this type. Figure 2.3 shows the matrix generation and solution times plotted against problem size, measured by number of planning units. Some have proposed that the age structure of the forest may have an effect on the solution times. Figure 2.4 indicates that mean age and the variation in ages of the management units in a problem does not significantly impact the solution time. However, the problems seem to be very similar in age, with the mean age being fairly young. Age effects may be seen if the variation of age in the planning problems or if data with older aged stands were considered, which were not available at this time. Figure 2.5 shows the effect of having, within a planning problem large (measured by number of management units) contiguous groups. As can be seen, large contiguous groups and matrix generation times seem to be more correlated than the solution time; however, it is noted that the longest solution times had the largest micro-groups. This is an expected outcome, since solution times are known to grow exponentially for NP hard integer programming problems. This is why decomposition is such an attractive technique for solving problems, in which the integer problems can be parsed.

Discussion and Conclusion

In order to carry out the forestry HPP model using a price directed mechanism, joint constraints are treated as soft instead of hard. This allows the resulting planning problem to be solved using Dantzig-Wolfe decomposition. To investigate the impact of this in terms of objectives being met and constraints being violated, a simulation study was constructed. Randomly generated planning problems sampled from a large forestry data set were solved using the proposed price directed method. The simulation aspect of the study provides a more robust analysis of the proposed method. The results suggest that there is little sacrifice in joint constraint violation and that objectives are achieved.

There are two primary benefits to decentralization. The computation of very difficult planning problems becomes tractable and implementation of the plan becomes easier. These were the two major concerns regarding FORPLAN, a planning model capable of solving large-scale forest planning problems developed by the USDA Forest Service (see Bare and Field 1986, Iverson and Alston 1986 and Johnson 1986). Following FORPLAN, there has been an emphasis on planning from the bottom up, which also improves tractability and implementation. However, the bottom-up approach does not recognize the importance of coupling (joining) constraints. Often, meeting joint constraints when planning from the bottom up comes at a huge cost in terms of the objective, due to the rule based heuristics that must be applied in the solution finding procedure. As can be seen in the results, decentralized planning, using resource prices accomplishes the same task as planning from the bottom up, but without loss in optimality. Price directed decomposition promotes interaction and resonance of the model, the decision-making panel and the implementers of the plan.

Another important technique used in the HPP model is aggregation and dissection techniques (see Rogers et al 1991 and Weintraub 1995). The data in this study is at the highest level of aggregation. Combining decentralization with aggregation and dissection is an obvious direction to proceed towards advancing the HPP forestry model.

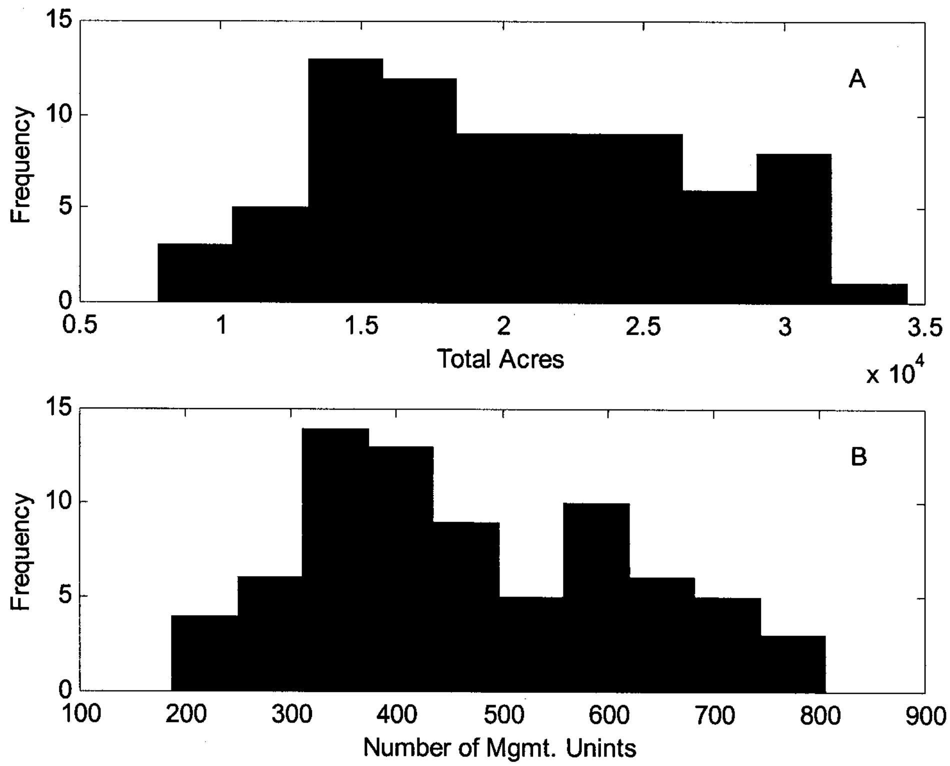

Figure 2.1
Histograms of total acres (A) and number of management units (B) contained in the randomly generated planning problems solved.

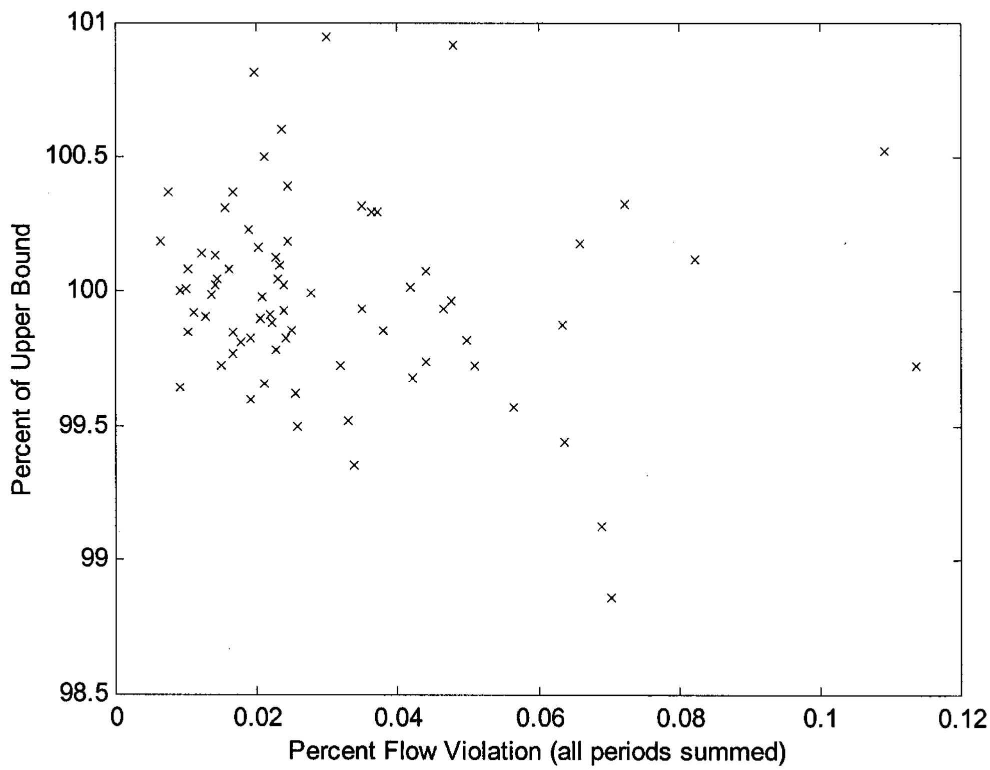

Figure 2.2
Percent of the upper bound (m_3) attained plotted against the percent of harvest flow violation m_{14} (micro-group formulation).

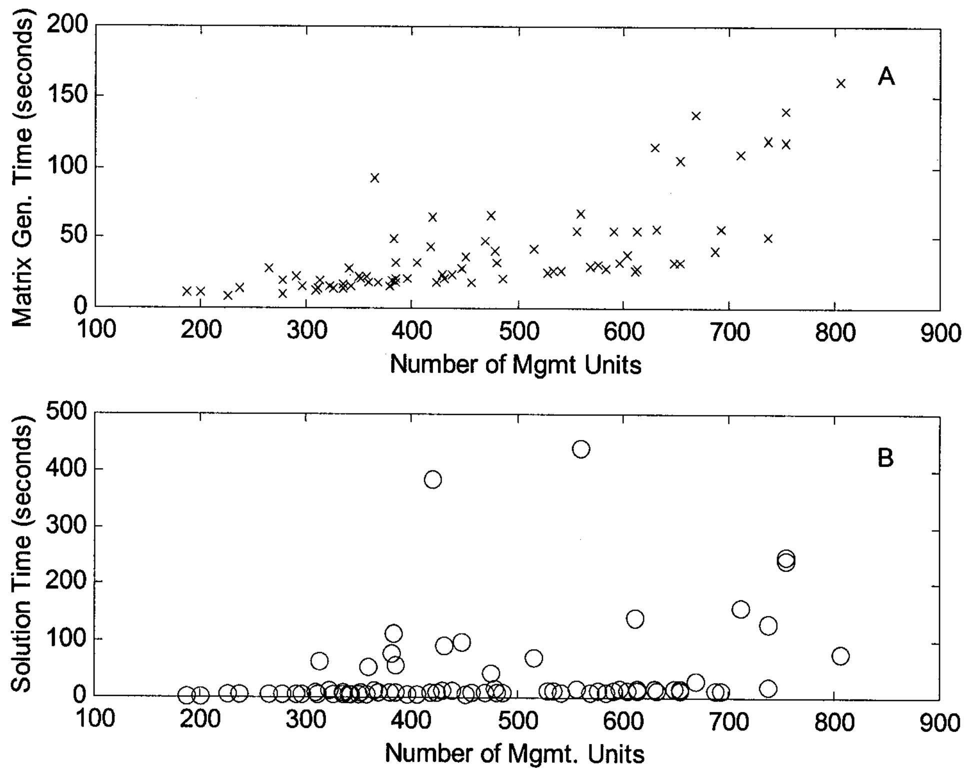

Figure 2.3
Matrix generation time (A) and Solution time (B) for each randomly generated problem (micro-group formulation) plotted against the number of management units in the problem.

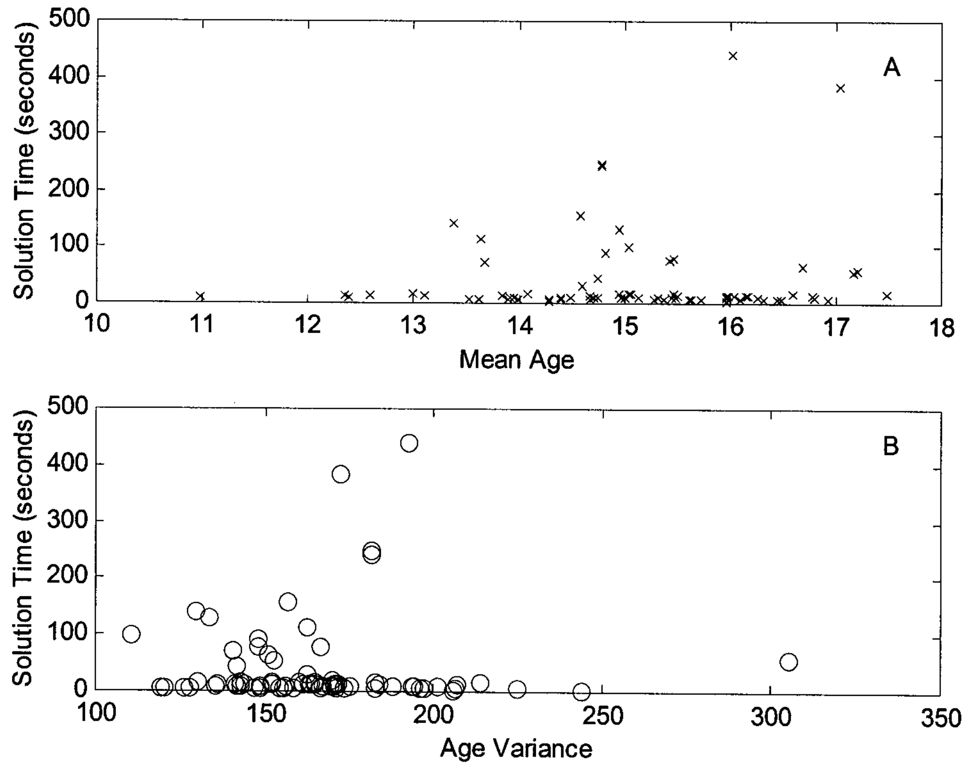

Figure 2.4
(A) Solution time plotted against mean stand age of all units within each planning randomly generated planning problem (micro-group formulation).
(B) Solution time plotted against the variance in stand ages for each randomly generated planning problem (micro-group formulation).

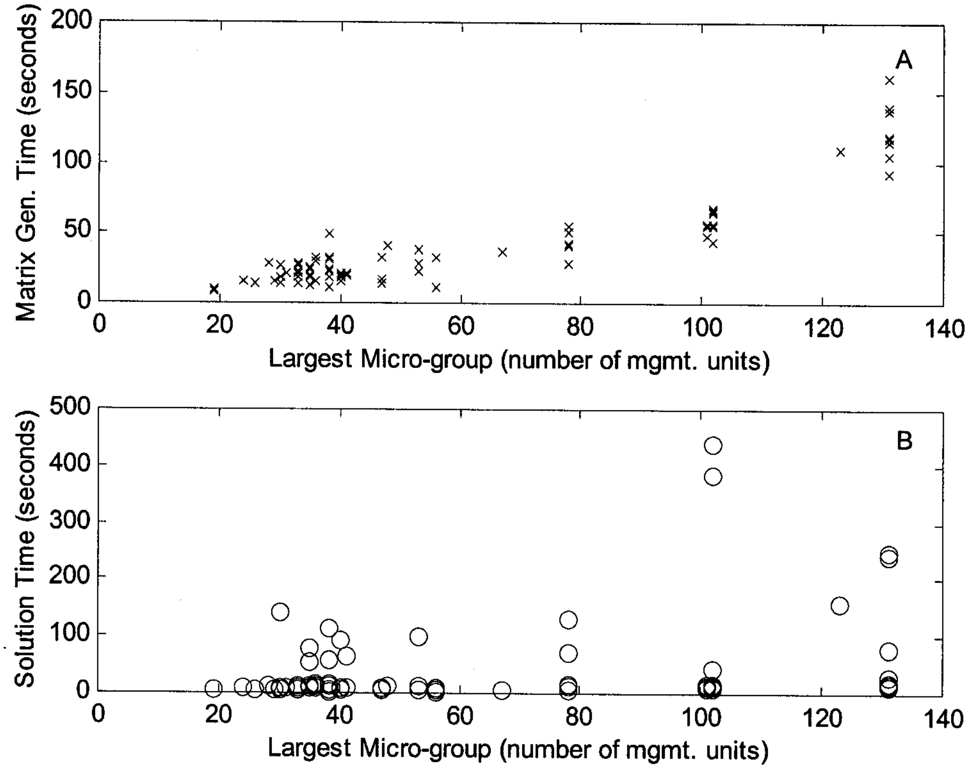

Figure 2.5
(A) Largest contiguous micro-group plotted against matrix generation time.
(B) Largest contiguous micro-group plotted against solution time.

Table 2.1 Means for recorded metrics

		Macro-Group	Micro-Group
mat gen time (seconds)	m_1	58.520093	40.14512
sol time (seconds)	m_2	22.2338	42.496693
master NPV ($)	m_3	76135815	76219096
usable NPV ($)	m_4	76158480	76239760
num planning iter	m_5	32.613333	26.373333
const violation (vol ft^3)	m_6	21132.451	22285.445
net violation (vol ft3)	m_7	-135113.91	-135750.13
total vol sched (vol ft3)	m_8	77524463	77656106
num groups	m_9	13.346667	131.98667
num of units in problem	m_{10}	468.02667	468.02667
num of units sched	m_{11}	388.22667	389.05333
total acres sched	m_{12}	18769.413	18794.213
$(m_3-m_4)/m_3$	m_{13}	-0.000329812	-0.00021617
m_6/m_8	m_{14}	0.000301936	0.000312785

Table 2.2 Correlation matrix for macro-group simulation

		m_1	m_2	m_3	m_4	m_5	m_6	m_7
mat gen time (seconds)	m_1	1.00	0.28	0.72	0.72	-0.03	-0.11	-0.74
sol time (seconds)	m_2	0.28	1.00	0.30	0.30	0.40	0.05	-0.31
master NPV ($)	m_3	0.72	0.30	1.00	1.00	0.19	-0.05	-0.99
usable NPV ($)	m_4	0.72	0.30	1.00	1.00	0.19	-0.05	-0.99
num planning iter	m_5	-0.03	0.40	0.19	0.19	1.00	-0.07	-0.19
const violation (vol ft^3)	m_6	-0.11	0.05	-0.05	-0.05	-0.07	1.00	0.05
net violation (vol ft3)	m_7	-0.74	-0.31	-0.99	-0.99	-0.19	0.05	1.00
total vol sched (vol ft3)	m_8	0.74	0.30	1.00	1.00	0.19	-0.05	-1.00
num groups	m_9	0.63	0.19	0.91	0.91	0.20	0.01	-0.91
num of units in problem	m_{10}	0.80	0.23	0.95	0.95	0.17	-0.05	-0.95
num of units sched	m_{11}	0.72	0.22	0.95	0.95	0.20	-0.04	-0.95
total acres sched	m_{12}	0.75	0.30	0.99	0.99	0.19	-0.03	-0.99
$(m_3-m_4)/m_3$	m_{13}	-0.03	0.11	0.03	0.02	0.05	-0.34	-0.04
m_6/m_8	m_{14}	-0.34	-0.08	-0.39	-0.38	-0.14	0.91	0.39

		m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}
mat gen time (seconds)	m_1	0.74	0.63	0.80	0.72	0.75	-0.03	-0.34
sol time (seconds)	m_2	0.30	0.19	0.23	0.22	0.30	0.11	-0.08
master NPV ($)	m_3	1.00	0.91	0.95	0.95	0.99	0.03	-0.39
usable NPV ($)	m_4	1.00	0.91	0.95	0.95	0.99	0.02	-0.38
num planning iter	m_5	0.19	0.20	0.17	0.20	0.19	0.05	-0.14
const violation (vol ft^3)	m_6	-0.05	0.01	-0.05	-0.04	-0.03	-0.34	0.91
net violation (vol ft3)	m_7	-1.00	-0.91	-0.95	-0.95	-0.99	-0.04	0.39
total vol sched (vol ft3)	m_8	1.00	0.92	0.96	0.96	0.99	0.04	-0.39
num groups	m_9	0.92	1.00	0.96	0.97	0.93	0.01	-0.31
num of units in problem	m_{10}	0.96	0.96	1.00	0.99	0.96	0.00	-0.38
num of units sched	m_{11}	0.96	0.97	0.99	1.00	0.96	0.04	-0.37
total acres sched	m_{12}	0.99	0.93	0.96	0.96	1.00	0.04	-0.37
$(m_3-m_4)/m_3$	m_{13}	0.04	0.01	0.00	0.04	0.04	1.00	-0.32
m_6/m_8	m_{14}	-0.39	-0.31	-0.38	-0.37	-0.37	-0.32	1.00

Table 2.3 Correlation matrix for micro-group simulation

		m_1	m_2	m_3	m_4	m_5	m_6	m_7
mat gen time (seconds)	m_1	1.00	0.40	0.63	0.63	0.20	0.06	-0.64
sol time (seconds)	m_2	0.40	1.00	0.34	0.34	0.75	0.24	-0.33
master NPV ($)	m_3	0.63	0.34	1.00	1.00	0.20	0.10	-1.00
usable NPV ($)	m_4	0.63	0.34	1.00	1.00	0.20	0.10	-1.00
num planning iter	m_5	0.20	0.75	0.20	0.20	1.00	0.06	-0.19
const violation (vol ft^3)	m_6	0.06	0.24	0.10	0.10	0.06	1.00	-0.09
net violation (vol ft3)	m_7	-0.64	-0.33	-1.00	-1.00	-0.19	-0.09	1.00
total vol sched (vol ft3)	m_8	0.65	0.33	1.00	1.00	0.19	0.10	-1.00
num groups	m_9	0.33	0.16	0.77	0.77	0.12	0.17	-0.77
num of units in problem	m_{10}	0.71	0.29	0.95	0.95	0.17	0.07	-0.95
num of units sched	m_{11}	0.62	0.29	0.95	0.95	0.18	0.08	-0.95
total acres sched	m_{12}	0.66	0.34	0.99	0.99	0.20	0.12	-0.99
$(m_3-m_4)/m_3$	m_{13}	-0.08	-0.08	-0.05	-0.06	0.16	-0.23	0.04
m_6/m_8	m_{14}	-0.24	0.02	-0.38	-0.38	-0.07	0.81	0.39

		m_8	m_9	m_{10}	m_{11}	m_{12}	m_{13}	m_{14}
mat gen time (seconds)	m_1	0.65	0.33	0.71	0.62	0.66	-0.08	-0.24
sol time (seconds)	m_2	0.33	0.16	0.29	0.29	0.34	-0.08	0.02
master NPV ($)	m_3	1.00	0.77	0.95	0.95	0.99	-0.05	-0.38
usable NPV ($)	m_4	1.00	0.77	0.95	0.95	0.99	-0.06	-0.38
num planning iter	m_5	0.19	0.12	0.17	0.18	0.20	0.16	-0.07
const violation (vol ft^3)	m_6	0.10	0.17	0.07	0.08	0.12	-0.23	0.81
net violation (vol ft3)	m_7	-1.00	-0.77	-0.95	-0.95	-0.99	0.04	0.39
total vol sched (vol ft3)	m_8	1.00	0.77	0.96	0.96	0.99	-0.04	-0.39
num groups	m_9	0.77	1.00	0.81	0.87	0.79	-0.08	-0.24
num of units in problem	m_{10}	0.96	0.81	1.00	0.99	0.96	-0.06	-0.39
num of units sched	m_{11}	0.96	0.87	0.99	1.00	0.96	-0.05	-0.38
total acres sched	m_{12}	0.99	0.79	0.96	0.96	1.00	-0.04	-0.37
$(m_3-m_4)/m_3$	m_{13}	-0.04	-0.08	-0.06	-0.05	-0.04	1.00	-0.14
m_6/m_8	m_{14}	-0.39	-0.24	-0.39	-0.38	-0.37	-0.14	1.00

Chapter 3: A Developed Aggregation and Disaggregation Technique Relevant for Integer Forestry Hierarchical Production Planning Problems

Introduction

Although computing power is ever increasing, allowing operational researchers to solve larger and larger decision models, problems are still routinely encountered which are beyond current technology. In order to consider large-scale models with significant detail, aggregation/ disaggregation methods are employed (Rogers et al. 1991). Moreover, the hierarchical production planning (HPP) model is often utilized to model large decision making ventures in structured organizations, in which aggregation techniques play a key role. Aggregation and disaggregation methods are often used to normalize the data relative to the decision. This study explores a formal aggregation/ disaggregation (A/D) method within the HPP model in order to forward current forest planning efforts.

A/D methods, like decomposition methods, are indispensable in carrying out the HPP model. In large-scale planning problems, decisions can often be related to hierarchical levels within organizations or to a particular time horizon. Often the terms strategic, tactical and operational are used to delineate the major three components of a decision. In making strategic decisions, for example, the detail of data, the detail of solution and the planning horizon is not the same as operational decisions. Aggregation/ disaggregation techniques can be used to manage this, keeping problem data at a minimum, so large, otherwise intractable problems can be solved, but without the loss of necessary detail and optimality.

Aggregation has been used extensively in forest planning. Each of the early forest planing models: Timber RAM (Navon 1971), MUSYC (Johnson and Jones 1979) and FORPLAN (Johnson and Crim1986), based on the models discussed in Johnson and Scheurman (1977), implicitly assume strata-based aggregation, also called modal by Weintraub (1995). In fact, the major improvements in the evolution of FORPLAN were based on aggregation flexibility (Iverson and Alston 1986). What eventually lead to FORPLAN's dismissal by many was its lack of disaggregation to spatially feasible solutions. The difficulty of disaggregating strata-based forest plans stimulated the use of two different approaches to solving the planning problem: the bottom up approach and the HPP model. Planning from the bottom up does not attempt to reduce the burden of a huge data set. Instead, this model employs heuristics, often rule based, to solve the resulting huge planning problem. This model does not find optimal solutions but focuses on finding feasible solutions. The HPP model reduces the data complexity where it is unnecessary and considers detailed data when necessary by using A/D methods and decomposition. The superiority of the HPP model is derived from its ability to address both global objectives and constraints and local (those occurring on only a smaller subset of the data) objectives and constraints simultaneously, whereas the bottom up model satisfies global constraints through rule based heuristics and considers global objectives in reduced priority. Additionally, the HPP model addresses problem optimality directly, whereas the bottom up approach has no method to do so. A major concern with the bottom-up approach is that it does not contain a formulation of the problem it attempts to solve independent of the algorithm used to solve it.

Several researchers, realizing the importance of optimality at both the global and local levels, have sought to develop the forestry HPP model using A/ D techniques. Hof and Pickens (1987) use a two tiered model, where entire tactical plans are aggregated into 0 – 1 variables at the upper level. The upper level in their model, for each landscape (sub-problem) chooses among the several plans presented for each landscape. Weintraub and Cholaky (1991) also present a two-tiered model in which aggregation is proposed. Road planning, which is detailed at the tactical level, is bundled into 0 – 1 proxy variables at the strategic level. A variable taking the value "1" indicates, for example, a road layout plan implemented on a specific area in a given time frame; this is similar to the aggregation approach used by Hof and Pickens (1987). Additionally Weintraub and Cholaky (1991) aggregate similar stands from the same management zone (modal aggregation) into single macro-stands at the strategic level. Davis and Martell (1992) designed a model which solves both strategic and tactical problems. The model uses aggregate time periods of 10 years in the strategic level model and uses 1 year periods in the tactical model. The tactical model makes up the first 10 years of the strategic model. In this case, solutions are not disaggregated; instead, the data is scoped to meet the level of detail where necessary. The strategic and tactical models are not linked by any type of feedback mechanism. Nelson and Errico (1993) present a descriptive hierarchical process carried out using simulation. They divide the forest into management zones that form spatial sub-problems. Feasible spatial alternatives are constructed heuristically using the four color theorem. Forest wide objectives and constraints are indirectly composed of aspatial data aggregated from the spatial sub-problems. This heuristic method is clearly a bottom up strategy, in which upper level objectives and constraints are explored through simulation rather than met. Bare and Liebermann (1994) present an HPP model very similar to Weintraub and Cholaky's. Their model aggregates both by time and space as one moves between the three tiers discussed: strategic, tactical and operational. The model allows for feedback if necessary (for example, if a higher level plan cannot be disaggregated feasibly at a lower level), but attempts to rectify inconsistencies within the tier using heuristics first. While aggregation is a consistent theme in these papers, the methodology is often less formal than presented in the operations research literature. Often the presentation of an unreduced model is lacking. This severely inhibits the study of the disaggregation process and the error analysis incurred from aggregation. A formal modeling procedure of the A/G process can strengthen the HPP forest planning model.

It appears that aggregation has been used since the mid 1960's and A/D methods supported with error bounds have been under study since Geoffrion's work

(1970 a, b, c). In linear programming, it is possible to aggregate columns, rows or both with error bounds (Zipkin 1980a, b). A clustering algorithm is generally used to find like rows and/ or columns to aggregate. Upon defining the clusters, a method of combing the elements into a single entity is used. Fixed-weight combination, often used, combines elements relative to their influence on the objective function. Using this method, a weighting vector (g) is used to transform the original components into a singe aggregate component. This same vector can also be used for disaggregation, upon solving the aggregate problem. Alternatively, optimal disaggregation can also be used to disaggregate the solution (Zipkin 1980). Taking [3.P1] as a primal problem example, given J columns determined to be similar enough for aggregation a single column (A_J) is formed from the J similar columns as in [3.1].

[3.P1]

$$\begin{aligned} &\max imize \quad cx \\ &subject\, to: \\ &\qquad Ax \leq b \\ &\qquad x \geq 0 \end{aligned}$$

[3.1] $$A_J = \sum_{j=1}^{J} A_j g_j$$

[3.2] $$g_j = \frac{c_j}{\sum_{j=1}^{J} c_j}$$

[3.3] $$c_J = \sum_{j=1}^{J} c_j g_j$$

g is referred to as the weighting vector. The aggregate column produced therefore emphasizes higher valued options. In linear programming, upon solving an aggregated problem, the solution can easily be disaggregated to a solution in terms of the original variables using the vector g. Hence, [3.4] yields the solution in its original, disaggregate form.

[3.4] $x_j = g_j x_J$

Under the assumption of a linear or general convex problem, it is noted that the disaggregate solution will be feasible if fixed weight aggregation and disaggregation are used (Zipkin 1980b), since the aggregate problem is a restriction of the original problem. Optimal disaggregation can also be used when fixed weight aggregation is employed to yield a feasible and improvement in the disaggregate solution (Zipkin 1980b). In this case, a sub-problem of the form shown in 3.P2 is solved for each of the clusters to disaggregate the aggregate solution.

(3.P2)

$$\begin{aligned}
&\max imize \quad c_J x_J \\
&subject\,to: \\
&\qquad A_j x_j \le g_J A_J^T x_J \\
&\qquad x_j \ge 0 \qquad j = 1,2,\ldots J
\end{aligned}$$

Unfortunately, extending many of the rigorous techniques of aggregation and disaggregation to integer programming is not possible. Forestry has experienced this in trying to disaggregate macro-stand (a strata-based aggregate column representing multiple spatially distinct stands, with similar inventories) solutions to individual stands. Constraint aggregation, however, has played a fundamental role in integer programming (Nemhaeuser and Wolsey 1988). Significant computational gain is generally noticed when multiple constraints are aggregated into one "covering" constraint. In fact, the default in commercial software such as CPLEX, preprocesses the constraint matrix in order to reduce the number of constraints. On the other hand, column aggregation with the intent of post-solution disaggregation has not generated such usable results. The disaggregation process results in multiplying a fraction within the weight vector g by the aggregated solution, which generally produces a non-integer. Hallefjord and Storoy (1990) provide improved bounds for 0 – 1 integer problems using a relaxation technique to carry out Zipkin's (1980c) bounding method used for LP.

Bounding the difference between the LP disaggregate and LP optimal value was derived by Zipkin 1980b and was also refined by Medelsshon 1980, Taylor 1983 and Frolik 1986. A-priori bounds are assigned upon forming the aggregate model, but before solving the model. A-posteriori bounds are placed on the model after the aggregate model has been solved. These bounds are tighter than the former. Using a simulation analysis similar to this study, Norman et al. (1999), demonstrate a-posteriori error bounds have significant correlation with actual error, but that a-priori error bounds are not significantly correlated with actual error. However, a-priori error bounds were reported to be significantly correlated to a-posteriori error bounds. Iterative aggregation/ disaggregation (IAD) methods have also been proposed as an improvement to strengthen error bounds. These methods use information from the dual variables corresponding to the reduced problem in order to update the weighting vector g. Dudkin, Rabinovich and Vakhutinsky (1987) discuss the convergence to optimal solutions of these methods. Jornsten and Leisten (1995) discuss the similarities of IAD and decomposition, as they apply to decentralized planning in organizations modeled using block angular linear programs. Unfortunately, none of these analytical error bounding methods extend easily to integer programs. It is therefore necessary to facilitate a different method of error analysis to examine aggregation and disaggregation applied to the forest planning problem, which is inherently integer.

In most cases forest planning problems are large enough to require aggregation in order to solve them. In the sequel, an aggregation/ disaggregation scheme is proposed for block angular forest planning problems. Instead of aggregating stands into macro-stands which is often done, for example Model I and II (Johnson and Scheurman), investments (forest management options) for each stand are aggregated based on similarity. Decomposition is used address the large number of management units. Groups of spatially contiguous units are planned independently using a modified Dantzig-Wolfe pricing scheme.

The objective of Chapter 3 is to derive error bounds in the use of aggregation/ disaggregation techniques applied to large, spatial integer forest planning problems with block angular structure, while still using the same model formulation and decomposition technique as in Chapter 2

Methods

The output of a planning model prescribes a guideline of current actions to take in order to meet objectives and constraints defined over the entire planning horizon. The level of detail necessary from the model depends upon its use. It has been noted by forest operational researchers that planning models have several uses. For instance, the model can be used to make strategic, tactical and operational decisions. Each of these decisions require different scope and detail; it is therefore unnecessary for the model to provide the same level of detail and scope over the entire planning horizon to satisfy informational requirements. On the other hand, it is necessary that information drawn from the model in these different states be commensurate. This demands a linked approach relying on systems analysis as it pertains to large-scale optimization problems. To this end, an aggregation/ disaggregation method using decomposition is proposed.

The model representing the planning problem should always be formulated in complete detail, before applying aggregation. The model describes, in the language of mathematics the desires and necessities of the planning effort. The formulation serves as a blueprint for the planning process. In this study, we seek to maximize the net present worth of the forest using a discount rate of 8% in the presence of flow (+ or – 10% among periods) and "green-up" restrictions (preclusion of adjacent unit harvests in the same period and adjacent periods). The outcome of an optimal plan is an assignment of all management units to a management option defined in terms of the 5 year periods that is optimal for the forest as a whole in the presence of the constraints considered. The unreduced, original model in this study appears in [3.P3].

[3.P3]

$$\max imize \quad \sum_{i=1}^{n} c_i x_i$$

subject to

1) $$\sum_{i=1}^{n} A_i x_i \leq \beta$$

2) $$B_i x_i \leq b_i \qquad i = 1,2,\ldots,n$$

3) $$x_i \in \{0,1\}$$

First note, that c_i and A_i are linear, making this model a linear integer programming problem. (x_i) is a binary vector representing the possible management alternatives before aggregation for each management unit in land base (group) i. Hence, (x_i) is composed of m (the number of management units in resource base i) vectors, where each of these m vectors has length k_m, equal to the number of management options considered for the particular unit. Thus, (c_i) gives the associated net present value of decision (x_i). Constraints [1] embody all constraints which relate the spatially distinct resource groups. In this case allowable harvest flow deviation. These constraints are treated as soft as in Chapter 2. Constraint [2] represents the decision space specific to each of the groups. In this case, the groups are composed of one or more spatially contiguous sets of harvest units which are inseparable due to the adjacency constraints (constraints 2).

This study uses two levels of aggregation to reduce the size of the problem. Fixed weight aggregation is used for all aggregation. Management options for units are first aggregated by management option type and harvest year, producing an intermediate aggregate problem, and then management option types are aggregated for each harvest year, producing the most aggregate problem. The difference between two management options with the same management option type is the timing of the silvilculture actions. For example, one management option may be thin in periods 2 and 5 and harvest in period 7, and another might be thin in periods 2 and 4 and harvest in period 6. However, these options would not be in the same aggregation group because the harvest period differs. A formal clustering method is not used since natural groupings exist. However, if a formal clustering method could be used, care would need to be taken to preserve the adjacency constraints. At all levels of aggregation, management units are preserved, so that spatial feasibility is preserved throughout the process. Upon solving the most aggregate model, specifying a harvest period for each management unit, the solution is disaggregated using a special form of optimal disaggregation, discussed in the sequel. The most aggregate model provides the harvest year for all management units in the presence of the harvest flow and adjacency constraints. Therefore, dissagregation to find the management option type can ignore adjacency constraints. Management option type for each unit is determined by solving the intermediate aggregate model with data corresponding to the possible harvest periods previously determined, in the presence of harvest flow restrictions. Upon solving this problem, a solution is found which contains harvest year, determined from the first problem and management option type. Therefore, at this point the only unknown is the management option within the management option type and harvest period specified. The final optimal disaggregation problem solves for the optimal management option for each unit given the solutions of the previous aggregate problems. Again, harvest flow is constrained during this disaggregation. As does the most aggregate problem, the intermediate problem "filters" the data to be considered in the most disaggregate problem. The aggregation and disaggregation process uses fixed weightings to filter out low valued decisions and then finds the highest valued decision among those remaining.

It is useful to analyze the affect of applying two levels of aggregation as opposed to one. The first important property of the bilevel aggregation is that it is also a single level aggregation, with a different weighting vector. Consider the problem of aggregating x into two clusters of y (the intermediate variable).

[3.5] $$\begin{aligned} y_1 &= x_1 g_1 + x_2 g_2; \quad g_1 + g_2 = 1 \\ y_2 &= x_3 g_3 + x_4 g_4; \quad g_3 + g_4 = 1 \end{aligned}$$

Next, consider the problem of aggregating y into one cluster of z (the most aggregate variable).

[3.6] $$z = y_1 \hat{g}_1 + y_2 \hat{g}_2; \qquad \hat{g}_1 + \hat{g}_2 = 1$$

Therefore, we verified that:

[3.7] $$\begin{aligned} z &= (x_1 g_1 + x_2 g_2)\hat{g}_1 + (x_3 g_3 + x_4 g_4)\hat{g}_2 \\ &= x_1 g_1 \hat{g}_1 + x_2 g_2 \hat{g}_1 + x_3 g_3 \hat{g}_2 + x_4 g_4 \hat{g}_2 \end{aligned}$$

It is easily seen that:

[3.8] $$g_1 \hat{g}_1 + g_2 \hat{g}_1 + g_3 \hat{g}_2 + g_4 \hat{g}_2 = 1$$

Upon defining the weighting vector as in [3.9], we see that the bilevel aggregation is a single fixed weight aggregation, but with different weights.

[3.9] $$\tilde{g} = (g_1 \hat{g}_1, g_2 \hat{g}_1, g_3 \hat{g}_2, g_4 \hat{g}_2)$$

It can be verified that the weighting vector in [3.9] is, generally, not the same weighting vector that would be obtained if fixed weight aggregation is used to aggregate all the management options by harvest period, excluding the consideration of management option type. [3.9] is the weighting vector obtained under the distinction of an intermediate clustering.

Although it would be very interesting to compare the use of different weighting vectors, it is outside of the scope of this study. The size of the sample problems solved would need to be reduced to a carry out this objective; it is therefore considered a topic for future research. Seventy-five planning problems are solved using the described A/D method and solved using an unreduced model for comparison. Due to the size of the resulting problems in full disaggregate form, it is not computationally feasible to analyze the error of the entire process. Instead, the error introduced in the transition from the most aggregate problem to the intermediate aggregate problem is analyzed. Therefore, along with the entire A/D procedure, the intermediate tier model is solved without aggregation. Hence, this single optimization problem solves for the treatment regime type and harvest period simultaneously in order to generate comparative results for the A/D approach. Using the most aggregate and intermediate aggregate forms allows the error analysis to proceed in the presence of adjacency and harvest flow constraints. Furthermore, this transition is representative of the problem encountered when an intermediate level is not acknowledged. The management option types, which are aggregated by harvest period could be alleviated. In doing this, all management options pertaining to a harvest period for a given unit would be aggregated. The only relevant difference of aggregating all the option types by harvest period versus all the options by harvest period is the number of members in each cluster. Of course, there would be far greater options aggregated per harvest period as opposed to option types. The presented error results are relevant for either case, so long as the number of members per aggregate variable are in the neighborhood as those in this study (discussed next). Unfortunately, it is difficult to estimate the error incurred upon reaching the final solution. It is also difficult to determine whether including the intermediate level problem reduces or increases the error incurred or equivalently, whether the alternative weighting vector [3.9] is better than using the standard fixed weight vector. However, including the intermediate problem appears to be necessary with regards to computational considerations.

The data set in this study consists of multiple simulated management options for each management unit. The data is specified by five-year periods. Each management unit is forecasted under an average of 101 management options with a maximum of 303, minimum of 1 and standard deviation of 73.8. The average number of harvest period options per management unit is 5.47 with a maximum of 8, a minimum of 1 and a standard deviation of 1.55. The mean number of management option types per harvest period is 3.5 with a maximum of 5, a minimum of 1 and a standard deviation of 1.62. Each unit is identified to a spatially contiguous group of units called a micro-group. A macro-group is composed of one or more micro-groups. Rogers et al. (1991) and others have suggested solving multiple randomly generated problems for gaining aggregation error information. Planning problems are randomly generated based on the group structure. Seventy-five planning problems composed of a random number of macro-groups (between 6 and 20 selected with equal probability) are used to generate simulation statistics. The macro-groups are drawn randomly with replacement from a population of 237. Contiguous groups with more than 150 management units are omitted from the population due to the large number of planning problems being solved. On average, each macro-group is composed of 10.04 contiguous micro-groups. The mean number of management units in a micro-group is 3.52, giving an average of 35.99 management units in each macro-group. Hence, the mean number of planning units per planning problem is 485.87. The largest problem generated had 806 management units and the smallest problem solved had 187 management units.

Model [3.P3], an integer program with block angular structure is representative of the planning problems solved at all levels of aggregation. Therefore, the same decomposition strategy discussed in Chapter 1 is used to solve the model at all levels of aggregation. The decomposition of the planning problem is done with respect to the macro-groups in this Chapter.

Results

The results are organized around the following four problems and their interrelation: the most aggregate problem (specifies harvest period for each unit), the intermediate aggregate problem (specifies management option type for each unit), the final disaggregation problem (specifies management option) and the unreduced intermediate level problem (specifies harvest period and management option type for each unit simultaneously). To give a sense of the entire problem and A/D process and to provide objective function value differences among the different levels of aggregation, solution results of the entire process are presented. The expected error of using the proposed A/D process is derived using the transition from the most aggregate problem to the intermediate results (a specification of harvest period and management option type).

The error introduced from using A/D is measured in terms of the objective function value (Rogers et al 1991). A bound on the error incurred from using aggregation provides the maximum distance one will be from the true optimal value of the problem given the proposed A/D procedure. In the case of integer programming, recall that these bounds must be derived by relaxing the integer constraints, in order to use the LP bound to approximate this error (see Hallefjord and Storoy 1991). Alternatively, the aggregation process may be studied through simulation using small enough sample problems, which can be solved in unreduced form, as is done in Norman et al. (1999).

Much of the time A/D is used to ease computational burden. However, in forest management, the level of aggregation can also represent the nature of the decision (Gunn 1992). For example, strategic decisions may only need to use the most aggregate problem's solution, while tactical and/ or operational decisions may need the solution of the most disaggregate solution. Of interest, is the difference in the objective values of the problems at different levels of aggregation. The differences will measure the value of the A/D procedure in terms of implementation. If these separate, but linked problems are used to model decision-making at different organizational levels, large deviations in these values will surely lead to a poorly managed enterprise. Figure 3.1 displays the percent deviation of NPV for the different levels of aggregate solutions. Category one shows the percent difference in the most aggregate and the intermediate objective function values, category two shows the percent difference between the intermediate and the most disaggregate problems' objective function values and category three displays the sum of the percent errors just listed. The total deviation of all transitions gives a measure of the overall consistency of the different level plans. The outlying data point in each category is caused by a planning problem which, in solving the intermediate problem, did not converge to the optimal solution given the maximum number of allowed planning iterations. This was determined by looking at the problem solution log. This mishap also could have been identified by comparing the disaggregate solution objective value to the aggregate objective value, which are largely different. The percent error of the outlier's most aggregate solution relative to the unreduced intermediate problem is 11.4%, which is clearly different from the 55% found at the intermediate level. Due to the mechanics of the A/D process the final disaggregate problem will be adversely affected by the intermediate solution. Its percent error relative to the unreduced intermediate problem is 67%. The results displayed in Figure 3.1 demonstrate that the A/G methodology produces consistent solutions in terms of NPV among the different levels of aggregation. Casting aside the outlier, the maximum total percent error encountered for the entire process (category 3) is 10.1%, the mean percent error 6.4% and standard deviation 1.1%.

While the previous discussion validates the consistency of NPV among different levels of aggregation, it does not provide a measure of loss in optimality; this is addressed using the most aggregate and intermediate aggregate problems. Two important aspects to surface in analyzing the error made from transitioning to the intermediate aggregate problem from the most aggregate problem are the magnitude of error and the dependence relation of the error and the problem size. The optimal solution to the problem of determining harvest period and management option type is given by the unreduced problem. Therefore, the optimal value of this problem provides the least upper bound (LUB) to the intermediate aggregate solution, specifying harvest period and management option type. Taking the ratio of the objective function value of the intermediate aggregate problem to this LUB, multiplied by 100 yields percent attainment. 100 minus this value gives percent error.

Figure 3.2 displays a plot of this percent error against the total volume scheduled in the planning problem, where total volume scheduled is used to measure the size of the problem. In viewing Figure 3.2, it appears that the percent error and the total volume scheduled are unrelated, as can be seen from the non increasing nature of the percent error data with respect to total volume scheduled. Moreover, with the outlier removed, the standard deviation (2.1%) about the mean error (7.9%) appears to be constant. Since the most disaggregate problem was too large to solve in unreduced form, the error of paramount interest, the difference in the optimal values of the entire unreduced problem, specifying harvest year and management option for each unit, and the aggregate problem could not be found. The produced results, presented as an estimation of possible error in carrying out the proposed A/G process, are intended to provide guidelines and stimulate further thinking in A/G error estimation procedures for the forestry planning problem that is inherently integer. Recall that if there are only a small number of management options being considered, and these options are aggregated by harvest period, then the error results relate to that problem. There is no mathematical difference in aggregating option types and options by harvest period, except in this problem the number of each type. Consult the data description for more information on the number of options and management options encountered in this study.

Discussion and Conclusion

The forest planning problem can often be represented using block angular form. This formulation recognizes two types of constraints: global and local. Forest planning problems are generally made up of several contiguous groups of land or land bases delineated by organizational constructs. These land bases are related to each other through global constraints in the planning problem. Decomposition allows decentralization of the plan with respect to these groups. However, in the case of most forest planning problems, the sub-problems encountered for each group are still too large to be solved exactly. Aggregation can be used without substantial loss in optimality to handle this cumbering affect. Moreover, if detailed solutions are unnecessary, the sub-problems can be modeled in aggregate form to eliminate significant computation and provide courser scale information that is commensurate with finer scale solutions.

The results in this study, using a non-analytical method to address the loss in optimality shows that A/D techniques can be used to solve large-scale forest planning problems which are inherently integer, finding feasible solutions without substantial loss in optimality. Although we were unable to find the complete loss in optimality of using two disaggregations (or the revised weighting vector (see [3.9]) which reflects the hierarchical grouping structure), the results suggest the proposed A/D functions without significant loss in optimality. The A/D method becomes more attractive when it is compared against past and some current practices, which make no attempt to bound the loss in optimality incurred from disaggregation.

The models presented in Johnson and Scheurman (1977) are used by many forestry organizations to plan forest management activities. These models, implemented in FORPLAN are representative of the so-called monolithic model. One of the major issues with Model I and II are the problems encountered in disaggregating solutions. These models suggest the proportion of acres of a macro-stand to be managed under a certain management option. There is no recognition of where in space these proportions are located. Often, this leads to splitting the management units or simply rounding the solution in order to implement the plan. The unreduced model from which Model I and II are derived is rarely mentioned. Therefore, the disaggregation to finer scale solutions happens in absence of any quantitative method, without bounds on the error incurred from diasagregation. Many have questioned the application of mathematical programming to forest planning problems because of the inability to disaggregate to feasible solutions (see Bare and Field 1986). It seems obvious that the aggregate model was not defined to make this aggregation easy. The proper process of model formulation followed by solution was never followed. Hence, the solution tool (mathematical programming) was blamed for the poor results, instead of the user's inexperience or lack of knowledge of the tool. Those developing the bottom-up approach to forest planning have ventured further from addressing the fundamental issue of problem formulation. This methodology offers no rigorous formulation to provide an error analysis.

The proper formulation of a planning model starts with a written mathematical description of the problem. If this formulation is seen to be unsolvable with current technology, then methods of aggregation, relaxation and decomposition are considered. Without a correctly written mathematical model, there is no way to assess the solution in terms of optimality of the original problem. The blueprint used throughout engineering, like the mathematical formulation of a problem, represents a well thought out plan written in a formalized planning language. One of the essential properties of a blueprint is it specifies the conceptual design independent of the actual development. A proper model formulation has a similar property: the specification of the model is independent of the algorithm used to solve it. Many of the formulations presented to solve forest planning problems do not have this property.

Often the first 5-10 years of a harvest plan demands a finer level of detail than considered in this Chapter, with possibly different or additional constraints and objectives. There are several ways of coping with this in a model which is based on a finer scale. Davis and Martel (1993) suggest representing the first 10 years of the plan in yearly periods, as opposed to 10 year periods representing the rest of the planning horizon. This is a nice approach so long as the objectives in these first few years are the same as those throughout the rest of the planning horizon. If this expansion in the number of time periods presents a computational burden, then aggregation could be performed on these periods. This should be done with a complete formulation of the unreduced model, so that a formal A/G method can be used, so that feasibility and optimality are addressed. If the near term objectives and constraints are different from the rest of the planning problem, for example, if they are linked to market forecasts, work force requirements and mill capabilities, then a different type of model may be necessary. The headquarters of the managing enterprise may be responsible for supplying raw resources to its divisions, for product conversion. If these divisions are producing different products and supplying different markets then there will be a vector of projected rates of return with a corresponding correlation matrix describing the interdependence of these rates. In this scenario it is desirable for headquarters to consider the profit maximization, risk adjusted rate of return. This model type represents a situation with conflicting objectives between the divisions and the headquarters. Hence, a compromise model must be employed. Chapters 2 and 3 have thoroughly considered the hierarchical production planning model, which is termed holistic because the objective of the planning problem is the sum of the divisions or geographical units' objectives. Chapter 4 will address the model with conflicting objectives: the hierarchical optimization problem (see Luo et al. 1996).

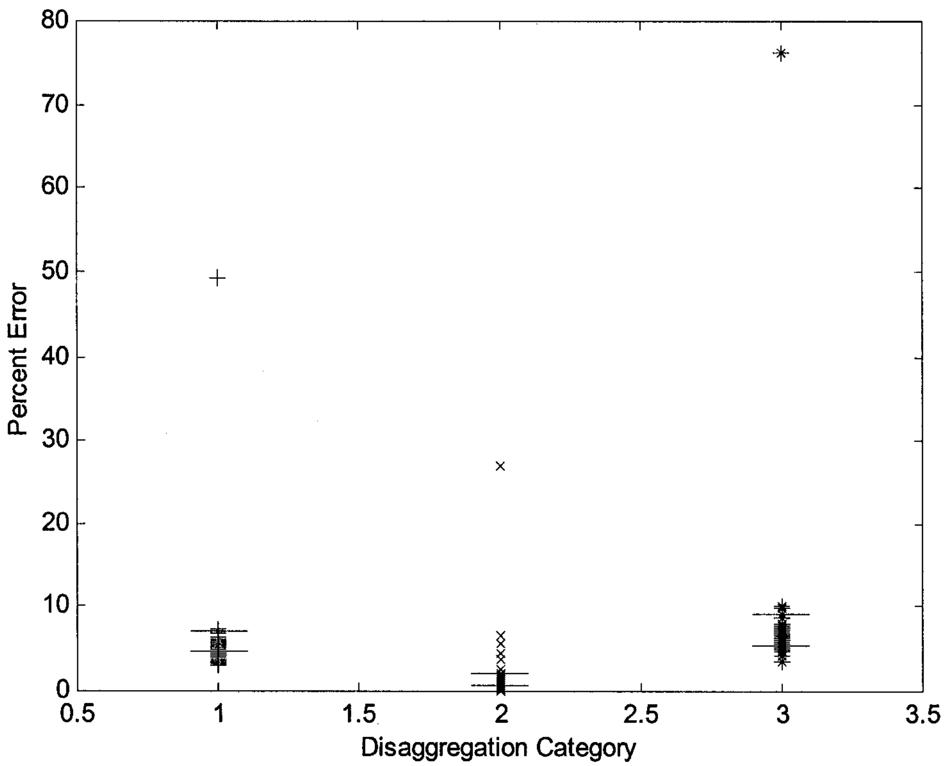

Figure 3.1
Percent difference of net present value for different aggregation levels. Error bars indicate 95% confidence of the mean. Category 1 shows the percent difference of the objective function values for the aggregate and intermediate problems, category two shows the percent difference of the objective function for the intermediate and most disaggregate problems and category 3 displays the absolute sum deviation of problems.

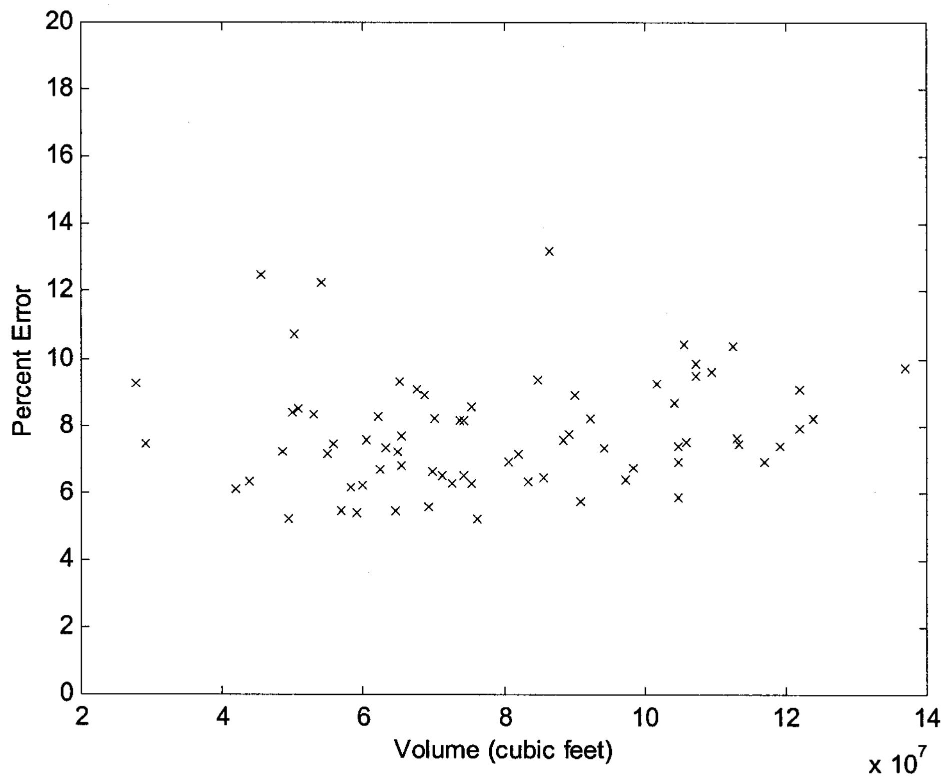

Figure 3.2
Percent error (= 100* (1-disaggregate NPV/ unreduced NPV)) incurred from problem aggregation plotted with total volume scheduled in the unreduced problem.

Chapter 4: A Bilevel, Mean-Variance Capital Rationing Model, Applied to the Product Diversified Forestry Corporation

Introduction

Often, large businesses decentralize management in order to reduce the effects of diminishing returns of scale. A typical infrastructure is a headquarters with multiple divisions (Burton and Obel 1977). A common objective for the headquarters is maximization of the rate of return or the value of the firm (Goedhard and Spronk 1995). The headquarters is responsible for steering the business in the right direction given forecasted market conditions. On the other hand, the leader(s) of each division is (are) responsible for acting in the best interest of that division. This leads to a divisional objective of maximizing the value of the division given the resources that headquarters allocates to it and whatever other resources it can obtain. With these two levels of management each pursuing interdependent objectives, an operational model that links them together is necessary.

The theory of quantitative portfolio management, pioneered by Markowitz (1959, 1987), has taken a central role in modern finance theory. Its extension to resource allocation simply requires the resources of the firm to be viewed as wealth to be invested in the different divisions of the firm. Hence, each division can be viewed as a security providing a rate of return with an associated risk. Likewise, the scarce resources of the firm can be viewed as wealth to be invested in the firm in order to control the rate of return and associated risk.

The integrated forest products/ timber producing firm contains an infrastructure that is amenable to risk diversification through resource allocation to its different divisions. Although there has been a clear shift in the ownership structure of forest resources held for timber production to companies which are not holding product conversion facilities, some companies still own large amounts of timberland and product conversion facilities. These companies, selling timber on the open market and producing forest products can shield themselves from risk by capital rationing using a model which extends the principles developed in portfolio selection theory. Viewing the capital rationing decision as a portfolio selection decision requires a substantial modeling overhaul. Consider a forestry firm that rations its timber resources to its different market sectors, for example engineered wood products, paper, solid wood products and timber sales on the open market. Each market sector can be considered a different investment with possibly different price and demand trends. Moreover, the harvested volume and/ or planned harvest can be considered as wealth to be invested into each of the market sectors. Hence, each division, producing in different markets is treated as an investment by the headquarters, while the harvest and other possible cash flows are considered wealth to be invested in each of these divisions. Since the productivity of each division is dependent upon the resources allocated to it by headquarters, the assumption of independence between the investment and the wealth invested in it, held by the mean variance model of Markowitz (1959) no longer holds.

The objective of Chapter 4 is to formulate the risk diversified forestry corporation capital rationing problem as a hierarchical optimization problem, and to discuss solution techniques for this formulation.

The Mean-Variance Model

Several formulations of the portfolio optimization problem have been given in the literature, see Markowitz (1987), Michaud (1998), Elton and Gruber (1999) and Allen (2000). An optimal portfolio can be described in terms of the expected rate of return and the associated risk of the portfolio. Under the mean – variance formulation (Markowitz 1959) the variance in the rate of return measures the risk of the investment. Therefore, there are efficient rates of return – risk combinations that make a portfolio optimal. Such a specification allows one to find an optimal investment strategy given a risk preference. A general formulation of the mean – variance formulation is given by [4.P1].

[4.P1]

$$\begin{aligned} &\max imize && (1-\lambda)Rx - \lambda(x'\Sigma x) \\ &subject\ to: && \\ & && x'\cdot 1 \le 1 \\ & && x \ge 0 \end{aligned}$$

x- is a n – dimensional decision variable representing the proportion of wealth invested in each investment.

R- is an n – dimensional vector giving the expected rate of return for each of the n investments.

Σ- is the covariance matrix, describing the variance in the expected rates of return for each of the n investments.

λ- indicates the risk preference of the investor.

Problem [4.P1] can also be thought of as a function of λ; in this case, problem [4.P1] would be repeatedly solved varying the parameter λ to develop the efficient portfolio frontier. The parameter λ allows the selected portfolio to depend on the investors personal feeling about risk.

The Model

The Hierarchical Mean Variance Model

Extending the mean variance model to allow interdependence between the investment and the wealth invested in it, such as the case in capital rationing requires the use of equilibrium constraints, in general. This, of course, assumes that the investment or division in the case of capital rationing does not have the same objective as the headquarters, which is the case when the division has some level of autonomy. Consider the forestry firm acting to maximize risk-adjusted returns in its rationing process of harvested volume. [4.P2] gives an abstract formulation of the problem.

[4.P2]

$$\max \quad (1-\lambda)\sum_{k=1}^{K} E_{\omega}[r_k(x_k, y_k, \omega_k)]x_k - \lambda x' \Sigma_{\omega}(r(x, y, \omega))x$$

$$st \quad \sum_{k=1}^{K} x_k \leq V$$

$$y_k \in \arg\max\{E[r_k(x_k, y_k, \omega_k)] : y_k \in C_k(x_k); y_k \in Y_k(\omega_k)\} \qquad k = 1,2,\ldots K$$

k is the number of divisions.

x is a vector made up of each of the x_k vectors, pertaining to the headquarters' decision.

y is a vector made up of each of the y_k vectors, pertaining to the decision of each division.

ω is a random vector made up of each of the ω_k vectors, describing the uncertain unfolding of future events; market demand and product prices in this case.

r is the function giving the rate of return of a decision x, y, with the underlying random variable ω.

E_ω is the expectation function with respect to ω.

Σ_ω is the covariance matrix of the rate of return vector r, with respect to ω.

V is the volume harvest that will be allocated to the different divisions.

$C_k(x_k,\omega_k)$ is the constraint set (decision space) for y_k dependent upon the decision made by the upper level and the uncertain future.

Y_k is the constraint set (decision space) for y_k not dependent upon the decision made by the upper level and the uncertain future.

In effort to promote solvability of problem [4.P2], the assumption that the support of ω is discrete or that it can be approximated by a discrete probability distribution is important. Therefore Q economic scenarios are considered, each having a varying affect on the outlook of the k divisions. The economic scenarios are representations of different exogenous effects on the firm. Each scenario represents a forecast which determines prices and demand trends for the different market sectors in which the divisions are engaged. These prices and demand trends are represented by the different cost coefficients and resource vectors of the lower level problems, which, are indexed by ν. An estimation of the probability of realizing each scenario is specified, and used to derive expectations. Upon carrying out the matrix multiplication in the objective function of [4.P2], [4.1] is obtained.

[4.1]

$$(1-\lambda)\sum_{k=1}^{K} E_{\omega}(r_k)x_k - \lambda\{\sum_{k=1}^{K}(E_{\omega}(r_k^2) - E_{\omega}(r_k)^2)x_k^2 - 2[\sum_{i<j} E_{\omega}(r_i r_j) - E_{\omega}(r_i)E_{\omega}(r_j)]x_i x_j\}$$

In considering Q discrete scenarios, with each scenario ν, occurring with probability p^{ν} [4.1] can be written as [4.2].

[4.2]

$$(1-\lambda)\sum_{k=1}^{K}(\sum_{\nu=1}^{Q} r_k^{\nu} p_k^{\nu})x_k - \lambda\sum_{k=1}^{K}[\sum_{\nu=1}^{Q}(r_k^{\nu})^2 p_k^{\nu} - (\sum_{\nu=1}^{Q} r_k^{\nu} p_k^{\nu})^2]x_k^2 -$$

$$2\lambda[\sum_{i<j}(\sum_{\nu=1}^{Q} r_i^{\nu} r_j^{\nu} p^{\nu} - (\sum_{\nu=1}^{Q} r_i^{\nu} p^{\nu})(\sum_{\nu=1}^{Q} r_j^{\nu} p^{\nu})]x_i x_j$$

The dependence of r, the rate of return on the decisions x and y, has been suppressed in the derivations above. Since the rate of return for each different scenario is controlled by the decision x of the upper level and then autonomously by y, it is necessary to specify a lower level reaction for each scenario and each division. Although it is more direct to extract the rate of return directly from the lower level instead of the decision y, since r is the only element used by the upper level, this creates a non-convex constraint within the lower level see [4.3]. [4.3]

$$r_k^{\nu} = \arg\max\{c_k^{\nu} y_k^{\nu} : 0 = \sum_{l=1}^{P} e^{-r_k^{\nu}} \bar{c}_k^{\nu} y_k^{\nu}; A_k^{\nu} y_k^{\nu} \le b_k^{\nu}; B_k^{\nu} y_k^{\nu} \le x_k^{\nu}\}$$

The theoretical implication of this is that the convergence to an optimal solution of the Karush-Kuhn-Tucker formulation may not satisfy the original problem. This is remedied in the sequel. This expression states that under scenario ν division k will maximize its net present value, which will determine a rate of return (the first constraint), will have to adhere to its production constraints independent of the decision made by the upper level (the second constraint), and will also have to adhere to the constraint imposed by the allocation of volume at the upper level (the third constraint). Putting the components of this problem together one obtains [4.P3].

[4.P3]

$$\max \quad (1-\lambda)\sum_{k=1}^{K}(\sum_{v=1}^{Q} r_k^v p_k^v)x_k - \lambda\sum_{k=1}^{K}[\sum_{v=1}^{Q}(r_k^v)^2 p_k^v - (\sum_{v=1}^{Q} r_k^v p_k^v)^2]x_k^2 - 2\lambda[\sum_{i<j}(\sum_{v=1}^{Q} r_i^v r_j^v p^v - (\sum_{v=1}^{Q} r_i^v p^v)(\sum_{v=1}^{Q} r_j^v p^v)]x_i x_j$$

st

$$\sum_{k=1}^{K} x_k \le V$$

$$0 = \sum_{l=1}^{P} e^{-r_k^v l}\bar{c}_k^v y_k^v \qquad \forall k,v$$

$$y_k^v = \arg\max\{c_k^v y_k^v : A_k^v y_k^v \le b_k^v; B_k^v y_k^v \le x_k\} \qquad \forall k,v$$

Notice that in [4.P3] the constraint specifying the rate of return has been moved to the upper level. As can be seen, this makes the lower level problem a linear programming problem. This appears to be important in deriving optimality conditions and solving the problem.

It is instructive to briefly analyze the model specifying for the firm's resource allocation problem and just how it might be used. Somewhere at the headquarters level in a corporation, market forecasts are made for each of the markets in which it invests. These forecasts are likely linked to some economic indicator, such as the interest rate. As a function of this indicator, a demand and price scenario is estimated. In [4.P3] these different scenarios are indexed by ν. Thus, for example, Q values for the future economic indicator are estimated, with probability p of realization. For each scenario ν, the lower levels problem data is specified; each division is constrained to produce less than demanded and must sell at a price that is set by the market, as estimated a-priori by headquarters, under that economic scenario. For each scenario ν, each division reacts with a decision y specifying a rate of return. Upon inspecting the ν rate of returns for each of the divisions the correlation of the rates for each division and the weighted expected rate of return for the corporation as a whole can be computed (this is the upper level objective). The upper level, in ascertaining the reaction of its divisions to all the scenarios simultaneously, is able to make a resource allocation decision, which maximizes the expected rate of return and mitigate risk at its preference level λ. The parameter λ, measures the risk preference of the firm. Therefore, even if λ were 0, the firm still maximizes the expected rate of return. The interpretation of $\lambda = 0$ is a firm which is indifferent about risk. On the other hand, if $\lambda = 1$ the upper level is only concerned about mitigating risk. In a sense, inasmuch as λ measures the risk preference of the firm, it also measures the similarity of the objectives between the upper and lower levels. When $\lambda = 0$ the problem could be modeled as holistic since the objectives of the two levels directly coincide. As might be noted, the problem only specifies a decision x and not really y, since y is dependent upon ω, which has not yet been realized.

Solution Methods

Several solution techniques have been proposed for the bilevel program, such as [4.P3]. Most of these make use of a reformulation of the problem to a non-linear programming problem. In general, bilevel programs and the resulting reformulation are non-convex programming problems (Anandalingam and Friesz 1992, Bard and Edmunds 1992 and Luo et al. 1996). This can be seen by reformulating the bilevel program in its Kurush Kuhn Tucker (KKT) formulation, as discussed in Luo et al. (1996). In this approach, the interpretation that the lower level decisions are chosen by the upper level is discussed in Bard and Edmunds (1992). The (KKT) form of [4.P3] is shown in [4.P4].

[4.P4]

$$\max \quad (1-\lambda)\sum_{k=1}^{K}(\sum_{v=1}^{Q} r_k^v p_k^v)x_k - \lambda\sum_{k=1}^{K}[\sum_{v=1}^{Q}(r_k^v)^2 p_k^v - (\sum_{v=1}^{Q} r_k^v p_k^v)^2]x_k^2 -$$
$$2\lambda[\sum_{i<j}(\sum_{v=1}^{Q} r_i^v r_j^v p^v - (\sum_{v=1}^{Q} r_i^v p^v)(\sum_{v=1}^{Q} r_j^v p^v)]x_i x_j$$

$s.t.$

$$\sum_{k=1}^{K} x_k \le V$$
$$0 = \sum_{l=1}^{P} e^{-r_k^v l}\bar{c}_k^v y_k^v$$
$$\nabla_y c_k^v y_k^v + \sum_{i=1}^{m_1}\lambda_i \nabla_y (A_{k\,i}^v y_{k\,i}^v - b_{k\,i}^v) + \sum_{j=1}^{m_2}\lambda_i \nabla_y (B_k^v y_k^v - x_k) = 0 \qquad \forall k,v$$
$$A_k^v y_k^v - b_k^v \le 0 \qquad \forall k,v$$
$$B_k^v y_k^v - x_k^v \le 0 \qquad \forall k,v$$
$$\lambda^T \begin{pmatrix} A_k^v y_k^v - b_k^v \\ B_k^v y_k^v - x_k \end{pmatrix} = 0 \qquad \forall k,v$$

The equivalence of [4.P3] and [4.P4] rests upon satisfying a sequentially bounded constraint qualification, convexity of the constraints at the lower level problems in the variable y and the existence and continuity of the third constraint, the KKT conditions for the lower level problem (the reader is referred to Luo et al 1996 for theoretical discussion) . Under the assumption of these conditions, if a triplet (λ,x,y) is a global minimizer of [4.P4], with the constraints satisfied, then (x,y) minimizes [4.P3]. Therefore, traditional nonlinear programming algorithms can be used to solve [4.P4], obtaining a solution to [4.P3]. Sequential Quadratic Programming (SQP) appears to be the most successful approach (Leiffer 2001), although much success has also been reported using other techniques. Nicholls (1995) uses a vertex search technique, similar to Bard's approach (1983) to solve a bilevel formulation of an aluminum smelter problem. Bard and Moore (1990) and Bard (1990) have worked out the branch and bound method for solving the bilevel program with linear or quadratic objectives and linear lower level constraints. Edmunds and Bard (1992) extend the branch and bound solution technique to also solve problems in which discrete variables are present in the upper level problem. Judice and Faustino (1994) compare their hybrid enumeration algorithm, to the branch and bound method of Bard and Moore (1990), indicating that their method consistently out-performed the branch and bound method. It appears that many of the methods being developed could be used to solve problem [4.P4].

Discussion

There are several interesting research questions that could be addressed in investigating model [4.P4]. Understanding the effect of the firms risk preference on the allocation of resources could be investigated by solving [4.P4] for different lambda. Another interesting study would be to investigate the utility of considering different economic scenarios, which accounts for future risk. This could be done by setting lambda to zero, generating several scenarios, solving the resulting model and comparing the output to the solution of the model when only the mean scenario is considered. Lambda should be set to zero since under the consideration of one scenario a variance has no meaning. Alternatively, the variance could be estimated a-priori, and lambda could be allowed to be greater than zero. This would measure the value of risk amelioration. The evaluation could be made using real data for a past situation, or the solutions of both models could be compared under several outcomes. Examining the mean value lost or gained with respect to different realized outcomes of each model (the one with several scenarios and the one with one mean scenario) would provide a good measure of the value of including uncertainty in the model. In order to evaluate the verity of the model, it would need to be compared to a current approach. If a forestry corporation was to divulge such information, and the model could be adapted to the firm's structure than this comparison could be done. All of these comparative methods could stimulate interesting results in future research.

These approaches were not followed at this time because of time constraints. The problem proposed in this Chapter is a dissertation topic in itself. The model is included in this dissertation as a comparative device to the holistic model. It seems clear that many of the models being presented within the hierarchical approach to forest management were contemplating, at least conceptually, both holistic and compromise models, without the exact theoretical knowledge and implications of compromise models, and the resulting hierarchical optimization problem. This Chapter has covered the general background of the compromise model with a detailed example to promote further thinking about model refinement within the hierarchical approach to forest management.

Chapter 5: Conclusion

As forest planning evolves, forest planning models must provide an accurate representation of new objectives and constraints as they appear in the forestry sector. The hierarchical approach to forest management has arrived, because it portrays the multilevel fashion in which decisions are made, and because the resulting planning problems appear to have multilevel structure, as well. This dissertation has shown the importance of precision in formulating these problems. The procedure for precise problem formulation followed by a properly derived solution technique of the holistic model provides a sound method for arriving at the hierarchical model often discussed in the forest planning literature. Deriving this interpretation from a rigorously formulated problem, instead of representing the problem with levels connected by an algorithm seems to contain significant theoretical implications for planning problems which can be decomposed spatially. Importantly, it identifies the problem considered as holistic in type.

Forest planners have and continue to define the role of the mathematical model in the multilevel approach to forest planning. This dissertation emphasizes the critical importance of model formulation as the first step in the construction of a model. The model formulation provides a mission statement of the planning effort, which accounts for the organizational structure of the planning entity and the entity being managed. The solution of the model is a subsequent step that provides a guide for decision-makers. Chapters 2 and 3 of this dissertation postulate that the holistic model resides within the hierarchical approach to forest management, and does not propose to model the decision making process itself, but instead supporting the decision with a quantitative method.

To further the discussion of model formulation, two different multilevel models were presented which are relevant for many forestry and also, more generally, natural resource applications. The two formulations are differentiated according to the objectives occurring at the different levels. The models can also be differentiated, in how the multilevel structure is realized. The holistic model, represented by the block angular program realizes multilevel structure upon decomposing the planning problem. The compromise model, on the other hand, realizes multilevel structure immediately in the formulation, due to the optimization problem (equilibrium) constraints. Interestingly, in solving large-scale block angular programs, decomposition is performed, and becomes part of the solution technique which also provides multilevel interpretation. In contrast, solving a bilevel program usually requires one to reformulate it as a single level, nonlinear optimization problem. Hence, in the solution techniques, the single level problem is transformed to a bilevel problem, and the bilevel program is transformed to a single level program. This should stimulate some thought, as to just how far one should proceed, when interpreting algorithmic features.

The large-scale optimization techniques used to solve and interpret the forest planning problem discussed in Chapters 2 and 3 present significant computational improvements. The results suggest that the integer forest planning problem of maximizing net present value with harvest flow and adjacency constraints can be solved efficiently, meeting objectives and constraints. By solving several problems instead of just one, confidence in the methods are displayed. The results displayed, suggest that foresters may no longer need to look to heuristic search methods which do not find optimal solutions to planning problems. Although the solution methods proposed here are also somewhat heuristic in nature, in that joint constraints are treated as soft, the techniques are derived from exact methods. Hence, the excellent numerical validation of these techniques, rest upon rigor and theory, which is evident in the derivation of the algorithms. In considering decomposition only (Chapter 2), all of the solutions found were within 1.5% (see Figure 2.2) of the upper bound on the optimal value.

Chapter 4, somewhat different from Chapters 2 and 3, formulates a stochastic compromise model, which serves two purposes in this dissertation. First, it provides a contrast to the holistic model, which seems to be the correct model type for the forest planning models discussed within the hierarchical approach in the forestry literature. Secondly, the stochastic compromise model formulates the corporate rationing problem faced by large timber companies which hold timber resources for conversion into forest products. Although there was not a dataset available to calibrate this model, its inclusion in this dissertation as an alternate formulation seems ostensible, since compromise models do not appear to have been presented in forestry. Among the many issues arising in natural resource management, are management scenarios with multiple players possessing different objectives and constraint sets. Public officials or organizations are often responsible for managing these different agents. The model of Chapter 4 provides the formulation and demonstrates the necessary transformations to solve hierarchical optimization problems. Therefore, this Chapter 4 provides the groundwork for future applications of these types of models in natural resource management.

Chapters 2-4 of this dissertation provide new insights and methods in the study of multilevel planning in forestry. Since management often proceeds across related disjoint geographies, within organizations that contain multilevel structure, and among organizations pursuing different objectives that can be influenced through policy directives, multilevel and decentralized planning seem to be at the forefront of natural resource management. This dissertation has added to the scientific understanding of multilevel planning in natural resource management in application, theory and algorithms.

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Vita

Sam Pittman is a resident and native of Seattle, Washington where he was born. While attending the University of Washington he has earned the following degrees: Bachelor of Science in Mathematics, Master of Science in Forest Biometrics and Master of Science in Applied Mathematics. In 2003 he completed his education at the University of Washington with a Doctorate of Philosophy in Forest Operations Research.