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Combinatorial Optimization in Forest Ecosystem Management Modeling

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Abstract: Modeling forest management activities has been tackled by scientists over the last two decades. Both simulation and optimization techniques have been used in solving forest management planning problems. With the introduction of ecosystems management that focuses on the sustainable production and maintenance of ecological, social and economical values, neither approach provided a credible solution technique to help design the complex structure of forest management activities. Alternative to these, is a group of meta-heuristic or combinatorial optimization techniques which have just gained the attention of forest modelers. In this paper, an attempt is made to introduce the concept of combinatorial optimization, to compare it to the traditional modeling approaches, to explain some of the meta-heuristic solution techniques such as simulated annealing, taboo search and genetic algorithms, and to discuss their implications in forest ecosystem management. It was suggested that these techniques have great potential in modeling ecosystem management in a near optimal fashion.

Key Words: Combinatorial Optimization, Ecosystem Management, Modeling, Sustainability

Kombine Optimizasyon Tekniklerinin Orman Ekosistem Amenajmanı Tasarım ve Planlamasındaki Rolü

Özet: Orman işletme faaliyetlerinin modellenmesi son yirmi yılın bilimsel çalışmalarına konu olmuştur. Simulasyon ve optimizasyon planlama teknikleri, orman amenajman planlarının yapımında başarıyla kullanılmasına rağmen ne yazık ki, her iki planlama tekniği de; ekonomik, ekolojik ve sosyal değerlerin sürdürülebilirliğini hedefleyen ekosistem amenajmanı tasarım ve planlama problemine tatminkar çözüm imkanları sunamamışlardır. Bunların yerine, alternatif olarak kombine optimizasyon (meta-buluşsal) teknikleri gündeme gelmiştir. İşte bu makalede; bu tekniklerin genel işleyiş prensipleri anlatılmış, bunlardan genetik algoritmalar, tabu arama, anneal benzetme yöntemleri işlenmiş, ekosistem amenajmanı problemine çözüm getiremeyen geleneksel planlama tekniklerine göre üstünlükleri tartışılmış ve bunların ekosistem planlamasındaki rolü üzerine durulmuştur. Sonuç olarak, kombine optimizasyon tekniklerinin orman ekosistem planlamasına optimale yakın çözüm imkanları sunan teknikler olduğu vurgulanmıştır.

Anahtar Sözcükler: Ekosistem Amenajmanı, Modelleme, Optimizasyon, Sürdürülebilirlik

Introduction

Over the last two decades, quantitative modeling of forest management scheduling has been a challenging research endeavor within a planning process. Perhaps the most significant aspect of that challenge is developing a sound forest modeling approach that accommodates spatial requirements such as block size and adjacency as well as multiple, often conflicting management objectives such as wood supply, wildlife habitat, water quality, and biodiversity.

Spatial requirements and multiple forest objectives are difficult to integrate in a forest management model. Spatial requirements simply relate to size, shape and juxtaposition of management units (i.e., harvest blocks). For example, formulating and solving a spatially feasible or applicable management plan that complies with given minimum and maximum harvest block size limits and adjacency (i.e., green-up delay) restrictions has been a challenging research subject in management modeling (Nelson and Fin, 1991; Baskent and Jordan, 1995). Management objectives are multifaceted and spatial in nature. As such, most often they do not share common measurement units and are described with different methods. For example, commodity objectives are usually quantified with the amount of wood while biodiversity objectives may be described with the number of species, amount of area or numerical and spatial distribution of different forest types over a landscape. Furthermore, the need in forest management to include spatial *configuration* of forest conditions, as well as their aspatial *composition*, increases the difficulty (Baskent and Jordan, 1995). Management objectives that incorporate spatial configuration preclude using a simple forest description with an *a priori* stratification (Nur et al., 2000). As a result, traditional modeling approaches or solution techniques are inefficient and ineffective in landscape management design. Finding a better approach is not straightforward, however.

In fact, spatial considerations along with the inclusion of multiple forest values have given birth to ecosystem management (EM). Essentially, it works on the premise that a sustainable flow of various resource values can be achieved by managing forests as ecosystems (Grumbine 1994; Baskent and Jordan, 1995; Baskerville, 1997). Forest ecosystem management emphasizes the control of the spatio-temporal dynamics of forest landscapes by orchestrating management interventions. Management interventions and their timings are identified with absolute geographic detail at the smallest forest management units, i.e., stands, so that spatio-temporal characteristics of the forest landscape, for example, size, shape, distribution, proximity and dispersion of forest patches, can be predicted and measured with respect to objectives. It, therefore, embodies two challenges: first, defining, quantifying and translating diverse social and ecological values into forest objectives, and second, designing spatially explicit management to achieve those objectives. While the former is the prerequisite for the management of forest ecosystems, the latter poses a challenge in modeling and solving the ecosystem management problem.

On the way to find a solution strategy for designing and solving the ecosystem management problem, this paper attempts to demonstrate the concept of meta-heuristics, introduce some of the combinatorial optimization techniques utilized and explain further the utility of simulated annealing in providing solutions where both forest composition and configuration objectives along with spatial consideration exist.

In Search of a Solution Approach

Up until now, a variety of modeling approaches involving a variety of forest descriptions and management objectives have been developed using mathematical optimizing and simulation techniques to solve the forest ecosystem management problem. Simulation involves a heuristic approach whereby important lessons in forest dynamics, including spatial configuration, may be learned on the way to finding a solution, i.e., intervention schedule. It is a relatively simple approach as it does not involve complex mathematical formulation in the solution procedure. It does not, however, produce an optimal solution due to its sequential search nature and failure to make inter-temporal tradeoffs. Nor is simulation effective where multiple management objectives exist. Landscape management, however, involves multiple objectives (composition and configuration), most of which are conflicting and spatial in nature, and often an optimal or near optimal solution is desired.

Optimizing approaches, on the other hand, have the appeal of guaranteeing an optimal schedule, even where multiple objectives exist. There are, however, a number of general limitations associated with the mathematical optimization techniques such as linear and goal programming in solving forest ecosystem management problems.

1. The relationship among the decision variables must be linear, yet some of the relationships in forest ecosystems management are non-linear.
2. These techniques create a fractional solution to treatments. For example, a solution would indicate that 23.98 ha of 30 ha Spruce-Fir stand or stand type must be harvested at period three for the optimal solution to hold true. However, on-the-ground implementation of such a fractional solution creates operational problems as to what portion of that stand to treat.
3. These techniques are very sensitive to the number of decision variables and constraints exhibiting combinatorial explosion with spatial realities that cause decision variables and constraints to increase exponentially. After a certain number of variables or constraints a solution cannot be sought, impeding the capability to accommodate additional decision options.
4. As a result of limitation #3, forest stands or cells must be aggregated into a homogeneous units such as age classes or stand types to reduce the

problem size for a solution. However, stand level details and spatial resolution are lost due to such aggregation.

5. Similar to the previous one, *a priori* forest stratification must occur in order to formulate forest management problems within the mathematical programming techniques, since they are deterministic-decision variables and constraints must be described quantitatively *a priori*. For example, harvest units (size, shape and spatial configuration) must be pre-defined to define the decision variables and associated constraints to formulate the problem for a feasible solution. Such *a priori* forest stratification limits the capability to look for alternative spatial configurations and arrangements of treatment units leading to a better solution.
6. They are almost impossible to formulate, however, when management objectives involve spatial configuration of forest conditions and their composition (Murray 1999; Nur et al., 2000).

Among these limitations, the issue of spatial relationships such as the integration of block size and adjacency constraints as well as patch size distribution in the process of forest management model building and solving, complicate significantly the process of model solving. While some relaxed optimization techniques, such as integer or mixed integer programming (MIP), have been used in accommodating spatial constraints such as block size and adjacency delay, MIP has shown little promise in solving real problems in a reasonable time (Kirby et al., 1986; Hof et al., 1994; Bettinger et al., 1999). Several limitations directly related to problem size and the non-linear nature of configuration objectives limit the utility of MIP approaches (Murray, 1999; Lockwood and Moore,1993; Bettinger et al., 1998). For example, Bettinger et al. (1998) used MIP to solve a simple 700-unit management problem with a single harvest choice over five periods, but failed to obtain a feasible solution in a reasonable time – it took several days to reach an optimal solution for even a 40-unit, hypothetical management problem. Optimization techniques do not look promising where configurational objectives, such as patch size distribution, are involved, even in a relatively small management problem. Perhaps that explains why no studies to date have shown a mathematical formulation involving patch size and distribution objectives.

Neither simulation nor mathematical optimizing approaches *alone* are capable of solving the forest landscape management design problem. A new alternative approach is needed. One approach is the aggregate-disaggregate approach, which solves forest management problems in two hierarchical steps: long-term strategic plan using optimization techniques (aggregate) and a short-term tactical plan using simulation (disaggregate) (Jamnick and Walters, 1993). At the strategic level, stand level information is aggregated into relatively homogeneous strata that usually involve very coarse descriptions with no geographical detail in order to reduce the problem size for use in optimization techniques. Strategic level planning determines aspatial intervention schedules and maximum sustainable flows of various resources over a given planning horizon. These guide subsequent tactical level planning. At the tactical level, management interventions are scheduled in a spatially explicit manner using simulation techniques. Commonly known as harvest block layout, this level of planning spatially aggregates forest stands into cut blocks, and assigns harvest sequences to stands subject to resource flows and regulatory constraints such as harvest adjacency delay.

One of the drawbacks to this approach is the dependency of the simulation approach on the strategic harvest schedule to assign timing choices to aggregate stand types. Furthermore, the strategic level optimal solution is no more valid when it is dis-aggregated to spatially allocate the schedule on the ground. In addition, some important spatial considerations such as control of patch size distribution, a proxy indicator of biodiversity objective, are not incorporated as a management goal. That said, the approach performs reasonably well in the absence of complex spatial management objectives.

Combinatorial Nature of the Problem

The forest ecosystem management problem, in fact, is combinatorial in nature as stands constitute basic units in spatial forest modeling, with each having potentially multiple treatment regimes over long planning horizons (Nur et al., 2000; Murray, 1999), i.e., the number of decision choices is factorially large, and as such cannot be examined exhaustively. Even given a simple single harvest activity, the problem still grows exponentially in the number of periods to plan for. For example, suppose one wishes to know how much of a given forest area can be harvested in a single period. If the area is composed of 20 units or stands, there are 2^{20} or $1.049x10^6$ potential arrangements of those 20 stands and if the area is composed of 100 stands, there are $1.267x10^{30}$ combinations. Now, consider that there are tens of thousands of stands and up to 10 harvest periods, then the number of alternatives quickly becomes *astronomically* or combinatorially large. Since deterministic algorithms like linear or goal programming are not suitable for problems of that size, as explained previously, the alternative is to consider meta-heuristics.

Combinatorial Optimization

Finding a solution to large combinatorial problems such as EM is similar to "finding a needle in a haystack". A particular class of algorithms, commonly labeled meta-heuristics or combinatorial optimization, such as simulated annealing and taboo search, have been able to provide "good enough" solutions in reasonable computational time, however (Lockwood and Moore, 1993; Boston and Bettinger, 1998; Baskent and Jordan, 2001). They are a class of intelligent search methods that have been developed since their inception in the early 1980s. They are designed to solve complex optimization problems where traditional methods have failed to be effective or efficient.

A meta-heuristic is defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for *exploring* and *exploiting* the search space (Baskent and Jordan, 2001; Beasley et al., 1993). It is based on the idea of making incremental improvements by changing elements of a solution iteratively. While EM offers a combinatorially large number of alternatives, many of them represent infeasible solutions and the feasible region is not a continuous space. Thus the strategy is to employ a smart search technique over the solution space. Essentially, a meta-heuristic is a hybrid search technique involving more than one algorithm, tailored to overcome certain "traps", i.e., local optima, in an extremely large combinatorial solution space. These heuristics have the ability to formulate a problem using discretionary rules that would be difficult to formulate mathematically (Glover and Laguna, 1997). In meta-heuristic parlance, for example, an EM design problem would be represented as either minimizing or maximizing an objective function subject to some constraints such as (Baskent and Jordan, 2001):

$$\text{Minimize } E_0 = \sum_{i=1}^{n} w_i F_i$$

where

E_0 = the objective function value for the current treatment schedule

w_i = the weighting coefficient that determines the relative importance of objective i.

F_i = the different penalty cost functions associated with n number of individual management objectives such as control of timber flow, opening size, and patch size distribution.

The objective function typically involves several components, each expressed as a summation of quantitative penalty function values and common non-monetary units and used as a mechanism for making tradeoffs among different objectives. The objective function thereby accommodates different objectives measured in different units, e.g., timber in cubic meters and patch size distribution in hectares.

Meta-heuristics include, but are not limited to: hill climbing or greedy random adaptive search procedures, simulated annealing, genetic algorithms and taboo searches and their hybrids. They basically differ from each other in the use of a move selection and solution mapping procedure. Some of these methods are described in the sections that follow.

Simulated Annealing

Simulated annealing (SA) has been proven useful in solving combinatorial problems such as bin packing, circuit design, the travelling salesman problem, and harvest scheduling (Kirkpatrick, 1984; Lockwood and Moore, 1993; Ohman and Eriksson, 1998). Finding the optimum schedule of dozens of interventions for thousands of stands over time is an example in forest management.

Simulated annealing strives to find an optimum solution to combinatorial problems by iteratively using *exploration* and *exploitation* search techniques (Beasley, 1993). Exploration is meant to investigate new and unknown areas in the problem solution space, whereas exploitation makes use of previously determined solution knowledge. A combination of these two iterative solution search techniques is quite effective; nonetheless, it is extremely difficult to find the best, or optimum, solution (combination). For one, the number of decision choices is usually factorially large, and cannot be examined exhaustively. For another, choices found favorable at one iteration do not necessarily lead to a favorable overall, i.e., global, solution.

Four basic components are needed in formulating and solving a problem such as EM with SA: a forest model, an objective function, a transition schema, and a control parameter (Baskent and Jordan, 2001). The forest model includes a concise characterization of the forest landscape, stand development patterns (yield curves) and management interventions, as well as an initial solution. The objective function is a mathematical expression defining forest values whose optimization is desired. Penalty cost functions are coupled with the objective function. They provide a mechanism whereby tradeoffs may be made among different values identified in the objective function. The transition schema determines how the solution is changed from one iteration to the next. The control parameter determines the probability of accepting inferior solutions, and provides a mechanism for decreasing their acceptance as the simulation proceeds.

To find the best solution, simulated annealing alters the intervention schedule repeatedly, evaluating the objective function value to accept or reject changes. As improvements are made, changes are accepted; however, unlike the hill climbing approach, changes that worsen the objective function value are conditionally accepted depending on a control parameter. The occasional acceptance of an inferior solution prevents the objective function from converging on a local optimum (Lockwood and Moore, 1993).

The control parameter (c) is an important parameter in simulated annealing. Large values result in a high probability of accepting inferior solutions. As a simulation proceeds, c is gradually reduced, either by a constant rate, 90% for example, or by other means, and the acceptance probability of inferior solutions is restricted accordingly. Ultimately c is reduced to a point where only improved solutions are accepted. Simulation eventually stops when a threshold value of the control parameter, or the objective function, is attained.

Lockwood and Moore (1993) applied simulated annealing to the problem of finding a harvest intervention schedule that maximized sustainable wood supply while adhering to harvest block size limits and an harvest adjacency delay. They demonstrated that SA could handle such spatial constraints with reasonable speed and, at the same time, provide a near optimal solution. Liu et al. (2000) developed an SA algorithm to solve a similar problem and showed that SA was able to generate solutions superior to the hill climbing algorithm. Murray and Church (1995) and Boston and Bettinger (1998) compared simulated annealing to other meta-heuristics, e.g., taboo search and MCIP, and found that SA was generally able to locate the best solution values to simple problems. Ohman and Eriksson (1998) demonstrated SA potential in maintaining core areas, i.e., contiguous old growth (Baskent and Jordan, 1995), using a small forest of 200 stands, a single treatment, a single rotation period, and a limited set of objectives. For landscape management problems, however, a large number of stands, a large set of management objectives and constraints, a large array of silvicultural treatments, and a long planning horizon exist. Baskent and Jordan (2001) developed and successfully demonstrated an ecosystem management model using the tSA technique to solve such a complex EM problem.

Taboo Search

Rather than selecting one choice (move) and deciding to implement it or not as is done in simulated annealing, a Taboo Search (TS) algorithm evaluates a number of adjacent solutions, generated by a number of smartly selected moves, and implements the move that improves the objective function value most (Glover and Laguna, 1997). If all of the moves are uphill moves then the TS implements the move that reduces the objective function value by the smallest amount. Although these occasional uphill moves provide a means for escaping local optima, a mechanism is required to prevent the algorithm from immediately returning to the previous value when that adjacent solution is revisited next time. The key feature of TS is the use of short-term memory to guide the searching of the solution space. It memorizes recent moves and once an attempt is made to evaluate any one of these moves, the algorithm remembers it and never returns to it. On the other hand, SA is a memory-less algorithm because its traversal of the solution space is completely random, and it may visit the same move many times over the iteration. In a taboo search, once a move has been accepted, that move is made taboo for a period of time (i.e., taboo tenure) to force the algorithm to *explore* other parts of the solution space. However, occasional moves may be allowed if they advance to a more desirable solution. This metaphor is known as an aspiration criteria.

Diversification is another important feature of TS. It is used when improvements in objective function value become too infrequent and a change is made simply to cause the algorithm to search another part of the solution space in anticipation of finding better solutions. Diversification may include complete restarts with a new random solution, or some larger scale perturbation of the current or candidate solution. The algorithm terminates when a fixed number of diversification moves are made without improving the objective function value.

The application of short-term memory, aspiration criteria and diversification in the search process make TS a unique and intelligent meta-heuristic technique. As such, it has been successfully applied to harvest unit and transportation system problems (Murray and Church, 1995), to wildlife and aquatic resource planning problems (Bettinger et al., 1998), and to harvest scheduling problems (Bettinger et al., 1999).

Genetic Algorithms

Genetic algorithms (GAs) are stochastic search algorithms designed to search large and complex non-continuous or non-linear spaces. They are based on the mechanics of natural selection and genetics (Goldberg, 1989). This is done by the creation within a machine of a population of individuals represented by chromosomes, a set of character strings. The process relates to different individuals competing for resources in the environment. Some are better than others. Those that are better are more likely to survive and propagate their genetic material. As a genetic algorithm runs, the operations performed on the population of chromosomes guide it toward better and better solutions to the problem. Since genetic algorithms are most often used for complex problems, the user may never know how close a given solution is to the true optimum.

What basically happens is that a pair of chromosomes (i.e., decision choices) cross each other, exchange chunks of genetic information and drift apart. This is the crossover operation that happens in an environment where the selection of who gets to mate is a function of the fitness of the individual, i.e., how good the individual is at competing in its environment. In the harvest scheduling problem, for example, each chromosome may refer to a permutation of the list of stand numbers that are being scheduled. If there are N stands being scheduled, then each chromosome would be a permutation of the integers from 1 to N. As the GA runs, the selection, mutation, and crossover operations make gradual changes to the ordering of the integers in the permutations on the chromosomes, i.e., the current treatment schedule changes. This procedure is similar to move generation in SA and TS algorithms.

These algorithms are computationally simple yet powerful in their search for improvement and have been applied successfully in several areas, such as scheduling, modeling of forest owner behavior, assignment, assembly line balancing, machine-component grouping and facility layout problems (Kim et al., 1993; Mullen, 1996). Application of GAs is limited in forestry. According to Mullen (1996), GAs have successfully been used in Southeast Forest Resources to develop operational harvest schedules for 90% of its timberland holdings in Florida and Georgia. For the fifteen forests that were scheduled, the GA program found spatially constrained harvest schedule solutions that had an average objective function only 1.7% less than non-spatially LP optimum solutions.

Discussions and Conclusions

Forest management design is evolving and becoming an intractable problem to solve. Traditional solution techniques are unable to provide a solution to the problem alone, since ecosystem management is a combinatorial problem. The inclusion of biodiversity objectives, maintenance of ecosystem integrity, social and economical concerns, wildlife requirements, recreational and protection (soil and water) objectives along with the traditional commodity based objectives dramatically increases the complexity of forest management planning and the problem size becomes astronomically large.

Meta-heuristics are alternative solution techniques to the ecosystem management problem. A few meta-heuristics are described and their potentials in forest management are discussed. Hill climbing is the simplest application, while taboo search, genetic algorithm and simulated annealing are the complex methods. While these methods belong to the same class of techniques, they differ in application, solution tracing and move generation methods. SA does both exploitation and exploration by occasional acceptance of inferior moves, i.e., choices, while TS implements the best moves available. However, TS uses short-term and long-term memory to control the direction of the solution path to guide it toward the true optimum. Genetic algorithms are somewhat different from both TS and SA and uses GA operators such as selection, mutation, crossover, fitness and replacement to manipulate the permutation on the chromosomes i.e., alternative treatment choices. Important in GAs is the application of crossover operations (similar to move generation), and what choice to drop and what choice to add from a current solution.

Murray and Church (1995) and Bettinger et al. (1999) compared the performance of SA and TS in solving a spatial harvest scheduling problem. According to them, there is a slight and insignificant difference between the algorithms, and the difference depends on the problem formulation, parameter settings and customized application of the algorithms. Nevertheless, their application depends highly on the formulation and algorithmic development of any heuristics, since they are highly flexible and customizable compared to traditional algorithms such as branch and bound algorithms.

All meta-heuristics generate solutions close to the optimum and computation costs are reasonable. They enable decision makers to assess the trade-offs between timber production and other non-timber forest output objectives as well as spatial conditions targeted. Thus, they may contribute to the understanding of the complex ecological and economic relationships within the framework of forest management design, and to avoiding *a priori* decisions due to lack of knowledge of these interactions and the unsuitability of traditional solution techniques.

The meta-heuristic solution techniques provide immense opportunity to solve EM problems, since they are powerful and considerably flexible to tailor and customize. For example, spatial requirements such as the harvest block size, adjacency delay issue and patch size distributions can easily be accommodated. They incorporate strategic forecasting and stand-specific treatment scheduling into a single planning process, ensuring that the integrity of information for decision making is kept intact. Therefore, spatially explicit management strategies can be developed to meet spatially explicit management objectives and constraints and thus a spatially and temporally feasible solution is generated. The approach avoids hard constraints, which often create an infeasible problem, and replaces them with soft constraints whereby objective priorities are specified.

Given the advantages of meta-heuristics in forest management modeling, combinatorial optimization techniques are, however, time demanding, highly parameterized, and may not guarantee the true global optimum solution. To circumvent these problems, particularly the latter, and thus to improve the solution quality, however, researchers are trying hybrid methods such as to combine linear programming with simulated annealing technique (Ohman and Eriksson, 2000). While not published yet, their preliminary results indicate that the integrated solution approach improved the solution quality about 9% in a simple spatial forest management formulation. With this in mind, there is an immense opportunity in meta-heuristics field to direct forest modeling research to provide solutions to the emerging ecosystem management problem where traditional modeling techniques have failed.

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