EXAMINING THE POTENTIAL OF PARTICLE SWARM OPTIMIZATION FOR SPATIAL FOREST PLANNING AND DEVELOPING A SOLUTION QUALITY INDEX FOR HEURISTIC TECHNIQUES

by

YONG SHAN

(Under the Direction of Pete Bettinger and Chris Cieszewski)

ABSTRACT

Both mathematical and heuristic methods have advanced rapidly in spatial forest planning over the past 20 years. In this research, we conduct a world-wide literature review and extensive analysis of the status and trends over the past two decades in spatial forest planning. The literature review results suggest that methods used in forest planning have shifted somewhat from exact analytical solution techniques to heuristic techniques. Limitations in mixed integer programming, heuristic parameter selection processes, modification and enhancements to heuristics, and measurements of heuristic solution quality are some of the gaps we have identified. Particle swarm optimization is a promising new population-based heuristic that might be useful for spatial forest planning. In my implementation of PSO to a southern U.S. forest planning problem, the algorithm gradually converged upon a final solution with some appropriate modifications, and a reasonable objective function value was reached. However, only 86% of the global optimal value could be reached, suggesting that PSO, acting alone, is not too useful for realistic forest planning problems. With regard to heuristics, most researchers and practitioners use various traditional statistics to assess the solution quality. In this research, we try to assess methods whereby one can develop a relationship to assess the quality of a new heuristic (when applied to a similar planning problem) without having to locate the exact, global optimum solution to the problem. A minor goal is to propose a method one can pursue to estimate heuristic performance in the absence of an exact solution to a problem. Three different statistical methods were applied to develop a measure of heuristic quality in spatial forest planning. My recommendation is to use a non-linear regression approach to estimate heuristic solution quality in the absence of a known optimal solution, because these models fit the experimental data well, and the relationships among variables are better represented. When used alone, PSO performed rather weakly in solving a typical southern forest planning problem. When testing new heuristics, researchers generally initiate new searches with randomly-defined initial solutions to ensure independence of data (final solutions). In my final chapter, I assess whether PSO, when initiated with a high-quality set of initial solutions (particles), can fine-tune and improve the overall quality of a resulting forest plan. Results indicate that PSO can improve upon the higher quality initial solutions generated by another heuristic. This work provided three advances to the forestry sciences: a published literature review illustrating the trends and gaps in spatial forest planning, an application of heuristics to forest planning problems, and the assessment methods for heuristic solution quality.

INDEX WORDS: Meta heuristics, Spatial forest fragmentation, Particle swarm optimization, Solution quality

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DEDICATION

To my wife Shuang Li who stands by and encourage me no matter what happens. To my parents, Shengke Shan and Hongmei Wang, who has encouraged me to set high goals and supported my education.

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I would like to give special thanks to my major advisor, Dr. Pete Bettinger for his continuous support. My dissertation has always been a priority. Unfortunately due to life's challenges and the changes that followed, my dissertation sometimes could not be the number one priority. Dr. Pete Bettinger encourages me not to give up under any situation. I realize that I need to keep going no matter what hits me. In my entire Ph.D. study life, he has been always ready to give me help, and advice. I have benefited greatly from his advice, his extensive knowledge and his kindness.

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CHAPTER 1

INTRODUCTION

Spatial forest planning involves recognizing the geographical location of land or other resources (e.g., road) and using this information to guide the development of a forest plan. For example, if we know that two stands of trees shared an edge (were adjacent), we could use this information to control the timing of proposed management activities. In many cases, the decision variables associated with a spatial forest planning problems are generally binary integers, thus these problems are complex, and often difficult to solve exactly (Bettinger et al., 2007).

Exact methods, such as mixed integer programming, could be applied to spatial forest planning problems if the computational requirements are not too high. Heuristic methods have also been widely adopted in forest planning, as suggested in a comprehensive review of mathematical forest planning methods in North American scientific journals (Bettinger and Chung 2004). A world-wide literature review and extensive analysis seems necessary to investigate the broader status, trends, and gaps related to spatial forest planning problems (Chapter 2). Potential gaps in spatial forest planning research may include: further investigation into mixed integer methods, applications of new heuristics to spatial problems, exploration of appropriate heuristic parameters, development of a solution quality index, integration with other fields utilizing spatial relationships, and a broader consideration of the non-peer-reviewed literature.

This research is aimed at addressing and advancing two gaps in forest planning science: assessment of a recently introduced population-based heuristic algorithm, and development of methods for constructing a solution quality index. As one might be aware, a number of new algorithms appear every year in the area of operations research, and applying those algorithms into forest planning practice is an interesting and on-going topic. One relevant classification of heuristic methods is to separate heuristics based on the use of a population of solutions, and based on the modification and improvement of a single solution (point-based methods). In practice, point-based solution methods are common (tabu search, simulated annealing, and threshold accepting). Genetic algorithms, one kind of population-based method that was inspired by nature and natural systems has been widely used in spatial forest planning problems. Other population-based heuristic methods like particle swarm optimization (PSO) have been successfully used in other fields, and therefore might be applicable in forest planning. In this dissertation, more discussion of the advantages and disadvantages of PSO are discovered when it is applied to a typical southern U.S. forest planning problem. Since in general heuristics cannot guarantee optimality, and since comparison to a known optimal solution may be elusive, the development of a measure of solution quality seems necessary. This gap in knowledge presents an opportunity for professional statisticians to apply statistical methods to qualify heuristic performance.

In sum, with this dissertation, I will (1) generate a world-wide literature review and extensive analysis of the status and trends in spatial forest planning over the past two decades; (2) apply PSO and its modification to a typical spatial forest planning problem of the southern U.S.; and (3) evaluate methods for developing a solution quality index to estimate heuristic performance when a global optimum solution is not known. This dissertation is divided into six chapters: the introduction (this Chapter), a world-wide literature review and extensive analysis of the status and trends over the past two decades (Chapter 2), an exploration of the application of particle swarm optimization to spatial forest planning problems (Chapter 3), the exploration of methods for constructions a solution quality index for heuristic methods in forest planning (Chapter 4), an investigation to determine whether PSO, when initiated with a high-quality set of initial solutions (particles), can fine-tune and improve the overall quality of a resulting forest plan (Chapter 5), and a summary and synthesis (Chapter 6).

Reference

Bettinger, P., K. Boston, Y.-H. Kim and J. Zhu (2007). "Landscape-level optimization using tabu search and stand density-related forest management prescriptions." European Journal of Operational Research 176(2): 1265-1282.

Bettinger, P. and W. Chung (2004). "The key literature of, and trends in, forest-level management planning in North America, 1950-2001." International Forestry Review 6(1): 40-50.

CHAPTER 2

LITERATURE REVIEW: TRENDS IN SPATIAL FOREST PLANNING[1]

[1]Shan, Y., P. Bettinger, C. Cieszewski, and R. Li. 2009. Trends in spatial forest planning. International Journal of Mathematical and Computational Forestry & Natural-Resources Sciences. 1(2): 86-112.(Reprinted here with permission of publisher).

ABSTRACT

Both mathematical and heuristic methods have advanced rapidly in spatial forest planning over the past 20 years. The review presented here is broader in both scope and depth (more analysis within spatial forest planning models). We conduct here a world-wide literature review and extensive analysis of the status and trends over the past two decades in spatial forest planning. In our investigation, we hope to understand the roles of objective and constraint functions in spatial forest planning. The literature review results suggest that methods used in forest planning have shifted somewhat from exact analytical solution techniques to heuristic techniques. In an effort to incorporate complex relationship into forest plans, other solution methods have also been evaluated for adoption in the planning process. Besides the economic and commodity production objectives, there is a noticeable increase in the proportion of ecological and social concerns in objective functions. In Europe, multi-parameter objective functions now seem to be in vogue, containing little or no constraints. In the U.S., single-parameter objective functions are still common, with multiple concerns recognized as constraints. In addition to the economic and commodity production constraints, adjacency and green-up relationships have recently been considered as important constraints in many areas of the world. Vector data are found to be more popular than raster data in the forest planning process, particularly in real-life applications of methods. In theoretical applications of methods, both vector and raster data are commonly used. Limitations in mixed integer programming, heuristic parameter selection processes, modification and enhancements to heuristics, and measurements of heuristic solution quality are some of the gaps we have identified.

Keywords: Geographic Information Systems(GIS), Spatial forest planning, Mathematical programming, Heuristics, Modeling techniques

INTRODUCTION

Although theoretically spatial order has always been a factor in the development of strategic and tactical forest plans, physically, incorporating spatial concerns into forest planning methods has advanced rapidly only over the past 20 years. This advance is coincident with the advances made in computer hardware and software technology, and satellite technology and geographic information systems (GIS), as well as changes in human values associated with forest conditions. Interestingly, while changes in forest structure occur globally, most of the concern related to the timing and juxtaposition of management activities is in developed countries. Forest regulations and voluntary efforts of managing forests for sustainability in these countries are the main areas of spatial forest planning concerns [29]. In addition, as many wildlife-habitat relationships continue to be better understood or advanced, the evaluation of these and other concerns has prompted advances in spatial forest planning concepts as well.

Certain laws and directives guide the use of spatial forest planning methods, and thus the need to adhere to regulations, to comply with the guidelines of voluntary certification programs, and to operate within published forest plans [29]. U.S. National Forests, for example, are regulated by the National Forest Management Act (United States Congress 1976), which provides guidance regarding the appropriate size of harvest units. In simply perusing the published forest plans, one can find information on the maximum sizes of clearcuts, the dispersion of the openings created, and guidance for the management of habitat patches on various national forest lands. Some U.S. states also have passed laws that limit the size of clearcutting activities on privately-owned land [29, 44]. Canadian provinces may also have regulations relating to the size, shape, and pattern of areas to be clearcut, as may other governments, such as Sweden, the United Kingdom, and Australia [44]. Further, voluntary certification programs and habitat conservation plans may contain inferences to compliance issues, such harvest planning strategies that contain goals related to the spatial management of forest land [29]. These laws and directives typically stem from the desire to alleviate the effects of forest management on forest fragmentation and other ecological processes, the creation of frost pockets that hinder reforestation, and public pressure related to aesthetic quality [44].

Over the last two decades, a number of researchers and practitioners have performed and reported reviews related to forest planning. For example, Church et al. (1998) describe how forest management issues are closely related to other similar issues in the location sciences. In addition, the quantitative basis for measuring spatial structure as a prerequisite to implementing forest landscape management has previously been characterized, and ecological goals assessed at the landscape level, especially those objectives concerning the negative effects of habitat fragmentation, have been discussed [11, 136]. Nowadays, in some areas of the world, forest landscape management uses an ecosystem-based approach, which requires different management paradigms, modeling approaches, and software engineering techniques. As a result, Baskent et al. (2000) discuss recently introduced planning methods one might use to design an ecosystem-based forest management plan. Although we recognize that others have also suggested that spatial forest planning is a trend in natural resources management. One review discussed the necessary factors that have led to its adoption and also describes why the planning process may be avoided [29].

A number of types of forest management problems related to the location sciences have been classified to emphasize the locational issues in forest management [58]. As early as 1990, researchers introduced the idea of heuristic simulation, and provided a brief review of its capabilities for accommodating spatial forest plans [71]. Besides North America and Europe, some developing countries also have accumulated significant research on spatial forest planning; for instance, Epstein et al. [72] provide a review on the application of operations research systems in Chilean forest industries. Besides the conventional single-objective plans, a review of multiple criteria decision support in forest management illustrates how these methods could be beneficial for one or more types of spatial forest planning problems[127]. Martell et al. (1998) review methods for strategic forest management, short-term forest planning, forest operations, and forest fire management, and discuss the opportunities and challenges for operational researchers. Nurullah et al. (2000) review the need for spatial stratification as a method to organize the geographical information. Murray (1999) reviews some specific constraint functions also have been reviewed, such as the unit and area restriction models, two basic kinds of adjacency constraints in harvest scheduling. One of the most common spatial constraints in forest planning is related to the adjacency and green-up of clearcut harvests, an area of research that has stimulated researchers and practitioners to find more efficient solution processes for spatial forest planning problems. As early as 1990, reviews concerning the analysis of adjacency constraints have been presented [217, 242]. Due to the combinatorial complexity of spatial forest planning problems, forest planning problems have become much more difficult to solve. Reviews of combinatorial problems induced by spatial forest harvest planning were presented by Weintraub et al. (2000a) and Weintraub and Murray (2006). Weintraub (2007) further reviews some traditional mathematic programming techniques, such as the use of integer programming for spatial forest planning.

A comprehensive review of mathematical forest planning in North American literature was presented by Bettinger and Chung (2004), providing forest managers and researchers who are involved in forest planning tasks with a good grasp of the trends in forest planning techniques associated with the change in the forest management planning environment. In contrast, the review presented here is broader in both scope (world-wide) and depth (more analysis within spatial forest planning models). Previous reviews have discussed the conceptual frameworks of spatial forest planning, and included a discussion of the spatial configuration related to the forest patches. In addition, various management approaches that could be used to conceptualize spatial forest planning problems were posed, along with a discussion of challenges related to spatial forest planning [14]. Compared to this, our forthcoming review considers a more extensive analysis of the status and trends over the past two decades. In our investigation, we hope to understand the roles of objective and constraint functions in spatial forest planning. The configuration of the objective function, for example, may provide information regarding shifts in what researchers and land managers want their spatial forest plans to accomplish. Constraint functions may also illustrate that more restrictions are being placed on forest plans, or that a different set of restrictions now applies, as opposed to twenty years ago. Thus, our objective is to expand a greater effort understanding the current status, trends, and gaps in the spatial forest planning literature.

METHODS

We conducted an extensive literature review of peer-reviewed spatial forest planning research based on a full search of twenty-three international journals and a limited examination of 19 other journals whenever there was an indication, through the review, that relevant spatial forest planning literature might be located there. This review is mainly concerned with the use of techniques for problem-solving, and not necessarily about how problems are structured or about how models are built. These latter two concerns are more difficult to understand given the various manners in which research results are presented. Therefore, we developed a classification process and used it to categorize the papers in various ways, including (a) the methods used to accommodate the planning model, (b) the types of objectives and constraints that were recognized, and (c) the size of problems that were being addressed. The full classification that we used can be found in Tables 2.1 through 2.3. We examined papers published from January 1989 and through December 2007.

Because of the complexity of natural resource management problems today, and given our previous knowledge of the literature, we expected that much of the literature reported the development, testing, and analysis of new techniques for accommodating spatial forest planning issues. The two basic groups of techniques involve heuristic methods and traditional mathematical programming methods. In our assessment, mathematical programming methods were sub-divided (Table 2.1) into exact techniques (linear programming, goal programming, integer programming, mixed integer programming (MIP), and non-linear programming) and other techniques (dynamic programming, simulation, and others). We consider exact techniques as those that are generally deemed to guarantee the location of an optimal solution to a planning problem. Heuristics and other techniques generally cannot provide this guarantee. Heuristic techniques were subdivided into seven commonly used methods (genetic algorithms (GA), Monte Carlo integer programming (MCIP), simulated annealing (SA), tabu search (TS), threshold accepting (TA), the raindrop method, and other heuristic methods).

Table 2.1: Categories for forest-level planning techniques described in peer-reviewed articles.

Major categories	Sub categories
Heuristics	Genetic algorithms
	Monte Carlo integer programming
	Stimulated annealing
	Tabu search
	Threshold accepting
	Raindrop
	Other heuristics
Exact techniques	Goal programming
	Integer programming
	Linear programming
	Mixed integer programming
	Non-linear programming
Other techniques	Dynamic programming
	Qualitative analysis
	Simulation
	Others

The type of forest planning methods applied to spatial planning problems is of interest from a number of perspectives: (a) some methods are more well-understood by practitioners than others, (b) some methods have been demonstrated over time to be robust or simply adequate, and (c) some methods are better for addressing certain problems than others, from both computational speed and computational complexity perspectives. We know that some research papers describe the use of up to eight planning techniques [24], while most describe only one or two. In these cases, a number of planning techniques may have been recorded as being used, all arising from a single paper. In cases where two or more techniques are present in a research paper, this usually suggests that a validation or comparison of techniques is performed. Further, in some instances a single technique (e.g., tabu search) may have been examined using several different formulations or modifications [201]. In cases such as these, the number of times a technique is noted as being used is limited to one instance. In other words, various modifications to techniques are not recorded beyond the fact that the type of technique is used.

Deciphering the formulation of planning problems is relatively straightforward in most research papers, but this is not universally the case. While a formal description of a planning problem may seem requisite, a number of papers have been published where it is difficult to ascertain the objective or constraints under analysis. We began our assessment of the literature with a preliminary categorization of the elements within the objective and constraints. The categories evolved as our assessment grew, however. Table 2.2 represents the major categories and sub-categories of objective functions that we determined. As we suggested, we began with a smaller set, and found that it needed expansion as the literature search proceeded, since some objectives were not assumed *a priori*. For example, economic and commodity production objectives are the most obvious forest planning objectives. In addition, we assumed wildlife habitat objectives would be found in the literature. However, during our search, we located research that used measures commonly considered as constraints (e.g., adjacency) in the objective function of planning problems.

Table 2.2: Objective functions categories for forest-level planning peer-reviewed articles.

Major categories	Sub categories
Economic and commodity production	Maximize net present value
	Maximize revenue
	Minimize discounted costs
	Wood flow
Wildlife habitat	Maximize acres in habitat
	Maximize species
Forest structure	
Biodiversity	
Recreation	
Other objectives	Fire
	Entomology
	Adjacency
	Landscape metrics
	Minimize shape index or clustering
	Minimize site disturbance
	Regeneration area
	Water yield

Table 2.3: Constraint categories for forest-level planning peer-reviewed articles

Major categories	Sub categories
Economic and commodity production	Net present value
	Revenue
	Budget
	Wood flow
Aquatics	Stream sediment
	Stream temperature
	Water yield
Forest structure or inventory	
Adjacency	
Road-related	
Wildlife	
Minimum or maximum harvest age	
Other constraints	Fire
	Entomology
	Biodiversity
	Carbon
	Optimal bucking
	Processing capacity or materials

With each forest and landowner comes a different set of objectives and constraints. The ideal situation of each landowner behaving rationally with economic or ecological objectives and institutional constraints on budgets and timing considerations does not necessarily hold. As a result, a wide variety of constraints were anticipated in the assessment of the literature. For example, we planned to locate economic and commodity production constraints as well as those related to habitat, adjacency, and forest structure (e.g. ending inventory). Some forest-level constraints were unexpected (entomology, carbon) and were represented by few papers; therefore the "other" category contains several diverse natural resource planning constraints. In a number of cases the constraints used in various research papers were embedded informally as thoughts within the text, and therefore required a careful reading of the methodology of each paper.

Over a period of six months, the main 23 journals we targeted were systematically reviewed by first viewing the titles of manuscripts to determine whether further analysis was necessary. The reference work within the literature we located led to other sources of research outside of our initial area of search. We also consulted the vitae of numerous scientists working in this field, if those vitae were available over the Internet. When we felt we had exhausted our search, we began to synthesize the contributions made thus far in spatial forest planning

RESULTS

Developing a comprehensive review of spatial forest planning literature is somewhat difficult given all of the potential venues in which peer-reviewed literature might be located. Some journals provide efficient access through the Internet, while others do not. In addition, our organization (University of Georgia) does not necessarily provide researchers direct, no-cost access to every journal. Undeterred, 245 papers were located that report results or discussion on spatial forest planning activities. We found over half of the papers on spatial forest plannings in either *Forest Science* (27.1%), the *Canadian Journal of Forest Research* (16.5%), *Forest Ecology and Management* (7.6%), or the *European Journal of Operational Research* (5.1%). These results were not unexpected since spatial forest planning approaches represent advances or new developments in operations research methods applied to natural resource management. These advances are better suited to journals that accommodate theoretical research, rather than journals that accommodate applied research transfer to forest managers. A number of other journals contained several papers on spatial forest planning, including *Silva Fennica*, *Scandinavian Journal of Forest Research*, *The Forestry Chronicle*, and *Ecological Modelling*. These findings were expected, since these journals have forestry or natural resource management as their main emphasis. A few other journals that do not have forestry or natural resource management as their main emphasis contained as many papers as these, however, including *Operations Research*, *Journal of Environmental Management*, and *Annals of Operations Research*. Some papers were located through limited searches in journals such as *Tree Physiology*, *Water Resources Bulletin*, *Location Science*, *Nonlinear Analysis*, and *Discrete Applied Mathematics*. The difficulty for researchers and managers new to the field is that at least 42 journals serve as sources for spatial forest planning literature. As a result, the ability to locate pertinent research may require a considerable commitment of time.

The number of peer-reviewed forest planning papers increased at a rate of about 1.5 papers per year during the 1990s (see Figure 2.1). The largest number of papers appearing in our literature review occurred in 2000. The rate of publication of papers has declined slightly since 2000. With the exception of a few odd years (e.g., in 2004, only 5 papers were located in the journals.), the rate of publication seems to be between 10 and 15 papers per year. While implementation of these techniques into real-world planning effects remains a challenge, we may be seeing the end of the exploratory phase of spatial forest planning. A number of the early papers on this subject described new methods for incorporating spatial concerns in a forest plan or described new problem-solving methods for spatial forest planning problems. Advances in these areas may continue, however many further example applications may not be seen as novel. In essence, we may be transitioning into a phase of competitive testing and analysis, which may require an expanded effort of a research team to produce a peer-reviewed manuscript.

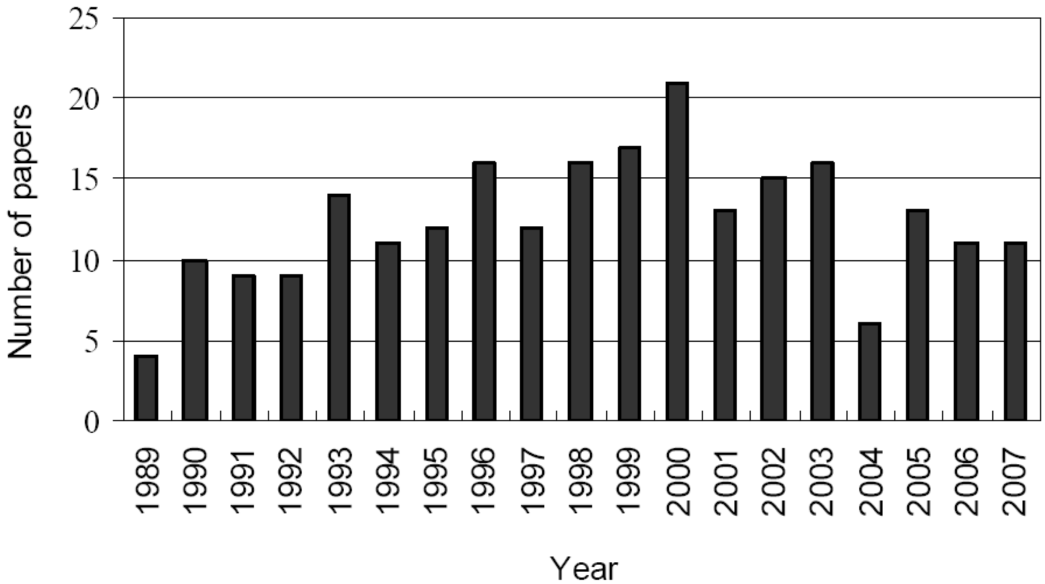

Figure 2.1: Number of publications in the spatial forest planning literature, by year

Solution Techniques for Spatial Forest Planning Problems

The results from our survey show that during the 1990s, exact methods were mainly used for problem solving or validation purposes (Figure 2.2). However, since about 2000, heuristics have become just as frequently used. Although linear programming and its derivatives are still illustrated in recently published papers, they are generally used to generate the exact or the "relaxed" solutions to a problem in order to validate heuristic methods (and other methods as well), or are limited to solving various small-size problems. Simulation methods are used consistently in research papers throughout this time span, however to a much lesser extent than heuristics. The results also show that dynamic programming has shown value as a forest-level planning technique, rather than simply as a stand-level optimization technique. It is important to realize that dynamic programming produces optimal solution to individual subproblem in some specific paper [107], and its combination with other approaches to get a non-exact solution to the master problem in the same paper.

It is well known that one of the disadvantages of heuristic methods is that one cannot prove the solution located is the best solution to the problem, whereas exact methods provide a guarantee of optimality. However, as problem sizes increase, it may be impossible to solve large problems using tractable analytical methods [150]. In addition to the common exact and heuristic methods, researchers have continuously attempted to solve spatial forest planning problems with new methods. Each year several of these new methods appear in journals. However, in some cases these new techniques cannot be applied to the wider range of forest planning problems without encountering some computational issues (e.g., [20]). For example, an optimized method based on cellular automata has been applied to solve spatial forest planning problem [93]; fuzzy multicriteria approval method which is based on approval voting has been used in forestry decision support [122], and ant colony optimization has been adopted for the risk management of wind damage in forest planning [247].

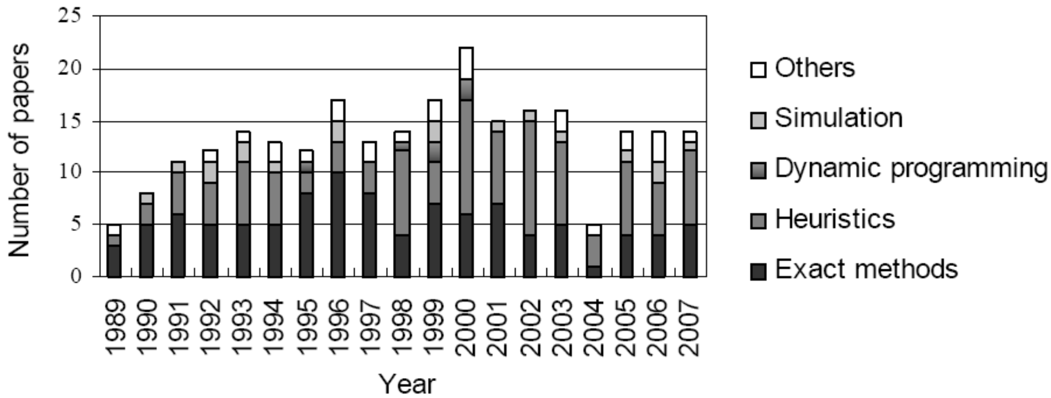

Figure 2.2: Type of mathematical programming technique in the spatial forest planning literature, by year

Researchers initially considered exact techniques (Table 2.4) as the most appropriate way to solve spatial forest planning problems. Goal programming (8 papers), integer programming (14 papers), mixed integer programming (29 papers), linear programming (64 papers) and non-linear programming (6 papers) have been used to solve economic and commodity production objective function problems, yet the problem size is usually limited to less than about 1,000 management units. Large and more complicated problems may require use of heuristics such as GA (15 papers), MCIP (17 papers), SA (33 papers), TS (25 papers), TA (4 papers), and the raindrop method [32].

Table 2.4: Related papers for forest-level planning techniques described in peer-reviewed articles.

Technique categories	Literature
Genetic algorithms	24, 42-45, 70, 75, 76, 148, 152, 163, 194, 225, 246, 247
Monte Carlo integer programming	8, 24, 41-43, 61, 67, 76, 89, 117, 139, 174, 177, 200, 201, 227
Stimulated annealing	12, 15, 24, 40, 41, 50, 54, 65, 66, 92, 93, 120, 146, 149, 150, 166, 172, 185-188, 191, 194, 206, 208, 213, 220, 222-224, 246, 247
Tabu search	17, 20-22, 24, 27, 30, 31, 41-45, 47, 52, 92, 134, 142, 164, 166, 172, 191, 194, 201, 246
Threshold accepting	24, 25, 50, 91, 191
Raindrop	32
Other heuristics	2, 5, 7, 24, 57, 60, 63, 66, 74, 84, 92, 93, 103, 121, 125, 130-132, 134, 137, 140, 148, 152, 156, 166, 170, 178, 184, 191, 192, 194, 204, 207, 226, 230, 231, 233, 234, 238, 241, 243, 244, 247
Goal programming	19, 38, 56, 69, 133, 138, 181, 237
Integer programming	7, 17, 21, 64, 82, 83, 156, 168, 169, 210-212, 240, 241
Linear programming	5, 15, 18, 20, 21, 33, 34, 39, 42, 45, 46, 48, 49, 55-57, 62, 64, 67, 68, 77, 79, 81, 88, 95, 98, 100, 103-106, 109, 115, 118, 141, 147, 153, 160, 162, 167, 168, 171, 173, 175, 177, 184, 186, 196, 199, 200, 202, 203, 205, 213, 215, 220, 226, 227, 229, 230, 233, 236, 238, 243
Mixed integer programming	2, 33, 35, 53, 60, 62, 73, 74, 96, 97, 101, 142, 157-159, 167, 174, 179, 180, 198, 218, 219, 230, 231, 233, 234, 238, 243, 245
Non-linear programming	99, 100, 102, 104, 106, 237
Dynamic programming	36-38, 107, 108, 110, 189
Qualitative analysis	114
Simulation	3, 10, 26, 28, 59, 85-88, 110, 113, 115, 119, 144, 162, 173, 182, 216, 239
Others	1, 4, 6, 9, 51, 80, 81, 90, 94, 122-126, 128, 143, 151, 154, 161, 176, 193, 195, 197, 214, 218, 221

MCIP is one of the earliest heuristic methods used in forest planning and it helped illustrate the importance of heuristic methods to the forest managers by allowing the solution of spatial forest planning problems that could not be solved using traditional exact methods. Some advantages of MCIP are that it is computationally fast, conceptually simple, and easy to program and modify [174]. Thus, it is not uncommon to find that about 70% of forest planning problems used the MCIP method on real (not theoretical) data. Within forest planning, it has been applied to problems related to economic [8] and commodity production problems [61, 117, 200], and those involving adjacency constraints [67, 139, 175], wildlife habitat [89], and road system management issues [174]. The literature indicates that around 65% of the MCIP examples were published before 2000. After that, MCIP has typically been used as a method with which to compare against other recently developed heuristic methods.

The concepts that form the basis for SA were first published by Metropolis et al. (1953) and are based on an algorithm that simulates the cooling of materials in a heat bath, a process known as annealing [24]. Generally speaking, SA is implemented as a 1-opt process, where changes to a single decision variable are considered. If the changes lead to a less desirable solution, the SA criterion is employed to determine whether or not to accept the proposed change in the solution. We determined that the number of papers describing SA for solving spatial forest planning problems is 33, which is the largest group among all the heuristic methods. Within forest planning, SA has been applied to problems related to economics [186, 220], commodity production [12, 150, 206], recreation [40], landscape design [54, 187, 188], adjacency issues [65, 213], road system management issues [66], regeneration [120], biodiversity [146], forest structure [149, 185], and wildlife habitat [224]. These results also illustrate that SA is widely used throughout the world, thus one of the most common heuristic techniques in natural resource planning and research. The locations of the work include Oceania, Asia, U.S.A., Europe, and Canada. Most papers, however, involve the latter three areas of the world.

TA is similar to simulated annealing in how it operates. However, TA accepts every new (proposed) solution that is not much worse (within a threshold) than the previous current solution, whereas in SA there is only a probability that a less desirable proposed solution would replace the current solution [24]. We only located four TA papers in the literature, and three of them [24, 50, 191] are used to compare with other heuristic methods. Only one paper [25] relied on the unique TA method to assess the ecological and economic goals in a forest plan.

Tabu search, which is one of the most extensively used heuristic methods for solving forestry-related problems, is a hill-climbing algorithm and combinatorial optimization technique. The search process arrives at the best solution by incrementally adding (or removing) decision choices to (or from) a solution, yet avoiding a continual re-selection of a subset of these choices based on their influence on the objective function [21]. Tabu search is also generally implemented as a 1-opt process, however improvements have been noted with the addition of intensification (2-opt) or diversification (frequency analysis or strategic oscillation) processes. Tabu search analyzes a "neighborhood" of proposed changes to a solution prior to selecting one, changes are then considered off-limits for a number of iterations of the model. Within forest planning it has been applied to problems related to economics [17, 45, 172, 194], commodity production [20, 21, 164, 191], stream sediment and temperature [27], adjacency issues [41, 43, 44, 47, 92], wildlife habitat [22, 30, 43], road system management issues [135, 201], and forest structure [52]. The literature illustrates that the size of the planning problems in the 25 tabu search papers we located are larger than 100 management units (75% of them among 100 to 1,000 units, others were larger than 1,000 units). There are usually two types of decision procedures in tabu search: a change to single-decision choices (1-opt moves) and changes to two-decision choices (2-opt moves). Since 1999, almost half of tabu search papers have discussed the advantages and disadvantages of using combinations of 1-opt and 2-opt. The use of 2-opt moves allowed the tabu search procedure to find better solutions because the changes in the objective function value are not as severe as with using a 1-opt neighborhood alone, where changes are made simply to the status of individual harvest units [21].

Genetic algorithms are a population-based, nature-inspired random search technique, and were first developed by Holland (1975) in an attempt to locate global optimal solutions to complex problems. With genetic algorithms, a population (set) of solutions is generated. These are then combined randomly or deterministically to create new solutions. The new solutions are then modified slightly through "mutations." The population is then updated, and the search continues until stopping criteria have been recognized. In concept, the method is not very appropriate for solving spatial forest-planning problems unless limited amounts of genetic material (pieces of forest plans) are incorporated into new solutions. However, as its development proceeded and given successful application in other areas, such as strategic planning, machine learning and so on, since about 2000, researchers and practitioners have successfully applied GAs to spatial forest planning problems. Within forest planning, it has been applied to problems related to economics [152], commodity production [75], adjacency issues [148], forest structure [76], wildlife habitat [163], and landscape design [225]. Some researchers have conducted comparisons between GA and other heuristic methods, such as SA, and TS. For each iteration of a GA model, there may be multiple changes to a forest plan, and thus GA is relatively slow compared to some of the other heuristic methods. Opinions vary on the application of GAs to spatial forest planning problems. In the study of Bettinger et al. (2002), it was concluded that a basic GA was not as good as SA and TS. The same conclusion was attained by Liu et al. (2006), who suggest that simulated annealing is more efficient than genetic algorithms for forest harvest scheduling problems. However, Pukkala and Kurttila (2005) pointed out that GA might be better than SA and TS in spatial problems. However, they also concluded that GA was not good in very simple problems, and the improved performance of GA in the most difficult problems can result from the fact that it was the only technique where a move could imply more than one change in the solution [194]. For spatial problems, the best GA algorithms may be those that transfer limited genetic material in the development of new (child) solutions. There still exist fertile areas of subjects to research, including variable mutation rates and crossover probabilities, or the use of dynamic penalty functions, with parameters self-modified with the convergence process [75].

Objective Function Components

The economic and commodity production concerns of landowners continue to account for the majority of objectives in spatial forest planning problems presented in the literature (Figure 2.3). However, long-term sustainable forest management challenges have prompted researchers to pay more attention to wildlife habitat, forest structure, biodiversity, recreation, and other objectives. As a result, about one-third of the spatial forest planning papers accommodate other goals in the objective function of the problems presented. These are either single-objective optimization problems, or more commonly, goal programming problems that use various forms of utility functions. Interestingly, in Europe, utility functions have become common aspects of spatial forest planning [143], yet in North America, penalties are more commonly added to single parameter objective functions [12]. Why this is the case has yet to be understood, but may be related to the goals and objectives of both the planners and the land managers.

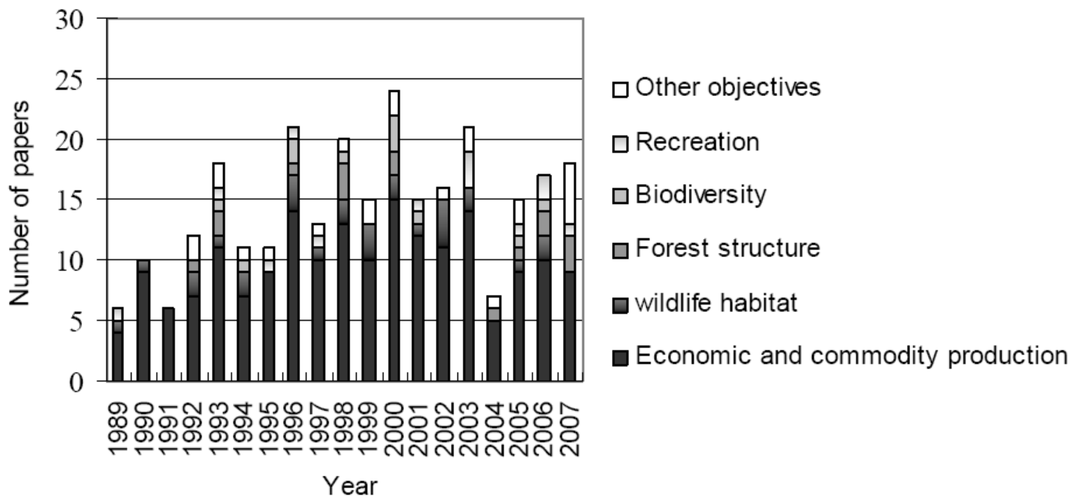

Figure 2.3: Objectives contained in the spatial forest planning literature, by year

The maximization of net present value (97 papers), revenue (28 papers), and wood production (76 papers) are still the highest-level issues of researchers and practitioners, as is the minimization of discounted costs (20 papers). Policy makers and private landowners continue to balance economic and commodity production objectives with other non-product objectives, however. Objectives which include maximizing area in habitat (19 papers) and maximizing wildlife species populations (9 papers) dominate the non-product objectives that researchers and practitioners have considered (Table 2.5). The population and habitat of a wildlife species is mostly affected by the landscape features and spatial distribution factors that are considered in a spatial forest planning process. Forest structure (16 papers), biodiversity (11 papers), recreation (12 papers) are also hot topics in spatial forest planning. Other objective function components have included those related to entomology (Hof et al. 1997), adjacency of harvests (8 papers), landscape metrics (6 papers), shape indexes or clustering (3 papers), site disturbances (3 papers), regeneration areas (Jorgensen et al. 1992), and water yield (4 papers). Papers that describe single-objective problems represented about 69.1% of the literature. Papers describing two-parameter objective functions represented about 19.1% of the literature, and the rest of the literature include more than three components in the objective function. As a result, we have seen an increase in the use of multiple objective function problems in spatial forest planning over the past ten years.

Table 2.5: Related papers for objective functions categories in forest-level planning peer-reviewed articles.

Objective categories	Literature
Maximize net present value	2, 4-8, 17-20, 27, 31, 36-39, 41-46, 50, 52, 53, 56, 57, 60, 62-64, 66, 69, 70, 73, 75-77, 80, 81, 90, 93, 107-109, 116, 122, 123, 126, 130, 134, 135, 140, 141, 143, 150, 152, 153, 157, 162, 164, 166, 169-173, 175, 185-188, 190, 194, 198-200, 202, 205, 206, 209, 213, 214, 219-221, 223, 230, 231, 233, 234, 236, 238, 241, 243-245
Maximize revenue	1, 32, 33, 48, 56, 65, 83, 102, 104, 105, 110, 121, 128, 138, 146, 158, 159, 161, 168, 174, 192-194, 196, 208, 218, 221, 227
Minimize discounted costs	20, 48, 61, 74, 89, 98, 99, 102, 103, 110, 113, 142, 154, 179, 180, 189, 201, 214, 233, 234, 240
Wood flow	10, 15, 20-22, 26, 30, 32, 34, 40, 47, 54, 55, 61, 67-70, 79, 82, 84-88, 91, 100-102, 115, 117, 119, 121, 123-126, 128, 130-133, 137, 142, 148-151, 156, 160, 176, 177, 181, 182, 184, 195-197, 199, 200, 206, 211, 212, 215, 216, 221, 224, 229, 238, 243, 246, 247
Maximize acres in habitat	1, 4, 22, 24, 49, 100, 137, 161, 163, 179, 180, 191, 194, 196, 197, 202, 203, 207, 240
Maximize species	33, 88, 96, 101, 126, 181, 186, 191, 204
Forest structure	40, 69, 91-93, 100, 125, 143, 149, 185, 191-193, 197, 221, 245
Biodiversity	19, 106, 122, 125, 131, 132, 140, 149, 194, 197, 222
Recreation	1, 40, 122, 123, 126, 128, 133, 143, 161, 181, 194, 195
Fire	214
Entomology	97
Adjacency	3, 9, 92, 93, 144, 150, 239, 247
Landscape metrics	54, 91, 100, 225, 246, 247
Minimize shape index or clustering	187, 188, 219
Minimize site disturbance	3, 126, 134
Regeneration area	93, 120
Water yield	95, 151, 197, 234

Constraint Components

Two constraints have dominated forest-planning problems over the last twenty years: (1) those that are fragmentation related, or involve harvest size or adjacency issues; and (2) those that involve economic measures or commodity production goals (Figure 2.4). The economic and commodity production constraints represent some of the more traditional constraints in forest plans. Economic and commodity production constraints (Table 2.6) include those related to net present value [51], revenue (10 papers), budgets (9 papers), and even wood-flow (113 papers). Adjacency and green-up relationships, which address the juxtaposition of harvests and habitat, are perhaps the single most widely used spatial constraints in forest planning today [32]. The papers that involve adjacency relationships are numerous (90 papers). While we are unable to determine cause or effect, spatial forest planning problems seem to have become more complex as time proceeded through our analysis, and there has been a shift from a reliance on exact techniques or Monte Carlo simulation to the use of various heuristics. In addition, the constraints incorporated into these manuscripts have become more complex in recent years, using functional relationships related to wildlife habitat, biodiversity, aquatic resources and others. We assume the need to incorporate the complex relationships prompted the exploration of alternative solution methods, however, one could argue that the use of alternative solution methods allows a more extensive set of resource evaluation rules to be incorporated into forest plans. In addition, validating these problems (when solved with heuristics) becomes problematic because exact methods often are incapable of solving the full problem.

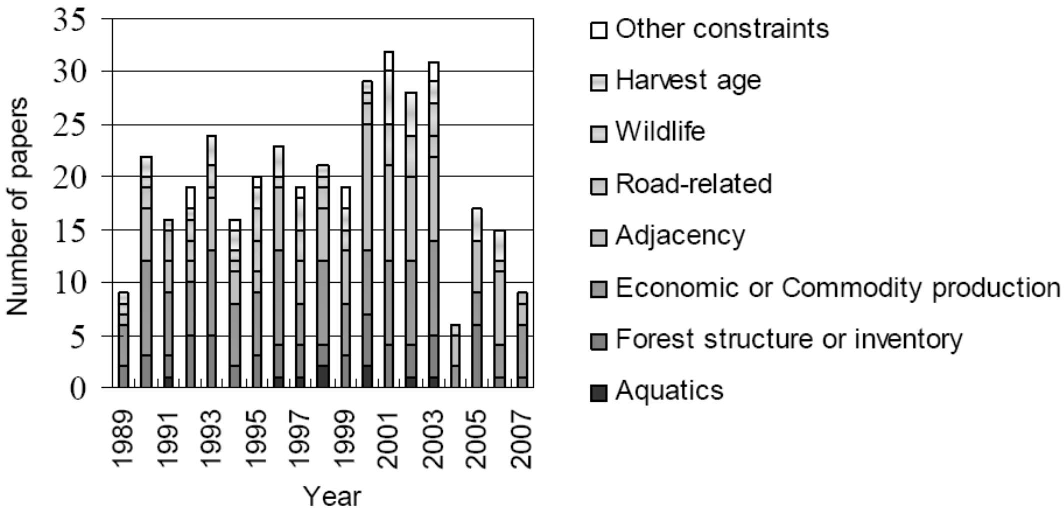

Figure 2.4: Constraints contained in the spatial forest planning literature, by year

Other constraint functions (Table 2.6) that have been considered include those related to forest structure or inventory (60 papers), road management (20 papers), wildlife (30 papers), minimum or maximum harvest ages (40 papers), and aquatics, which includes stream sediment (7 papers), stream temperature (2 papers), water yield (5 papers). In addition, other noteworthy constraints include fire, entomology, biodiversity, carbon, optimal bucking, processing capacity or materials.

Table 2.6: Related papers for constraint categories for forest-level planning peer-reviewed articles

Constraint categories	Literature
Net present value	51
Revenue	48, 138, 166, 168, 174, 175, 181, 202, 208, 238
Budget	55, 68, 82, 117, 133, 141, 164, 179, 181
Wood flow	2, 5, 6, 8, 15, 18, 20, 21, 24, 26, 27, 31, 40-49, 52, 53, 60-65, 67, 68, 70, 73, 75-77, 79-82, 84, 90, 96, 98, 99, 103-106, 108, 109, 113, 115, 116, 133-135, 137, 138, 141, 142, 148, 153, 157-162, 164, 166, 168, 169, 171, 173-178, 181, 183, 186, 187, 189, 190, 196, 198, 199, 201, 205, 206, 209, 211, 215, 218-220, 222, 223, 226, 229-231, 233, 236, 238, 241, 243, 245
Stream sediment	27, 31, 151, 220, 231, 233, 238
Stream temperature	27, 31
Water yield	35, 133, 151, 205, 220
Forest structure or inventory	5-7, 17-19, 21, 28, 39, 46, 51, 52, 57, 59, 62, 64, 65, 68, 76, 77, 80, 83, 95, 104-106, 109, 110, 116, 117, 120, 138, 156-158, 160-162, 171, 173, 175, 176, 182, 185, 186, 188, 189, 196, 198, 200, 202, 205, 208, 209, 216, 227, 229, 230, 241
Adjacency	7, 9, 10, 15, 17, 24, 26, 32, 36-38, 41-45, 52, 53, 60, 61, 63-67, 76, 81-88, 90, 94, 100, 107, 108, 111, 117-119, 134, 139, 144, 146, 148, 149, 151, 154, 156-159, 166-170, 174-177, 184, 185, 190, 198, 200, 201, 208-213, 215, 216, 218-220, 222, 223, 226, 227, 230, 239, 241, 243
Road-related	2, 10, 60, 66, 74, 82, 104, 105, 134, 142, 166, 174, 177, 189, 201, 231, 233, 238
Wildlife	25, 30, 33, 34, 42, 49, 50, 62, 87, 89, 94, 100, 101, 103, 106, 133, 147, 151, 161, 172, 180, 181, 200, 202-204, 220, 224, 227, 240
Minimum or maximum harvest age	8, 19, 24-26, 28, 30, 34, 42-44, 51, 65, 67, 77, 83-88, 95, 98, 102, 103, 109, 111, 148, 159, 161, 171, 176-178, 182, 212, 216, 227, 243, 244
Fire	199
Entomology	97, 162
Biodiversity	19, 133, 146
Carbon	135
Optimal bucking	73, 141
Processing capacity or materials	6, 48, 80

Type of Data used in Forest Planning Research

The type of the data that has been used in spatial forest planning research is characterized as hypothetical and real, and raster and vector. We used our best judgment, where necessary, to make these determinations. Raster data and vector data are the two basic GIS data structures that we considered in the review. Raster data is characterized by regular-shaped grid cells (pixels) obtained from satellites or other geoprocessing methods. This data structure can be manipulated quickly by a computer, thus computations are generally more efficient. Vector data includes points, lines, and polygons (irregularly shaped), which are derived from air photo image interpretation, digitizing, and land surveys. Since this data is relatively easy to obtain and use, it is not uncommon to find that vector data is more prevalent in forest planning problems compared to raster data (Figure 2.5). Within the 245 papers we located, we determined that 50 used raster data, 107 used vector data, and 10 used both, which means that about one-third of the papers did not explicitly refer to one of these two data structures (we considered the review papers to not mention either of them). Although it is hard to argue against the fact that vector data is prevalent in the planning process, the trends indicate that researchers and practitioners may be suggesting that a single data structure is not enough to satisfy the needs of complex spatial forest planning and research. In order to further describe the type of data used, we classified it as real or hypothetical (Figure 2.6). It seems obvious that researchers would want to test their methods on real data, but due to the complexity of the planning problems, researchers at many times resort to testing their methods on hypothetical data. Among the 245 papers we reviewed, 140 used real data, 72 used hypothetical data, and 5 used both. Through our interpretation of the literature, we concluded that 143 of the papers represent applications and 87 lacks an example of the use of the techniques in applied spatial forest planning, and of course 18 are review papers (Figure 2.7). As a result, many of the applied research papers utilize hypothetical data. Two reasons for this include the difficulty in obtaining large databases describing actual landscapes, and the inability to obtain permission to illustrate an organization's data in a published research paper.

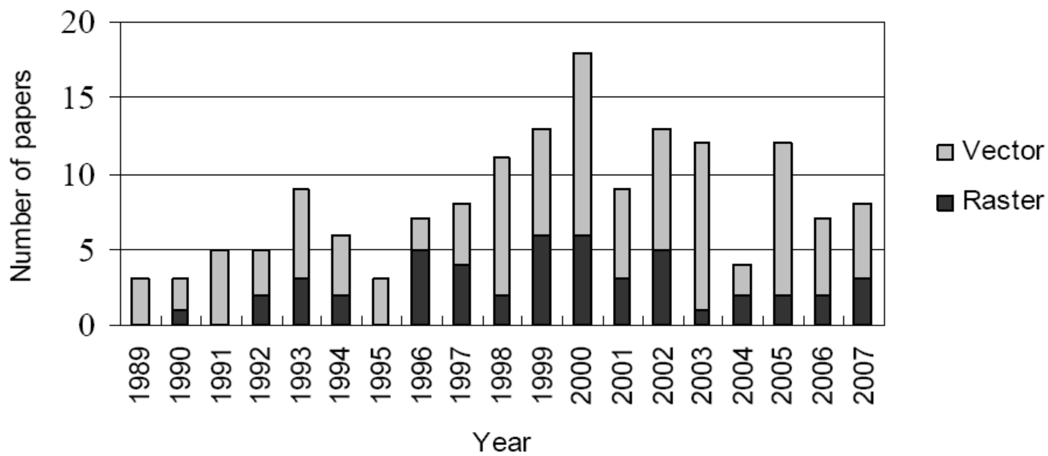

Figure 2.5: Vector and Raster data in the spatial forest planning literature, by year

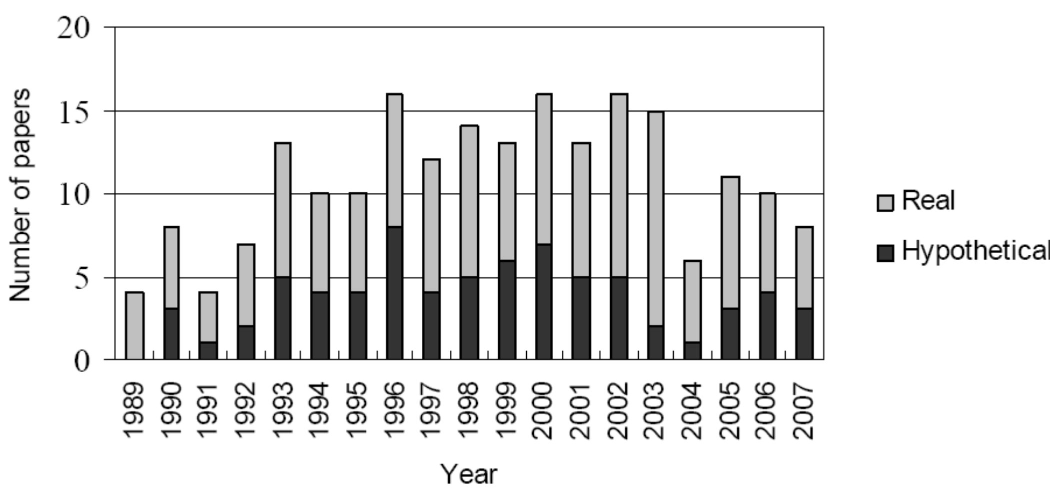

Figure 2.6: Real and theoretical data in the spatial forest planning literature, by year

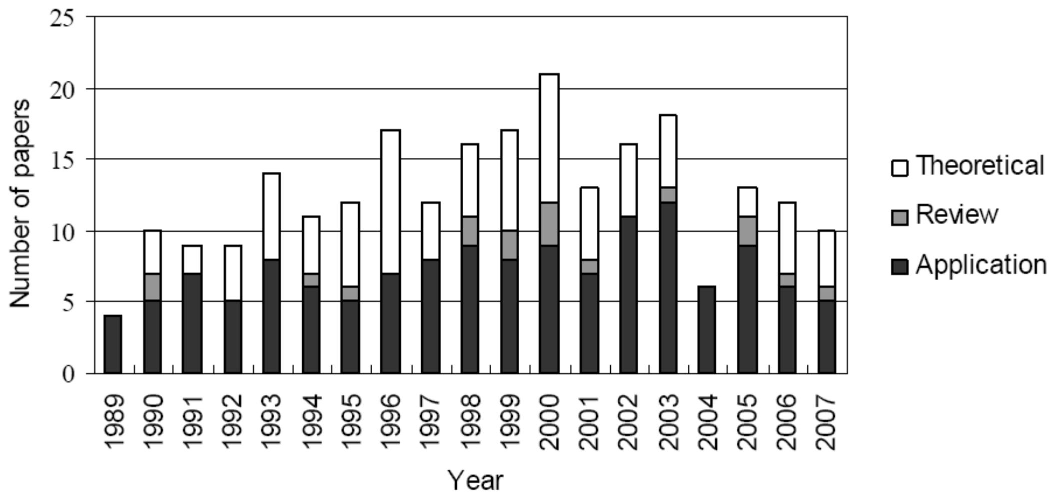

Figure 2.7: Type of papers in spatial forest planning literature, by year

Geographic Location of the Problems

While the importance of forest planning has been realized worldwide, research on forest planning is costly and the objectives nowadays do not concern economic or commodity production. Thus, developing countries may be short of such funds for conducting forest-planning research or may not place high importance on its use in forest management. In the literature, the countries or continents where most of the published forest planning problems are geographically situated (Figure 2.8) are: USA (68 papers), Canada (34 papers), and Europe (48 papers). However, researchers and practitioners have also solved some spatial forest planning problems in Oceania (6 papers), South America (7 papers), Asia [54, 241], and Africa [181].

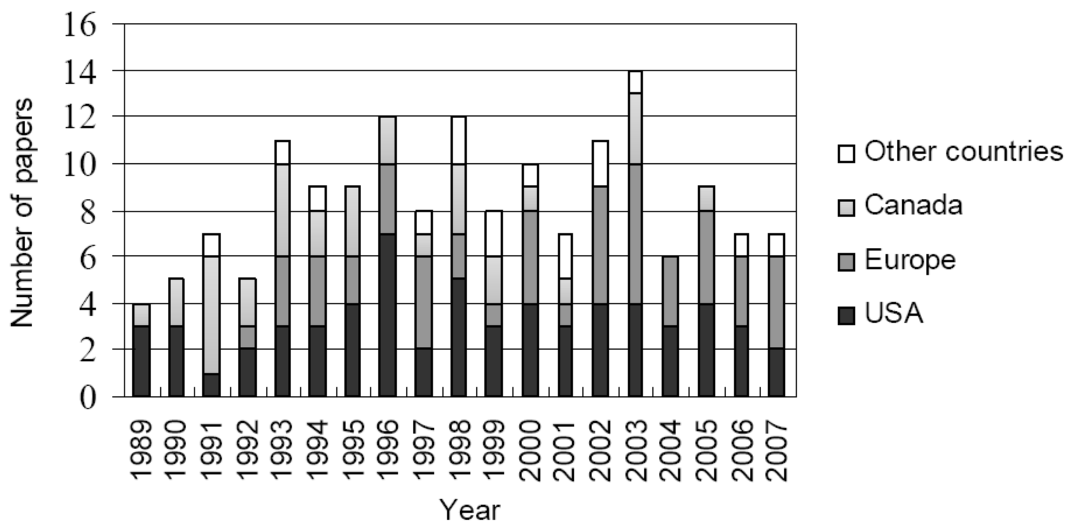

Figure 2.8: Location of spatial forest planning analyses, by year

Spatial Concerns

As we noted earlier, spatial forest planning is used to examine patterns and trends in the spatial development of landscapes, and focuses on forestry and natural resource management activities and the specific tools used to develop, implement, and evaluate forest plans and alternative policies [29]. These are core elements of spatial forest planning. Control of these concerns has been accomplished through the objective function and constraints of the problem formulation (see tables 2.5 and 2.6). Therefore, given the structure of the model being used and the creativity of the planner, there are a number of ways by which one can acknowledge and accommodate spatial concerns in forest plans. An increase in the spatial restrictions or objectives in forest planning problems is evident by the results (Figure 2.9). In our classification of objectives, spatial objectives include those related to wildlife habitat (some maximizing acres in habitat are not spatial), forest structure, adjacency, and many others. The spatial constraints include adjacency, aquatics, forest structure or inventory, wildlife, and road management. Only 37 papers among 245 papers we found used non-spatial models. Among these, a few attempt to address hypothetical problems [16, 98, 99, 102, 113, 115, 203, 209] and related these to potential practical application.

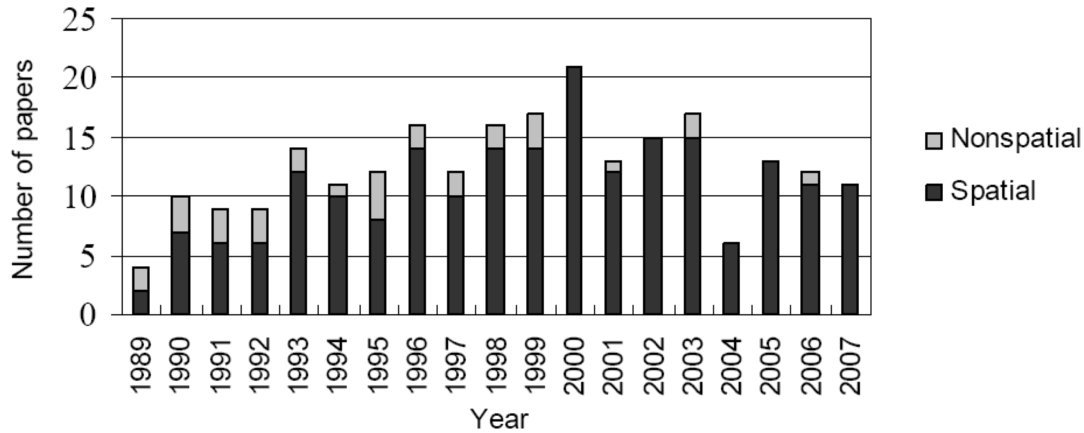

Figure 2.9: Number of papers that include spatial goals, by year

The use of Geographic Information Systems (GIS)

Since the introduction of GIS in natural resource management, there has been a logical increase in the application of GIS to forest planning (Figure 2.10). The role of GIS technology in spatial forest planning has, however changed significantly, from the source of input to the analysis tool of spatial models. One vital function of GIS is the ability to address locational issues, and to manage information in digital form, through an attribute database. GIS has also traditionally been used in forestry to store maps in electronic form and to make calculations, such as areas and distances [14]. However, if the spatial restrictions or objectives were not included in a forest planning problem formulation, and subsequent spatial analysis was necessary, GIS is used to only address these post-plan development issues. More recently, its use has been extended to analyses of potential land uses and other complex problems, which have a spatial context. However, it is not uncommon to see GIS used as an input facilitator rather than as an analysis tool.

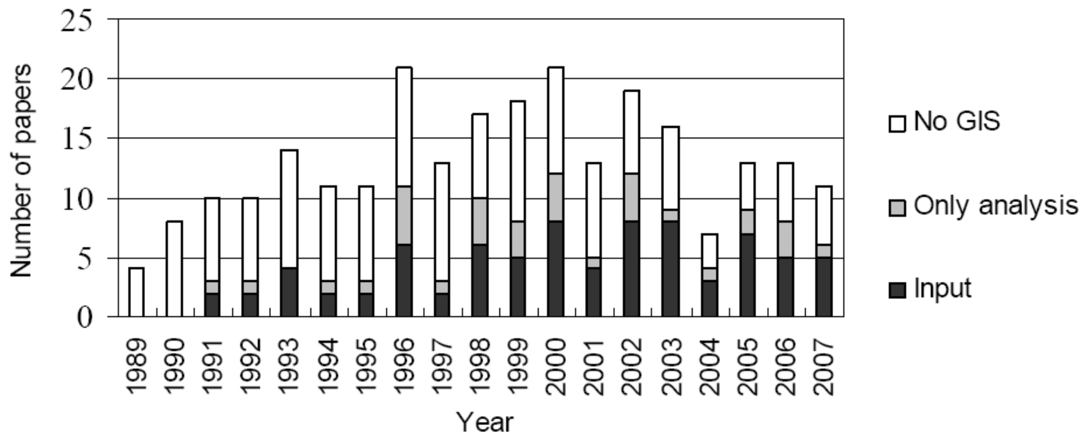

Figure 2.10: GIS use in spatial forest planning literature, by year

DISCUSSION

There are still many important areas in quantitative forest planning that need to be further studied. Although we have discussed that MIP methods are limited by problem size and are difficult to use for solving spatial problems, researchers and practitioners still attempt to use innovative formulations of MIP to obtain exact answers. For example, two MIP harvest-scheduling formulations have been developed to solve area-based adjacency problems [159]. Forest planning problems with patch size constraints or objectives that are essential for wildlife habitat concerns have also been addressed with new formulations of MIP [198]. Finding ways to apply exact methods, especially mixed integer programming, to very large problems without running into restrictions of the number of constraints, or without requiring extensive computational time to solve the problems is an area worth further research.

As we know, a large number of new algorithms appear every year in the area of operations research, and applying those algorithms to forest planning practice is an interesting topic. One relevant classification of heuristic methods is to separate heuristics that are based on populations of solutions from heuristics that are based on a single change to a solution (point-based algorithms). A point-based algorithm will only have one unique solution per iteration, and we update the best one with the new obtained solution if it is better than the best we have found before. With a point-based algorithm, we only need to define the current solution and use a metaheuristic to obtain a new solution. With a population-based algorithm, we have to define the current population and new population in each iteration. Additionally, we also need to initiate the population size and define the maximum population size allowed. Other population-based heuristic methods like particle swarm optimization, which has been successfully used in other areas including optimization of artificial neural networks, image processing, and computational biology, could also been applied in forest planning. More discussion of the advantages and disadvantages should follow, and they should be tested against various standard forest planning problems.

No matter what heuristic techniques one adopts to solve spatial forest planning problems, choosing the appropriate parameters seems to require the most attention. This issue is treated lightly in many papers, thus a broader explanation of the parameters for typical forest planning problems is needed in future work. One might ask whether there ways to estimate the parameters based on the type and size of a problem (Figure 2.11), rather than needing to perform a number of trials to locate the acceptable range of parameters. Ultimately we need to find ways to estimate the appropriate parameters rather than have the user try to identify them, taking this process out of their hands.

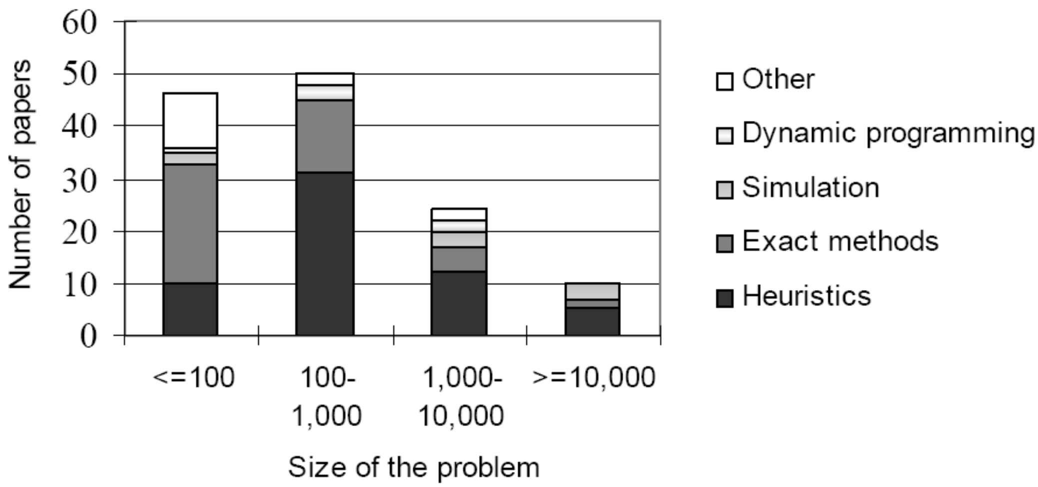

Figure 2.11: Size of the problem in spatial forest planning literature

Addressing limitations of the search process is also an area requiring more work. As we discussed, it is probably better for GA to swap small amounts of genetic material during each iteration of a spatial forest planning process, because the transfer of large amounts of genetic material during the crossover results in numerous violations of spatial constraints. The same is true in spatial forest planning problems when the mutation rate is high. After addressing these types of limitations, GA and its modifications could be more effectively used for spatial forest planning problems. Recently, an intelligent mechanism of combining standard heuristic methods such as TS, SA, TS, and the raindrop method has been developed by Li (2007). Using such a mechanism to study how to intelligently combine GA with other heuristics is new, and needs additional research to determine the most effective meta heuristic model.

Since heuristics cannot guarantee optimality, the development of a measure of quality is necessary. What we usually do in validations heuristic results is to assess the solution value, solution running time, complexity of programming codes, and various statistics including maximum value, minimum value, mean, standard deviation, and the estimated global optimum.

These are often compared against results generated by other heuristic techniques, or ideally against an exact solution generated by traditional mathematical programming techniques. However, if the exact solution is elusive, a comparison against other heuristics only provides relative validation. One might logically ask about the quality of solutions generated by the other heuristics, and whether this comparison sheds light on overall solution quality. As a result, one gap in the literature is the development of a solution quality index. This opens an area of research for professional statisticians to apply new statistics to validate heuristic results.

Another fertile area of research involves integrating the theories and technologies of heuristics with relationships developed in other areas. For example, we could develop effective partnerships between landscape ecology and forest planning. Landscape ecologists have made significant contributions to the subject the conservation biology. Since forestry entails the alteration of landscapes, the theory and tools of landscape ecology could be integrated into a forest planning process. As the field of landscape ecology grows, its concepts and tools (e.g. remote sensing, GIS, spatial statistics, spatially explicit modeling) are increasingly being used in ecological disciplines including forestry [78]. As we know, modeling ecological processes across scales, including scaling up and scaling down, is essential in landscape ecology. In forest planning, we divide the planning into strategic, tactical and operational levels. We will also face the scaling up and scaling down problem. We could work together with landscape ecologists to integrate these problems. For example the objective function with respect to maximizing acres in wildlife habitat, Bettinger et al. (2002) mentioned that could be divided to strata-based goals, minimum-patch-size goals, and complementary-patch goals, to illustrate that the range of factors one can consider.

At this time, we have not considered the publications from the conference proceedings, graduate-level dissertations and public agencies and advances have been reported in these gray literature, so we leave this job for other researchers. In addition, although we have found theoretical papers in our review that do not specifically relate to spatial forest planning, we did not study the relationship between these and any related applied paper. This should be a time-consuming, but interesting job, because we may eventually infer the kinds of theory in that may have successful application in forest planning.

CONCLUSIONS

We investigated the difference between the early period (1995 and prior) and recent period (2000 and after) with respect to spatial forest planning research (Figure 2.12). The results illustrate that researchers and practitioners have relied more on heuristic techniques in the latter period than the early period. At the same time, we find that researchers and practitioners still attempt to use traditional, exact methods no matter what the period is being considered. Due to the increase in the complexity of the planning environment, the type of objective function has shifted slightly from commodity production to other concerns. When the constraint components in the papers are considered, we find that reliance on wildlife, aquatics, and biodiversity constraints have not changed much as time has passed. However, less emphasis has been placed on economics or commodity production in the latter period than the early period, and more emphasis has been placed on other constraints in the latter period.

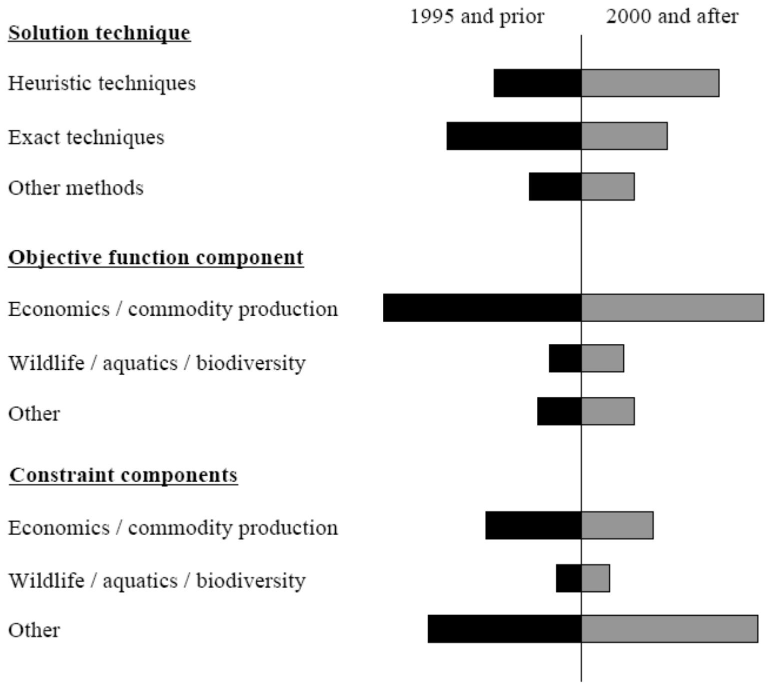

Figure 2.12: Differences between the early period and recent period

The type of spatial forest planning problems being solved has evolved over the past 20 years. The trends suggest that forest-level planning publications have increased in the journals examined over the past fifty years, however the number of publications seem to have stabilized in the last few years [23], and perhaps has been decreasing since 2002. While we found the rate of publication easing in the last few years, the reason for this is not clear. For example, one could argue that the science has matured significantly, and that novel approaches to illustrating solutions to complex management problems are becoming moot. In fact many approaches to spatial forest planning have been proposed. Perhaps the questions now lie with determining efficient methods for designing constraint sets, or with designing adaptive heuristics that leave parameterization to the algorithm rather than the user. The rate has not eased due to a reduction in available journals. In fact it is arguable that the aims and scope of many international journals leave open the opportunity to publish spatial forest planning research. In addition, a number of new online journals have appeared in the last decade, providing more outlets for research results. One aspect concurrent with the maturing of the science relates to the validation of results. Perhaps higher standards in this area have influenced the quality of peer-reviewed literature, although we did not test this hypothesis here.

It is difficult to predict which methods will dominate quantitative forest planning in the future. The two comprehensive reviews we located both discussed the possibility that the hierarchal structure could be divided into strategic, tactical and operational planning. Strategic forest plans attempt to develop broad strategies related to harvest levels, habitat levels, and economic expectations. Tactical forest plans determine where activities will be placed on a landscape and may require integer decision variables [23]. The operational level involves the determination of a land use plan for an area of the forest, and forest operations problems that represent short-term issues, such as harvesting, production, hauling, planting, pest control, fire management, and road building and maintenance [166]. Since exact methods have the advantage of ensuring that the solution one finds is optimal, the use of these seems valuable for all three levels of planning. However, most planning problems we now face are either tactical or operational, and involve complex problems with discrete integer variables, thus researchers and practitioners have embarked upon solving these problems using heuristic methods.

From this extensive and world-wide forest planning review, we are convinced that the past 20 years represents the seminal period for the development of the spatial forest planning methods. The literature review results convince us that methods used in spatial forest planning have shifted from exact algorithms to heuristic techniques. At the same time, researchers and practitioners have attempted to adopt various other methods to solve forest planning problems. In addition to the economic and commodity production objectives, an increase in ecological and social objectives has been noted. Besides economic and commodity production constraints, adjacency and green-up relationships are now also considered important constraints for industrial and managers in North America. Compared with raster data, vector data are more often used in the planning process. Hypothetical data are used by researchers to introduce new methods or compare various methods. To the extent that forest planning is of concern to forest policy makers, hypothetical examples are of as much value as specific real-life examples, although it was not unexpected to find that 35% of the papers failed to address a real-life problem. The geographic extent of the papers we located is world-wide, however not evenly spread across the world: the United States, Canada, and Europe provide most of the work in this area. Spatial restrictions or objectives in the process are the trend for the forest planning problems. GIS technology is a widely-used tool in forestry and natural resource management, yet thus far has had limited application (generally used as an input tool) in the forest planning process. More research should be conducted to continue to integrate GIS with forest planning algorithms. The gaps in knowledge that we have identified leave room for further investigation into mixed integer methods, applications of new heuristics to spatial problems, exploration of appropriate heuristic parameters, development of a solution quality index, integration with other fields utilizing spatial relationships, and a broader examination of the non-peer-reviewed literature.

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CHAPTER 3

APPLICATION OF PARTICLE SWARM OPTIMIZATION FOR SOLVING SPATIALLY CONSTRAINED FOREST PLANNING PROBLEMS[1]

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ABSTRACT

Locating alternative scheduling methods to address complex spatial forest planning problems is an important body of research and development in forest planning. As a problem grows in size, it may exceed anticipated time limits for locating a solution using mathematical programming approaches. Therefore one alternative is to generate feasible and efficient solutions with heuristics. Particle swarm optimization (PSO) is a promising new population-based heuristic for spatial forest planning, and is applied here in order to maximize the net present value of a forest plan. The algorithm gradually converged upon a final solution with some appropriate modifications, and a reasonable objective function value was reached. However, only 86% of global the optimal value could be located with PSO. As a result, from the work presented here we conclude that PSO might only be useful for refining "good" solutions to typical spatially-constrained forest plans.

Keywords: Spatial forest planning, Mathematical programming, Heuristics, Modeling techniques

INTRODUCTION

Forest management design is considered to be a challenging part of the management planning process (Baskent and Jordan 2002). It can include spatial goals, such as adjacency constraints, forest structure, and spatial patterns of habitats for wildlife populations (Bettinger et al. 2002). Additionally, non-spatial goals are commonly included in the design, such as economic analyses (net present value, economics, optimal stand rotation ages), and commodity goals (wood production, wood supply, harvest scheduling, sustained yield, allowable cut)

(Bettinger and Chung 2004). Green-up (adjacency) constraints, which address the juxtaposition of harvests and habitat, are considered to be the most widely used spatial constraints in forest planning today (Bettinger and Zhu 2006). With spatial goals included, forest planning problems are combinatorial problems by nature (Bettinger et al., 2002). Our former research has reported that most spatial forest planning research (about 40%) has been centered on problems facing the management of western U.S. forests, about 20% has been centered on European forest management problems, and about 20% focuses on Canadian forest management problems (Shan et al., 2008). In the United States, the most common green-up constraint is the maximum clearcut size limitation.

Two general bodies of research and development in forest planning are: (1) to find ways to incorporate complex goals into traditional, exact algorithms (such as linear and integer programming); and (2) to find alternative scheduling methods to solve the complex spatial forest planning problems (Bettinger et al. 2007). Consequently, two basic methodologies are traditional mathematical programming methods and heuristic methods. Mathematical programming methods are sub-divided into exact techniques (linear programming, goal programming, integer programming, mixed integer programming, and non-linear programming) and other techniques (dynamic programming, simulation, and others). When problems are intractable or solution processes exceed the time limits for mathematical programming approaches, feasible and efficient solutions can be produced with heuristics (Bettinger et al. 2003). One relevant classification of heuristic methods is to separate them based on whether a population of solutions is needed or whether a single solution is modified and improved. A point-based (single solution) algorithm will only have a unique solution per iteration, and we update the best one with new solution obtained if it is better than the best we have found before. In point-based algorithms, we only need to define the current solution and use meta-heuristics to find a new solution. With population-based algorithms, we have to define a current population of feasible forest plans and a new population in each iteration. Additionally, we also need to initiate the population size and define the maximum population size allowed. Heuristic algorithms based on single solutions are currently the most widely acceptable methods in forest planning, perhaps because they involve more intuitive processes than the others. As one of the earliest and easiest heuristic method, Monte Caro Integer Programming (MCIP) is capable of quickly generating feasible solutions to the complex integer problems (Nelson and Brodie 1990). Simulated annealing (SA) is widely used in the natural resource planning and has been successfully evaluated by Crowe and Nelson (2005) on a range of harvest scheduling problem instances. Threshold Accepting (TA) is another heuristic method similar to SA, and has been used to solve spatial forest planning problems with ecological and economic goals (Bettinger et al. 2003). Although Tabu search (TS) may not be an optimal choice for agricultural systems (Mayer et al., 1998), enhancements to TS can allow it to produce high-quality feasible solutions (Legus et al., 2007). Another recently developed point-based heuristic algorithm is the raindrop method (Bettinger and Zhu 2006). Ant colony optimization (Zeng et al. 2007b), genetic algorithms (Hassan et al. 2005), and particle swarm optimization (PSO) (Shi and Eberhart 2000) are all examples of population-based heuristics.

PSO is a promising new population-based heuristic developed by Eberhart and Kennedy (Eberhart et al. 1996; Kennedy and Eberhart 1995). The original goal of PSO was to graphically simulate the stylish but unpredictable choreography of a bird flock. Later on, from the view of evolution algorithms, it was realized that the conceptual model of PSO could be used as an optimizer. It is said that the most practical potential areas for the application of PSO are in multi-objective optimization, classification, pattern recognition, biological system modeling, scheduling (planning), signal processing, games, robotic applications, decision making, simulation, and identification (Eberhart and Shi 2001). Some specific areas such as multi-objective optimization, planning, and decision-making have many similarities with spatial forest planning problems. My hypothesis is that PSO should be effective for development of efficient spatial forest plans, yet it may require some modifications. Limited trials on the effectiveness of PSO in spatial forest planning has shown that it either has great potential in the area of forest planning (Pukkala 2009), or very limited potential (Potter et al., 2009).

Given the relative lack of attention of PSO in forest planning, it is still considered a new technique to spatial forest planning problems. This work is aimed at applying PSO to a typical southern forestry planning problem that involves maximizing net present value of planned management activities while adhering to green-up, adjacency, and periodic (20-year) timber harvest constraints.

METHODS

Introduction to PSO

The basic formulation of PSO is shown below:

$$v_{id}^{t+1} = w v_{id}^{t} + \varphi_1 \beta_1 (p_{id}^{t} - x_{id}^{t}) + \varphi_2 \beta_2 (p_{gd}^{t} - x_{id}^{t})$$
$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}$$

Where w is the inertial weight which controls the impact of the previous history of velocities on the current population, φ_1 and φ_2 are constants which determine the balance between the influence of the individual’s knowledge (φ_1) and that of the group (φ_2), β_1 and β_2 are uniformly distributed random numbers defined by some upper limit $\beta_{\max}$. p_{id}^{t} and p_{gd}^{t} are the individual’s previous best position and the group’s previous best position. v_{id}^{t} is the current velocity, and x_{id}^{t} is the current position in the dimension considered. In PSO, the initial swarm propagates in the design space towards the optimal solution over a number of iterations based on not only the information from the particle itself, but also on the information shared by all members of the swarm (Hassan et al., 2005). PSO's advantages include that it is relatively easy to implement, it requires only primitive mathematical operators, and it has the capability of escaping local optima (Salman et al. 2002).

The standard PSO could only optimize problems in which the elements of the solution are continuous real numbers (Pugh and Martinoli 2006). We modify the standard PSO algorithm for solving problems with binary-valued solution elements (i.e., binary decision variables). The revised equations are shown below:

$$v_{id}^{t+1} = wv_{id}^{t} + \varphi_1\beta_1(p_{id}^{t} - x_{id}^{t}) + \varphi_2\beta_2(p_{gd}^{t} - x_{id}^{t})$$

$$x_{id}^{t+1} = \begin{cases} 1 & if\,(rand() < S(v_{id}^{t+1})) \\ 0 & Otherwise \end{cases}$$

Where $S(v_{id}^{t+1})$ is the sigmoid function

$$S(v_{id}^{t+1}) = \frac{1}{1+e^{-v_{id}^{t+1}}}$$

Particles' velocities on each dimension are clamped to a maximum velocity *Vmax* which is a parameter specified by the user, and *Vmax* determines the resolution, with which regions between the present position and the target (best so far) position are searched (Eberhart and Shi 2007). A high *Vmax* means that particles might fly past good solutions, while a low *Vmax*, on the other hand, means that particles may not explore sufficiently beyond locally good regions (Eberhart and Shi 2007). An inertia weight is used to better control exploration and exploitation (Pan and Wang 2008). A large inertial weight facilitates the global exploration (searching new areas), while a small one tends to facilitate local exploration (Parsopoulos and Vrahatis 2002).

Problem formulation

A geographic information system (GIS) database containing 100 vector polygons of stands covering 5,000 acres was created for the forest planning exercise. Since we assumed later that the maximum clearcut limitation was 240 acres, the polygon sizes ranged from 26 to 240 acres. The initial forest age class distribution over the entire forest land was simulated as uniformly distributed between age 0 and age 40. One of two site-indices (60 and 70, base age 25) was randomly assigned to each stand. We consider 10 management regimes based on projections from SIMS, which is a state-of-the-art forest stand growth simulator for the southern United States developed by Forest Tech International. In these 10 management regimes (Table 3.1), we assumed the following: hand planting costs $38.41 per acre; seedling cost $44.18 per thousand; burning treatment cost $34.41 per acre; and medium chemical treatment cost $97.61 per acre (Folegatti et al. 2007). At the same time, we assumed that 726 trees per acre are planted, and the first year survival rate is 90%.

The stumpage prices were obtained from Timber-Mart-South (4Q, 2008), and were assumed to be $8.38 per ton for pulpwood, $17.64 per ton for chip-n-saw and $27.62 per ton for sawtimber. At the same time, the discount rate we consider is 6%.

Table 3.1: Ten management regimes obtained from SIMS.

Regime	Description
1	Thin at age 12 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre.
2	Thin at age 14 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre.
3	Thin at age 16 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre.
4	Thin at age 12 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre. Then again at age 18 from below to a residual basal area of 50 ft^2/acre.
5	Thin at age 14 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre. Then again at age 20 from below to a residual basal area of 50 ft^2/acre.
6	Thin at age 16 at 5^{th} row + selection to a residual basal area of 55 ft^2/acre. Then again at age 22 from below to a residual basal area of 50 ft^2/acre.
7	Thin at age 12 at 5^{th} row + selection to a residual basal area of 65 ft^2/acre. Then again at age 18 from below to a residual basal area of 60 ft^2/acre. Finally at age 24 from below to a residual basal area of 55 ft^2/acre.
8	Thin at age 14 at 5^{th} row + selection to a residual basal area of 65 ft^2/acre. Then again at age 20 from below to a residual basal area of 60 ft^2/acre. Finally at age 26 from below to a residual basal area of 55 ft^2/acre.
9	Thin at age 16 at 5^{th} row + selection to a residual basal area of 65 ft^2/acre. Then again at age 22 from below to a residual basal area of 60 ft^2/acre. Finally at age 28 from below to a residual basal area of 55 ft^2/acre.
10	No thinning

The spatial forest planning problem was formulated with a planning objective of maximizing the net present value. Timber products were assumed as the only profitable outcome. The planning horizon is 20 years long with 1-year long planning periods. We assumed the unit restriction model (URM) (Murray 1999) of adjacency. Wood-flow constraints were applied in order to make sustainable and stable yields over the 20 year planning horizon. In other words, the harvested volume in each period should not deviate too far from the average (maximum 20% deviation in this case). An ending inventory constraint was assumed, which prevented the depletion of timber stands at the end of planning horizon, where at least 90% of the original timber volume was required to remain. A minimum cutting age constraint was considered, where trees less than 20 years old are not considered to be clearcut. All in all, this is similar to a typical planning problem for a southern U.S. company. The problem formulation is:

Maximize CV+TV-RC (1)

$$CV = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{r=1}^{R} X_{itr}(V_{itr.saw}P_{saw} + V_{itr.cn}P_{cn} + V_{itr.pulp}P_{pulp}) / (1+d)^{t-0.5} \quad (2)$$

$$TV = \sum_{i=1}^{N}\sum_{t=1}^{T}\sum_{r=1}^{R} X_{itr}(V'_{itr.saw}P_{saw} + V'_{itr.cn}P_{cn} + V'_{itr.pulp}P_{pulp}) / (1+d)^{t-0.5} \quad (3)$$

$$\text{RC} = \sum_{i=1}^{N}\sum_{t=1}^{T} X_{itr}((P_{hand} + P_{burn} + P_{chem})A_i + 726*0.9A_i * P_{seed} / 1000) / (1+d)^{t-0.5} \ \forall r \quad (4)$$

subject to :

$$\sum_{r=1}^{R}\sum_{t=1}^{T} X_{itr} \le 1 \ \forall i \quad (5)$$

$$X_{itr} + X_{jtr} \le 1 \ \forall i, r, j \in N_i \quad (6)$$

$$0.8 * \sum_{i=1}^{N} \sum_{r=1}^{R} X_{itr} V_{itr} \leq \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r=1}^{R} X_{itr} V_{itr} / T \quad if \quad \sum_{i=1}^{N} \sum_{r=1}^{R} X_{itr} V_{itr} > \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r=1}^{R} X_{itr} V_{itr} / T \quad \forall t$$
$$0.8 * \sum_{i=1}^{N} \sum_{r=1}^{R} X_{itr} V_{itr} \geq \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r=1}^{R} X_{itr} V_{itr} / T \quad if \quad \sum_{i=1}^{N} \sum_{r=1}^{R} X_{itr} V_{itr} < \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{r=1}^{R} X_{itr} V_{itr} / T \quad \forall t \tag{7}$$

$$\sum_{i=1}^{N} V_{il} \geq 0.9 * \sum_{i=1}^{N} V_{i0} \tag{8}$$

$$Age_{itr} \geq 20 \; if \;\; X_{itr} = 1 \tag{9}$$

Equation 1 is the objective function, which is to maximize the Net Present Value (NPV). Equations 2 and 3 are used to develop the clearcut and thinning revenue components of the objective function. Equation 4 is used to develop the regeneration cost component of the objective function. Equation 5 indicates that each stand could be only harvested once during the planning horizon. Equation 6 describes the URM constraint which indicates that there is a one-year green-up requirement between adjacent clearcut harvests. Equation 7 assures the wood harvested in each time period is within 20% of the annual average harvest volume. Equation 8 represents the ending-inventory constraint. Equation 9 refers to the minimum harvest age constraint.

Where

A_i = area of stand i

Age_{itr} = the age of management unit *i* at time *t* period for assigned *r* management regime

CV = clearcut value

d = discount rate assumed

i,j = an arbitrary harvested unit

N = total number of harvest units

N_i = the set of all harvest units adjacent to unit *i*

P_{cn} = stumpage price for chip-n-saw timber

P_{pulp} = stumpage price for pulpwood

P_{saw} = stumpage price for sawtimber

P_{hand} = hand plant cost

P_{burn} = burn treatment cost

P_{chem} = medium chemical cost

P_{seed} = seedling cost

t = period in which harvest activities occur

r = management regime under which harvest activities occur

RC = Regeneration cost

T = total number of time periods in the planning horizon

TV = thinning value

V_{i0} = total timber volume in the stands before any harvest activities

V_{il} = timber volume left on the stands after the planning horizon

V_{itr} = timber volume harvested in time period t, from management unit i under management regime r

$V_{itr.cn}$ = chip-n-saw volume harvested in time period t, from management unit i under management regime r

$V_{itr.pulp}$ = pulpwood volume harvested in time period t, from management unit i under management regime r

$V_{itr.saw}$ = sawtimber volume harvested in time period *t*, from management unit *i* under management regime *r*

$V'_{itr.cn}$ = chip-n-saw volume thinned in time period *t*, from management unit *i* under management regime *r*

$V'_{itr.pulp}$ = pulpwood volume thinned in time period *t*, from management unit *i* under management regime *r*

$V'_{itr.saw}$ = sawtimber volume thinned in time period *t*, from management unit *i* under management regime *r*

$$X_{itr} = \begin{cases} 1 & \text{if management unit } i \text{ is treated in time period } t \text{ under management regime } r \\ 0 & \text{otherwise} \end{cases}$$

Among the various types of adjacency constraints, Type I nondominated constraints have been shown to result in significantly lower solution times, new ordinary adjacency matrix have also shown to perform better in problems containing mainly immature forests, and pairwise constraints have been sown to perform better in forest planning problems containing overmature and old-growth forests (Bettinger and Zhu 2006). Since our example forest problems contain mature forests, in this research, adjacency constraints were formulated as pairwise type among the various adjacency formulations.

Application of PSO

Regarding the problem where we intend to maximize the net present value of forest plans, we use a landscape represented by 100 management units, and each can be scheduled for management with one of ten possible management regimes. Therefore, the length of a PSO particle vector is 200, and the first 100 cells represent the cutting period for each stand. The last 100 cells represent the regime number for each stand.

A standard PSO was applied to solve the designed problem. Since for these choices of the acceleration coefficients, no single choice is superior to the others (Omran 2004), for a standard PSO, we choose φ_1 as 1.8 and φ_2 as 1.5 because we want a larger cognitive parameter than a social parameter but with $\varphi_1 + \varphi_2 \leq 4$ (Parsopoulos and Vrahatis 2002: Carlisle and Dozier, 2001) is assumed to provide better solutions. An inertia weight was tested that ranged from 0.1 to 0.9 with an interval of 0.01. The population was tested using 8 different values: 50, 100, 200, 500, 1000, 2000, 5000, 10000. The maximum velocity was tested that ranged from 1 to 9 with an interval of 1. The standard PSO could not find a solution with those parameter settings.

Several modifications were implemented in this study. We added a repair process to PSO to fix infeasible harvest plans. In each generation of the evolution of the PSO, the position of all particles are checked and particles with infeasible position combinations (schedules) with respect to clearcut timing and placement are repaired before the swarm evolves again, using this approach:

1) Scan the particles in the population. If there is any violation of adjacency rules in a particle, go to step 2.
2) Find all pairs of stands that violate adjacency rules in the particle. For each pair that violates the adjacency rules, change the timing of the second stand to another cutting period (adding or subtracting 1 on the value of the piece of the particle)
3) Check the particle again, if some new violations are created during repair process, go back to step 2 until the all violations are fixed.
4) Go back to step 1 until all particles are once again feasible and eligible for evolution.

A major problem relates to the starting conditions, where each particle (solution) is randomly developed. Here, it is very common for a particle to violate the constraints. This condition is against the swarming spirit of PSO since all particles are assumed to survive (be feasible) in the next iteration in PSO. For our problem, with a population of 100 particles (solutions), on average, more than 99 particles are regenerated in the first iteration of the search process. A penalty function term was added to the original fitness function to make the particles representing infeasible solutions have a low fitness score (empirically set to 10^6).

Since PSO is likely to become stuck in local minima, we would randomly choose a certain amount of particles whose velocities will be reset in order to force swarms out of local minima to trigger a new search process (Cui et al. 2008).

The disturbance strategy could be described as below:

$$If \;\; t - t_u > u, \; Then \;\; reset \;\; v$$

Where t_u is the iterative step of the global best adaptive value that has been updated and searched recently. During this process, a certain number of particles according to a random probability *r* will be selected and the velocities of them will be reset if the continuous step *u* (a natural number) iterations of the global best adaptive value that we have looked have been not been updated.

With the development of experience with the inertia weight, although the maximum velocity factor couldn't always be eliminated, the particle swarm algorithm works well if *Vmax* is a function of the other parameters (Eberhart and Shi 2007). By doing this, we don't need much other information to set *Vmax* each time the particle swarm algorithm is used.

RESULTS

Eight different starting populations were tested (50, 100, 200, 500, 1,000, 2,000, 5,000, 10,000) and 100 solutions were generated using each population size. Table 3.2 summarize these results under a specific parameter setting (set inertia weight as 0.3 and φ_1 and φ_2 as both 2 respectively). I found that the population size did not significantly affect the results for this problem. Although an increase in the number of particles increases diversity, thereby limiting the effects of initial conditions and reducing the possibility of being trapped in local minima (Omran 2004), this did not affect the generation of high-quality final solutions.

Table 3.2 Results (net present value in us dollars) from the modified PSO using different population sizes.

Population size	Maximum (best)	Minimum (worst)	Average	Standard deviation
50	14,806,807.95	9,321,748.85	12,442,105.28	1,243,239.92
100	14,875,715.26	8,954,197.95	12,397,153.41	1,281,016.00
200	14,655,700.59	8,748,367.83	12,020,780.35	1,238,831.25
500	14,835,925.39	9,433,300.69	12,296,153.51	1,227,562.16
1,000	14,789,432.42	8,862,149.37	12,239,738.42	1,223,684.28
2,000	14,792,573.11	8,912,146.04	12,068,420.31	1,203,916.03
5,000	14,801,284.06	9,014,716.30	12,190,426.73	1,295,715.70
10,000	14,811,027.16	9,002,153.74	12,310,364.43	1,282,175.45

An inertia weight was tested that ranged from 0.1 to 0.8 with an interval of 0.1 (100 solutions generated using each inertia weight). Since no significant effect of population size was assumed, a population size of 50 is chosen to conduct further analysis. Table 3.3 summarizes these results under a specific parameter setting (set the population size to 50 and φ_1 and φ_2 to 2). From these results, we find that inertia weight should be relatively low. For our spatial forest planning problem, the best solution was generated with a 0.3 inertia weight, which to some extent achieves a balance between global and local exploration.

Table 3.3 Results (net present value in us dollars) from the modified PSO using different inertia weights.

Inertia weight	Maximum (best)	Minimum (worst)	Average	Standard deviation
0.1	14,197,071.99	8,948,748.39	12,368,232.54	1,278,793.57
0.2	14,698,014.05	9,046,706.24	12,396,809.29	1,265,921.35
0.3	14,806,807.95	9,321,748.85	12,442,105.28	1,243,239.92
0.4	14,795,712.64	9,267,098.25	12,410,625.36	1,270,257.18
0.5	14,640,928.38	9,105,074.39	12,330,843.17	1,269,809.25
0.6	14,681,619.05	9,143,298.07	12,301,842.08	1,257,294.32
0.7	14,690,357.16	9,054,672.81	12,291,678.27	1,272,358.28
0.8	14,701,735.29	9,026,735.42	12,281,738.62	1,278,861.07

Four sets of the acceleration coefficients, φ_1 and φ_2, were then evaluated for the spatial forest planning problem, and Table 3.4 summarizes these results (set population size = 50 and inertia weight = 0.3) based on 100 solutions for each set. When φ_1 is higher than φ_2, no single choice is superior to the others. As a result, the same φ_1 and φ_2 values were adopted as the standard PSO (1.8 and 1.5).

Table 3.4 Results (net present value in us dollars) from the modified PSO using different acceleration coefficients.

Acceleration coefficients	Maximum (best)	Minimum (worst)	Average	Standard Deviation
$\varphi_1=2$ $\varphi_2=2$	14,806,807.95	9,321,748.85	12,442,105.28	1,243,239.92
$\varphi_1=1.8$ $\varphi_2=1.5$	14,826,928.31	9,423,174.92	12,492,807.36	1,239,248.06
$\varphi_1=1.9$ $\varphi_2=1.4$	14,807,963.47	9,364,186.79	12,486,702.18	1,244,309.13
$\varphi_1=1.5$ $\varphi_2=1.8$	14,784,382.07	9,295,186.21	12,394,803.81	1,244,246.04

After these preliminary tests, one hundred solutions were then generated by the modified PSO for our hypothetical 100-unit southern U.S. forest problem (Figure 3.1). The parameter setting is population size = 50, inertia weight = 0.3 and $\varphi_1=1.8$ $\varphi_2=1.5$. The best objective function value we could locate is $14,875,715.26 which is about the 86% of the corresponding integer programming solution ($17,219,130). All of the results provided here were developed using a personal computer equipped with a 3.0 MHz Pentium processor and a 1.0GB memory. The PSO algorithm was developed using the JAVA programming language, and the average time to generate a solution using a modified PSO was about 5 minutes when using parameter settings noted above.

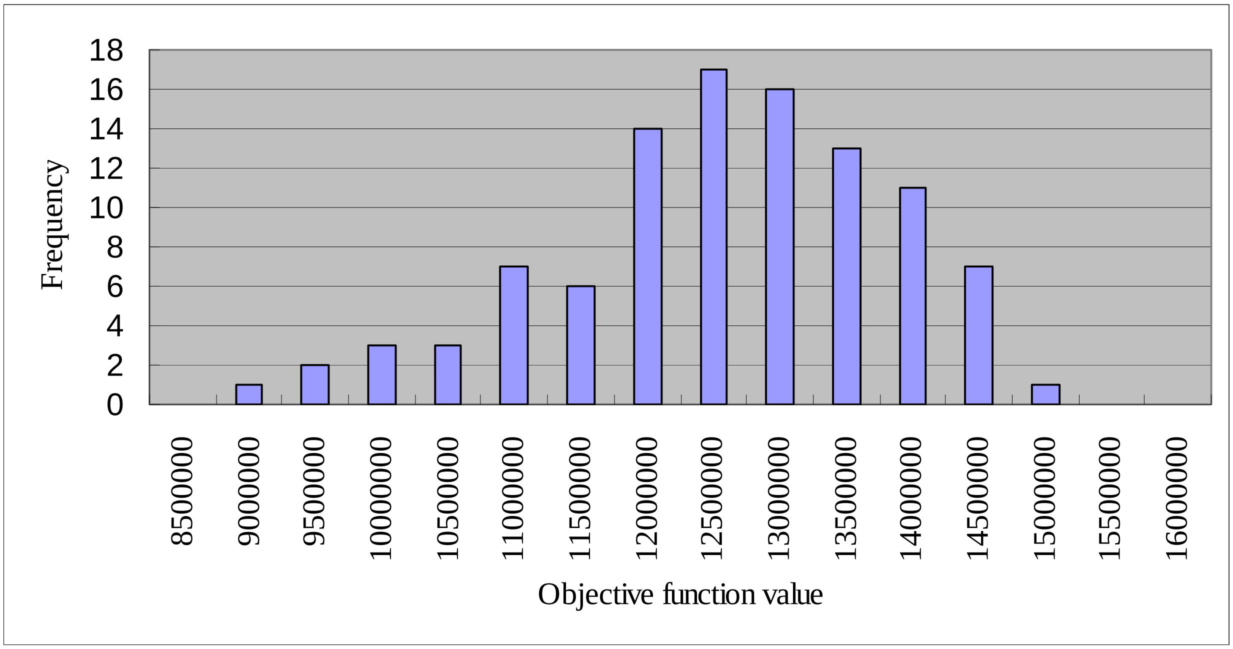

Figure 3.1 Distribution of the 100 modified PSO solutions on the 100-unit spatial forest planning problem.

DISCUSSION AND CONCLUSIONS

In this study it was necessary to modify the standard PSO process for typical combinatorial problems in forest planning. Without modification, PSO is not possible to generate a solution that will meet all the constraints. The algorithm gradually converged upon a final solution with some appropriate modifications, and a reasonable objective function value was reached. Without modification, a standard PSO could not solve the typical southern forestry planning problem. One possible reason is that the swarm of particles may prematurely converge (Van den Bergh 2002). The revised PSO is quite different from the original PSO because forest planning problems are conceptually different from the unpredictable choreography of a bird flock (an unconstrained problem) for which PSO was originally designed. However, with the problem illustrated here, only 86% of the optimal value could be located. By comparison, Potter et al. (2009) reported that PSO did not work well for a small problem which attempted to maximize the even-flow of harvested timber volume.

In order to use PSO on a constrained spatial forest planning problem, one major problem we found is that a large number of particles (solutions) in a new generation may be infeasible. Potential solutions to this problem include: (1) keep the particles in the feasible space by changing the position updating formulas; (2) abandon those infeasible particles; (3) apply a penalty to those particles that are infeasible (as suggested by Richards and Gunn 2003). My modified PSO contained all three these solutions. Several further improvements in PSO maybe necessary to improve results. Bi et al. (2008) improved a PSO algorithm based on statistical laws of fitting values and dynamic learning factors. They proposed that "bad" particles should evolve by a "social model" to accelerate convergence, and "good" particles should be evolved by "cognitive model" to enhance the converging precision. The related φ_1 and φ_2 then should be not be constant (as I assumed), and instead should be controlled by some function, and the best function should be located experimentally. Although this modification seems complex, it suggests an area for further exploration. In addition, since this is an integer problem, further exploration into the appropriate φ_1 and φ_2 values would seem necessary. We may find, for example, that $\varphi_1+\varphi_2 \geq 4$ would be more appropriate in these cases.

Another approach to using inertia weights is to adapt them using a fuzzy system. The classical fuzzy system is usually composed of a set of rules, several inputs, and one output. Shi and Eberhart (2000) published one paper on this approach, with the global best fitness for the current generation and the current inertia weight as two inputs. The output is then the change in inertia weight. Shi and Eberhart (2000) reported that this works well on the benchmark functions, such as asymmetric initialization.

Another interesting conclusion from this work presented here is that PSO might only be useful for refining “good” solutions to forest planning problems. In order to test this hypothesis, a short chapter (chapter 5) will be included in this dissertation to determine whether PSO is effective for these types of problems when the initial solutions are relatively good, as compared to randomly generated. In other research fields, PSO is usually combined with a point-based search process in a meta-heuristic (multiple heuristic) process to improve solution quality. In one case, PSO was combined with a local search process to address the traveling salesman problem (Li et al. 2006). Simulated annealing has also been combined with PSO to solve the partner selection problem in the research of virtual organizations and supply chain management (Zhao et al. 2005).

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CHAPTER 4

THE DEVELOPMENT OF A SOLUTION QUALITY INDEX FOR HEURISTIC TECHNIQUES USED IN SPATIAL FOREST PLANNING[1]

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ABSTRACT

Heuristic optimization algorithms seek to locate good feasible solutions to spatial forest planning problems in circumstances where the complexities of the problem, or the limited time available, do not allow the development of an exact solution. With regard to heuristics, most researchers and practitioners use various traditional statistics to assess the solution quality. In this research, we try to assess methods whereby one can develop a relationship to assess the quality of a new heuristic (when applied to a similar planning problem) without having to locate an exact solution. A minor goal is to propose a method one can pursue to estimate heuristic performance in the absence of an exact solution to a problem. Three different statistical methods were applied to develop a measure of heuristic quality in spatial forest planning. RMSE is used to compare with different models. My recommendation is to use a non-linear regression approach. However, more work should be conducted to determine whether a non-linear regression model can be adapted to different kinds of spatial forest planning problems.

Keywords: Statistical methods, Mathematical programming, Modeling techniques

INTRODUCTION

Forest planning models that optimize the spatial arrangement of forest resources to meet a set of management goals could be categorized as traditional mathematical optimization techniques and non-traditional heuristic programming or simulation techniques (Bettinger et al. 2002). Mathematical programming is frequently used to address non-spatial forest planning problems. Although mixed integer programming and integer programming have been used to solve forest planning problems with green-up constraints, and while many problems have to be relatively to be treatable small (Yoshimoto and Brodie 1994a), advances in computer technology are allowing large problems to be solved exactly, yet these may require a significant amount of processing time.

Heuristic optimization algorithms seek to locate good feasible solutions to spatial forest planning problems in circumstances where the complexities of the problem, or the limited time available, do not allow the development of an exact solution. With regard to heuristics, most researchers and practitioners use various statistics such as the maximum value, minimum value, mean value, standard deviation, and an estimated global optimum solution to assess the solution quality. Although worst case scenarios and probabilistic analysis of algorithms have produced insight on some classic models, most of the heuristics developed for spatial forest planning problems must be evaluated empirically—by applying procedures to a collection of specific instances (i.e., a sample of solutions) and comparing the observed solution quality and computational burden.

The ultimate goal of this work is to assess methods whereby one can develop a relationship to assess the quality of a new heuristic (when applied to a similar planning problem) without having to locate an exact solution. A minor goal is to propose a method one can pursue to estimate heuristic performance in the absence of an exact solution to a problem. Therefore, this research will examine methods one can pursue to evaluate solution quality of heuristics when a global solution is unknown, and provide direction for similar assessments of heuristics applied to other problems.

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METHODS

In order to develop a process for evaluating heuristic solution quality, context must be described. Therefore, this section outlines the forest planning problem to be addressed, the data used, the heuristic techniques assessed, and the statistical processes that are examined.

Problem formulation

A spatial forest planning problem was designed with a planning objective of maximizing an even-flow of wood volume. For simplicity, a clearcut was assumed to be the only treatment on the forestland. At the same time, we assumed the unit restriction model (URM) (Murray 1999) would be used to restrict the timing and placement of harvests. Here, no two contiguous stands were allowed to be treated in the same planning period. A wood-flow objective was assumed in order to provide sustainable and stable yields over a planning horizon. In other words, the planned harvested volume in a time period should not deviate too far from planned harvest volumes in other time periods.

The problem formulation for this situation is:

Minimize $\sum_{t=1}^{T}(H_t - T)^2$ (1)

Subject to

$X_{it} + X_{jt} \leq 1 \quad \forall i, j \in N_i$ (2)

$\sum_{i=1}^{N}(X_{it}V_{it}A_i)\text{-H}_t\text{=0} \quad \forall t$ (3)

$\sum_{t=1}^{T} X_{it} \leq 1 \quad \forall i$ (4)

Where

A_i = area of management unit i

i, j = an arbitrary harvested unit

N = total number of harvest units

N_i = the set of all harvest units adjacent to unit i

t = period in which harvest activities occur

T = total number of time periods in the planning horizon

H_t = total scheduled harvest volume for time period t

V_{it} = timber volume harvested in time period t, from management unit i

$$X_{it} = \begin{cases} 1 & \text{if management unit } i \text{ is treated in time period } t \\ 0 & \text{otherwise} \end{cases}$$

Equation 1 is the objective function which is to minimize the deviation of periodic planned harvests from a harvest target. Equation 2 describes the URM adjacency constraint. Equation 3 is an accounting row that adds up the planned harvests for each time period. Equation 4 indicates that each stand could be only harvested once during the planning horizon.

Forest data

Five hypothetical forests are used and assumed to be in need of management under the previously-described problem formulation. The Slash Tract is 6250 ha in size, and forest volumes (tons per acre) were randomly assigned to each age (0 to 30 years) based on slash pine (*Pinus elliottii* Engelm.) volumes found in Bailey et al. (1982). All 625 stands, designed as a 25 by 25 unit grid with each grid cell representing 10 ha, have uniform stocking and 15% fusiform rust (*Cronartium fusiforme* Hedgcock & Hunt ex Cummins) stem cankers. Each time period is 5 years long, thus there are 15 years in the time horizon.

The North Tract consists of 40 stands covering 631 ha with parcels of 9, 18, and 36 ha. Each stand is assigned randomly with potential northern U.S. hardwood yields for white oak (*Quercus alba* L.), red oak (*Quercus rubra* L.), and other red oaks (e.g., *Quercus palustris* Muenchh.). The estimated volumes for oak-hickory forest types in Wisconsin (Essex and Hahn 1976) are used as the yields. As with the Slash Tract, there are also 3 time periods, yet each are one decade long, thus the time horizon here is 30 years.

The Lincoln Tract is a coniferous forest located in the western United States (Bettinger et al. 2009a). The forest is contiguous, with 87 stands covering 4,550.3 acres (1,841.5 ha). Most of the area is covered with Douglas-fir (*Pseudotsuga Menziesii*) stands with a minor percentage of western hemlock (*Tsuga heterophylla*) and other conifers. Here, the time horizon is 15 years long, and is divided into 3 five-year time periods. The volume per acre is expressed in units of thousand board feet (MBF).

A pine and hardwood forest located in the southern United States, the Putnam Tract, is composed of 81 timber stands, with 2,062 acres (1,053 ha) in a contiguous block. The primary component of the tract is the pine plantations of various ages, while another 25 percent is natural pine stands and 17 percent is hardwood stands. Here, the time horizon is 15 years, divided into 3 five-year time periods. The timber volume is expressed in cords per acre on this forested property.

The Western Tract contains 73 vector polygons of stands covering 1,012 ha forest, commonly referred to as the Daniel Pickett Forest (Davis et al. 2001). Potential board foot volumes for typical western U.S. forests are assigned to these polygons, and the average size of polygons in this forest is around 13.6 ha (Bettinger and Zhu 2006). Here, three decades represent the length of the time horizon, which is divided into one-decade time periods for planning purposes. The timber volumes for this problem are expressed as MBF per acre.

Heuristic algorithms

Eight heuristic algorithms were developed to address the planning problem for the five forested properties.

Genetic algorithms

Genetic algorithms (GA) are population-based heuristic techniques based on natural selection and natural genetics (Goldberg, 1989). The term genetic algorithm was first used by Bagley (1967) in his dissertation utilizing genetic algorithms to find parameter sets in evaluation functions for playing the game of Hexapwan (Eberhart and Shi 2007). GA has then been successfully used in a variety of areas including music generation, genetic synthesis, strategic planning, and machine learning (Srinivas and Patnaik 1994). Many researchers have applied GA to forest planning problems (Bettinger et al. 2002; Boston and Bettinger 2001a; Boston and Bettinger 2001b; Boston and Bettinger 2002; Boston and Bettinger 2006; Ducheyne et al. 2004; Falcao and Borges 2002; Falcao and Borges 2001; Liu et al. 2006; Lu and Eriksson 2000; Moore et al. 2000; Pukkala and Kurttila 2005; Venema et al. 2005; Zeng et al. 2007a; Zeng et al. 2007b).With genetic algorithms, a population of feasible solutions is generated preliminarily, and each solution is represented by a chromosome. Solutions are then selected from the population based on deterministic rules or completely at random. These are then split and combined to create new solutions through a crossover process. The new solutions may then be modified slightly through a mutation process. The population is then updated, and the search continues until stopping criteria have been recognized.

In our implementation of the GA technique, a population of random feasible chromosomes is generated. One iteration is the mating of two solutions from the population.

Here, a crossover point is randomly selected, the chromosomes split, and recombined to form two children. The resulting two children are subject to potential mutations at each gene (management unit) indicating changing harvest timing. The search process stops when the total number of iterations have passed. When the search has completed, the value of the best solution is reported. After several initial trials, the most favorable parameters are chosen based on computing time and solution quality.

In our implementation of GA, based on several trial and error runs of the search process on the five tracts, following parameters were adopted:

Population size: 500

Iterations: 1,000,000

Mutation rate: 0.01

Modified genetic algorithm

For spatial forest planning problems, the best GA algorithms may be those that are modified from the original basic model. Therefore, in this research, some additional features were considered besides the simple GA: steady-state algorithm, and adaptive mutation. It is known that simple GA uses non-overlapping populations. During each generation, GA creates a brand new (but not totally unique) population of individuals consisting of new offspring created by selecting and mating from the previous population. It is assumed that GA is completely dependent upon the ability of the parents to create higher quality offspring before they are removed. However, it is not possible that all of the good traits can be passed to the offspring, which means that we may lose some good traits in the next generation. The steady-state feature indicates that there are overlapping populations. The advantage of steady-state is that it is tolerant of poor offspring. Here, we preserve the best individuals from a given generation in the next generation by removing the worst individuals in order to return the population to its original size. Generally speaking, the quality of new offspring will determine whether they stay in the population. Finally, mutation is thought to act primarily to keep the population diverse during the search process. It is assumed that for different problems, there would be different mutation rates. Generally, the mutation rate for a problem is constant, but one can use a fluctuating mutation rate that is based on each child's fitness value. We call it adaptive mutation. In this experiment, if the fitness of the children is below the average fitness, we will use a 0.9 as the mutation rate; else we use 0.11 as the mutation rate. The other parameters are kept the same as what we adopted in standard GA.

Monte Carlo integer programming

In forest management, Monte Carlo integer programming (MCIP) was first used in the area of stand-level analysis (Bullard et al. 1985). MCIP was then applied to forest-level problems (Clements et al. 1990), such as area-based planning (Nelson and Brodie 1990), and road network problems (Nelson and Finn 1991). Since it is basically a simple sampling technique, MCIP has been used to develop the initial solution for other newly developed heuristic algorithms. The standard implementation of MCIP is to randomly select units for treatment, and develop a schedule one planning period at a time until the volume goal has been met for all periods, or until a user-specified number of solutions has been examined (Boston and Bettinger 1999). One key decision made when using MCIP is the number of iterations for the model to run. Without a time limit given, since this is a sampling technique, there is a higher probability one will locate good solutions. However, results may vary significantly from the global optimal solution, since basic

MCIP does not involve any advanced intelligence to direct the search process to the optimum solution (Li 2007).

In our implementation of MCIP, based on several trial and error runs of the search process on the five tracts, following parameters was adopted:

Total Iterations: 20,000

Simulated annealing

Simulated Annealing (SA) is a point-based heuristic technique that relies on a set of logic to iteratively adjust a solution, allocating and reallocating resources to various uses, until a very good solution to a problem has been located (Bettinger et al. 2007). The original concept of simulated annealing (SA) was first published by Metropolis et al. (1953). SA has been used to address a variety of forest planning problems with different objectives, including economics (Öhman and Eriksson 2002; Turner et al. 2002), commodity production (Baskent and Jordan 2002; Lockwood and Moore 1993; Seo et al. 2005), recreation (Bos 1993), landscape design (Chen and Gadow 2002; Öhman and Lamas 2003; Öhman and Lamas 2005), adjacency issues (Crowe and Nelson 2005; Tarp and Helles 1997), road system management issues (Dahlin and Sallnas 1993), regeneration (Jorgensen et al. 1992), biodiversity (Lichtenstein and Montgomery 2003), forest structure (Liu et al. 2000; Öhman and Eriksson 1998), and wildlife habitat (Van Deusen 2001). The ability of SA to avoid being trapped in a local optimum is made possible by the occasional acceptance of inferior solutions (Lockwood and Moore 1993). Beginning with a high temperature, the method follows an approach related to the simulation of energy levels in cooling solids by generating a sequence of states (Jorgensen et al. 1992). Randomly chosen units and assigned periods of harvest usually represent an initial solution. With the change of one unit and related period of harvest in the current solution, a new solution is created. If the solution is not an improvement, an acceptance value is calculated, and the solution will still be used if the acceptance value is greater than a uniform, continuously distributed, random variable between 0 and 1.

The formula to calculate the acceptance value is based on the Boltzman probability function:

$$P(S) = \exp(-(S_2 - S_1)/ck)$$

Where $P(S)$ is the probability (between 0 and 1) to accept the inferior solution, k the Boltzman constant, and S_2 and S_1 are the solution values after and before the random change. The essential parameter here is c, the cooling rate. The larger the value c is, the higher the probability for accepting inferior solutions.

The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of SA:

Initial temperature: 10,000,000

Iterations per temperature: 1,000

Cooling rate: 0.999

Threshold accepting

Threshold accepting (TA) is a point-based heuristic technique that operates similarly to simulated annealing, and was introduced by Dueck and Scheuer (1990). In SA, there is only a small probability that a inferior solution would be accepted and replace the current solution, while in TA, every new solution within a pre-defined limit (threshold) of the value of the current solution will be accepted (Bettinger et al. 2002). Compared to SA, fewer publications are available showing how TA to solve forest planning problems (Bettinger et al. 2002; Bettinger et al. 2003; Calkin et al. 2002; Heinonen et al. 2007; Pukkala and Heinonen 2006). In our implementation of TA, a large initial threshold is assigned. The number of iterations per threshold is also tracked to prevent the search from stalling. If there is a long time between increasing solutions, the threshold will be decreased based on threshold change value defined. Another parameter we need to define is unsuccessful iterations per threshold which indicates how many unsuccessful iterations (those that result in infeasibilities) will be allowed before the search moves to the next threshold. This too is used to prevent the search process from stalling.

The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of TA:

Initial threshold: 10,000,000

Iterations per threshold: 1,000

Threshold change: 250

Unsuccessful iteration per threshold: 1,000

Tabu search

Tabu search (TS), one of the most extensively used point-based heuristic techniques in forest planning, was first introduced by Glover (1990) as a hill-climbing algorithm and combinatorial optimization technique. To date, TS has been applied to problems related to economics (Batten et al. 2005; Boston and Bettinger 2006; Nalle et al. 2004; Pukkala and Kurttila 2005), commodity production (Bettinger et al. 2007; Bettinger et al. 1999a; Murphy 1998; Pukkala and Heinonen 2006), stream sediment and temperature (Bettinger et al. 1998a), adjacency issues (Boston and Bettinger 1999; Boston and Bettinger 2001b; Boston and Bettinger

2002; Brumelle et al. 1998; Heinonen and Pukkala 2004), wildlife habitat (Bettinger et al. 1999b; Bettinger et al. 1997; Boston and Bettinger 2001b), road system management issues (Krcmar et al. 2001; Richards and Gunn 2003), and forest structure issues (Caro et al. 2003). Compared with other techniques that are mainly stochastic in nature, TS involves a deterministic search process. The advantage of this characteristic is that it provides very good solutions that are close to the optimal solution if the search process can avoid becoming trapped in local optimal. The disadvantage is that it may need more time to develop a high-quality solution since a large number of potential changes to a solution may have to be assessed prior to selecting one.

The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of TS:

Tabu state assumed: 60

Total iterations: 100,000

Particle swarm optimization

Particle swarm optimization (PSO), first developed by Kennedy and Eberhart (1995), is a heuristic optimization algorithm that has its origins in the simulation of social behavior. PSO consists of a population of particles (individual solutions) flying through hyperspace. Each particle in PSO is represented by a velocity and a position associated with a fitness value that provides an indication of its performance in the problem space. Before evolution, the positions and speeds of particles in the swarm are initialized randomly. During evolution, each particle retains a memory of the best position it has visited and is also aware of the best position found by any other particle. PSO's advantages include that it can be implemented in fewer lines of computer code than other heuristic algorithms discussed here, it requires only primitive mathematical operators, and it has the capability of escaping local optima (Salman et. al. 2002).

The basic formulation of PSO is shown below:

$$v_{id}^{t+1} = wv_{id}^{t} + \varphi_1\beta_1(p_{id}^{t} - x_{id}^{t}) + \varphi_2\beta_2(p_{gd}^{t} - x_{id}^{t})$$
$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}$$

Where w is the inertial weight which control the impact of the previous history of velocities on the current, φ_1 and φ_2 are constants which determine the balance between the influence of the individual's knowledge (φ_1) and that of the group (φ_2), β_1 and β_2 are uniformly distributed random numbers defined by some upper limit ($\beta_{\max}$). p_{id}^{t} and p_{gd}^{t} are the individual's previous best position and the group's previous best position. x_{id}^{t} is the current position in the dimension considered.

The standard PSO can only optimize problems in which the elements of the solution are continuous real numbers (Pugh and Martinoli 2006). We modified the standard PSO algorithm to solve problems with binary solution elements. The modified equations are shown below:

$$v_{id}^{t+1} = wv_{id}^{t} + \varphi_1\beta_1(p_{id}^{t} - x_{id}^{t}) + \varphi_2\beta_2(p_{gd}^{t} - x_{id}^{t})$$
$$x_{id}^{t+1} = \begin{cases} 1 & if\ (rand() < S(v_{id}^{t+1})) \\ 0 & Otherwise \end{cases}$$

Where $S(v_{id}^{t+1})$ is the sigmoid function

$$S(v_{id}^{t+1}) = \frac{1}{1+e^{-v_{id}^{t+1}}}$$

The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of PSO:

Swarm size: 100

Inertial weight: 0.95

Cognitive weight: 1.8

Social weight: 1.5

Velocity max: 5

Representation: integer string

Raindrop method

The raindrop (RD) method is another point-based (single solution) search process first developed by Bettinger and Zhu (2006) to mitigate adjacency constraint violations in forest planning problems in a radiating manner. Like other point-based heuristic methods mentioned in this research, RD begins with a random solution, and then utilizes random and determine changes to the solution. The characteristics of RD are: 1) an iteration of the process includes a stochastic change, then a deterministic adjustment to other affected management units where constraints are violated such that the next best harvest timing is selected for these that results in no violation of constraints geographically closer to the initial random change (violation of constraints can occur further away from the initial random change); 2) the process avoids the use of parameters normally used in other heuristics to avoid the subjective nature of user-defined parameters. In our implementation of RD, we need to only define two key parameters: 1) the total number of iterations, since the basic RD does not have an intelligent stopping criteria; 2) the number of iterations to make the heuristic revert to the previous best solution. Through extensive testing, it is suggested that RD to be used for problems with relatively simple spatial forest planning constraints, and problems that do not involve young initial age class distributions (Zhu et al. 2007).

The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of RD:

Total iterations: 100,000

Revert to best solution each iteration every 4 iterations

Statistical Methods

For each heuristic algorithm, 100 solutions will be generated. The minimum, maximum, range (maximum – minimum), average, and standard deviation of the objective function values divided by the maximum objective function value are some traditional statistical measures one can develop from each set of heuristic solutions. At the same time, since all the five problems were solved using Integer Programming (IP), the average solution divided by IP solution was considered as our response variable. The range divided by the maximum, the standard deviation divided by the maximum, the percentage of solutions whose value are within 2% of related maximum, the percentage of solutions whose value are within 5% of related maximum, and the percentage of solutions whose value are within 10% of related maximum were also selected as the predictor variables.

Our first attempt at developing a method for assessing the quality of heuristic solutions is to use multiple linear regression to predict the performance of a new heuristic algorithm when applied to the problem presented earlier. Our second attempt is to use non-linear regression to predict the performance of a new heuristic algorithm. Since it is assumed that artificial neural network (ANNs) are suitable for predicting the performance of the related algorithms, our last attempt is to use ANNs. The objective in this experiment is three-fold: first, develop statistical models using multiple linear regression and non-linear regression, then choose the appropriate ANN architecture for the model, and finally compare these three approaches.

Linear and non-linear methods were analyzed using the R computing system which is an open-source software environment for statistical computing and graphics (Venables and Ripley 2002). There are many available computer software packages for analyzing ANNs. We chose a public domain package, WEKA (Waikato Environment for Knowledge Analysis), which was developed at the University of Waikato in New Zealand (Witten and Frank 2005).

Artificial neural networks solve difficult problems through the cooperation of highly interconnected but simple artificial neurons. Basically, the processing elements of a neural network are similar to the neurons in the brain consisting of many simple computational elements arranged in layers, and much of the success of neural networks is due to such characteristics as non-linear processing and parallel processing (Yeh 1998). During this experiment, several neural networks with different architectures were automatically trained and tested by the MultilayerPerceptron method which is based on back-propagation in the WEKA package. A back-propagation neural network employs a steepest gradient descent algorithm to minimize the error function of a multilayer network with respect to the network's weights (Guan and Gertner 1991). Basically, there is an input layer where data are presented to the neural network, an output layer that holds the response of the network to the input, and it is the intermediate layers (hidden layers) that enable these networks to represent the interaction between inputs as well as the nonlinear property between inputs and outputs (Yeh 1998). The nodes in the network are all sigmoid except the output which is a linear unit. We used the linear scale function in WEKA to assure a range of [0, 1] on the input layer because without scaling, the models will treat widely varying inputs as more important than the narrower range inputs. We set the learning rate as 0.3, the momentum as 0.2, and the initial weights in the range of ±0.3. We then tested it on various different hidden layers. We used the same seed for the initial network weights in order to compare results. At the same time, each network will have the same number of epochs (2000) to train through, and the same value (10) to dictate how many times in a row the validation set error can get worse before training is terminated.

The 100 solutions generated from each heuristic can be considered to be an independent sample from a population of solutions because each heuristic algorithm began with a randomly initiated solution (Golden and Alt 1979, Los and Lardinois 1982). The variables are defined as:

Y: The average solution value divided by the IP solution

RM: The range divided by the maximum solution value

SM: The standard deviation divided by the maximum solution value

X2: The percentage of solutions whose values are within 2% of the related maximum solution value

X5: The percentage of solutions whose values are within 5% of related maximum solution value

X10: The percentage of solutions whose values are within 10% of related maximum solution value

RESULTS

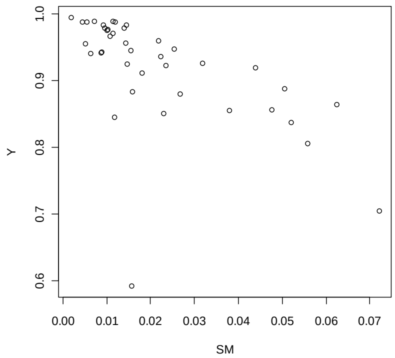
A very quick and traditional comparison for each heuristic algorithm is to investigate the best solution for the related problems. The values shown in Table 4.1 represent the best solutions for the 100 sample solutions generated by the eight heuristic methods. The solutions generated from MCIP, PSO and standard GA are generally considered to be of lower-quality. For example, on the Lincoln Tract, PSO, GA and MCIP do not seem to be appropriate for developing solutions. The North Tract, Putnam Tract, and Western Tract are also more difficult to solve with these three. And for the Slash Tract, GA and PSO provided the worst results given the parameters chosen through pre-study testing phases.

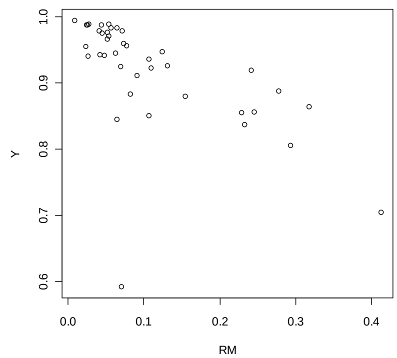
Table 4.1 Quality of the best solutions generated by eight heuristic techniques

Heuristic Algorithms	Lincoln[a]	North[b]	Putnam[c]	Slash[d]	Western[e]
MGA	109,826	26,841	36,131	8,218,120	98,848
GA	100,995	26,740	35,879	7,372,370	95,713
MCIP	105,193	26,612	35,726	7,804,530	93,543
RD	112,991	26,899	36,168	8,470,450	99,388
SA	111,028	26,818	35,627	8,144,820	98,430
TA	111,339	26,873	36,168	8,152,610	99,059
TS	111,469	26,775	35,869	8,088,130	98,298
PSO	92,414	26,696	34,628	7,624,720	96,382

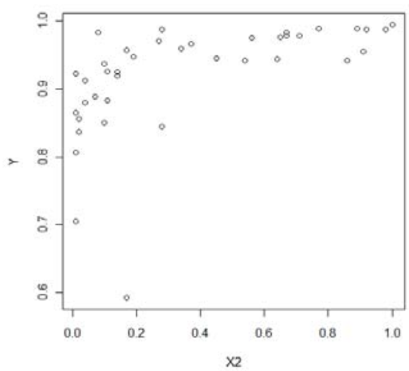
[a] MBF (thousand board feet)
[b] MBF (thousand board feet)
[c] Cords
[d] Tons
[e] MBF (thousand board feet)

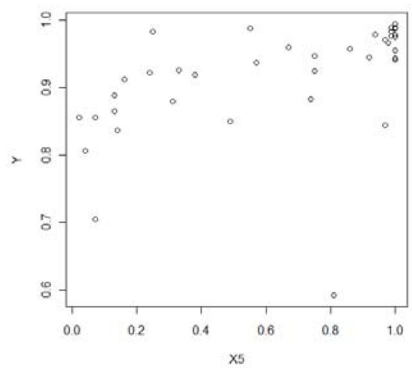
When starting statistical analysis, identification of whether the dependent variable has a linear or non-linear relationship is necessary, and can be accomplished through a simple plot of the dependent variable against each independent predictor variable. Figure 4.1 represents the plots between each predictor variable (SM, RM, X2, X5, X10) and the response variable (Y).



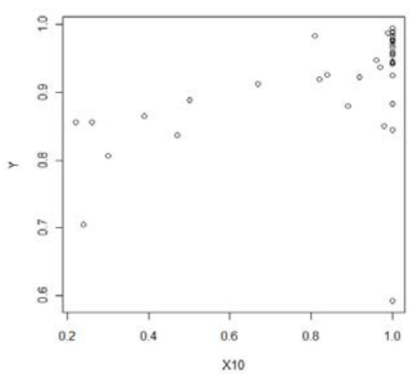


(a) (b)





(c) (d)



(e)

Figure 4.1 Five plots of the response variable (Y) to the predictor variables (SM, RM, X2, X5, and X10).

Multiple linear regression

With linear regression, one is frequently trying to fit a line (or a plane, in higher dimensions) through a cloud of data points. A general linear model has the form:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{k-1} X_{i,k-1} + \varepsilon_i$$

Where $i=1,\ldots,n$ and usually ε_i are normally distributed. In doing so, one may need to transform either the X or Y variables (or both) so that the relation between X and Y after transformation is approximately linear. Another key process in a multiple regression model is the variable selection process. There are various ways to select the variables which are used in a multiple regression model. There is no one best way, although most people would agree that one wants the simplest possible model which explains the response variable adequately. The difficulties lie in determining what is adequate and in deciding what trade-offs to make in terms of model complexity. For our data, if no transformations were considered, there are 32 possible models which could be examined. With any single transformation in each predictor variable, there are 16 more models to consider. If a transformation is applied to the response variable, another 16 more models need to be considered.

The correlation between two variables is considered to be a measure of the direction and strength of their linear relationship. The range of the correlation coefficient values is from -1 to 1, with a correlation near zero indicating there is either no relationship between two variables, or that their relationship is not linear. A large positive correlation (close to 1) means that as the value of one variable increases, the value of the other variable also increases. Conversely, a large negative correlation (close to -1) means that as the value of one variable decreases, the value of the other variable decreases. In examining the correlation matrix (Table 4.2), we see a strong positive correlation between variables SM and RM. This is due to the fact that both variables have the same denominator.

Table 4.3 represents a summary of the best linear models with 0-, 1-, 2-, 3-, 4-, 5-variables in this experiment. Two methods were adopted to select appropriate linear model: R^2 and RMSE. There is no one "best" choice, although most people prefer the simplest possible model which explains the response variable adequately. Therefore, the model with two variables (RM^2 , X2) is chosen as the appropriate model.

Table 4.2. Correlation Matrix for the predictor variables.

	SM	RM	X2	X5	X10
SM	1.00	0.99	-0.72	-0.85	-0.88
RM	0.99	1.00	-0.69	-0.83	-0.89
X2	-0.72	-0.69	1.00	0.82	0.59
X5	-0.85	-0.83	0.82	1.00	0.85
X10	-0.88	-0.89	0.59	0.85	1.00

RM: The range divided by the maximum solution value
SM: The standard deviation divided by the maximum solution value
X2: The percentage of solutions whose values are within 2% of the related maximum solution value
X5: The percentage of solutions whose values are within 5% of related maximum solution value
X10: The percentage of solutions whose values are within 10% of related maximum solution value

Table 4.3 Summary of best 0-, 1-, 2-, 3-, 4-, 5- variable models.

Variable number	R^2	Variables in Model	RMSE
0	0.000	(intercept)	0.082
1	0.354	RM	0.067
2	0.428	RM^2 , X2	0.064
3	0.459	RM^2 , X2, X5	0.063
4	0.466	RM^2 , X2, X5, X10	0.063
5	0.470	SM, RM^2 , X2, X5, X1	0.064

RM: The range divided by the maximum solution value
SM: The standard deviation divided by the maximum solution value
X2: The percentage of solutions whose values are within 2% of the related maximum solution value
X5: The percentage of solutions whose values are within 5% of related maximum solution value
X10: The percentage of solutions whose values are within 10% of related maximum solution value

Non-linear regression

The mean surface in a linear regression is a plane in sample space, while in non-linear regression it may be an arbitrary curved surface (Venables and Ripley 2002). The general form of a non-linear regression model is:

$$Y_i = f(X_{i1}, X_{i2}...X_{i,k}, \theta_1, \theta_2...\theta_p) + e_i$$

Where x is a vector of covariates, θ is a p-component vector of unknown parameters and e_i is a N(0, σ^2) error term. Without theoretical and empirical support, it is very difficult to develop non-linear regression model. Our approach here is to make our non-linear model follow some pattern of the plots. From Figure 4.1 (a) and (b), we see that SM and RM have a similar pattern, thus a cubic equation would be appropriate to represent such pattern (Figure 4.2). By similar reasoning, a double rectangular function is good to fit Y on X2 (Figure 4.3)

The model we used to fit Y on SM:

$$Y = 1.029 - 10.687\,SM + 291.46\,SM^2 - 2817.953\,SM^3$$

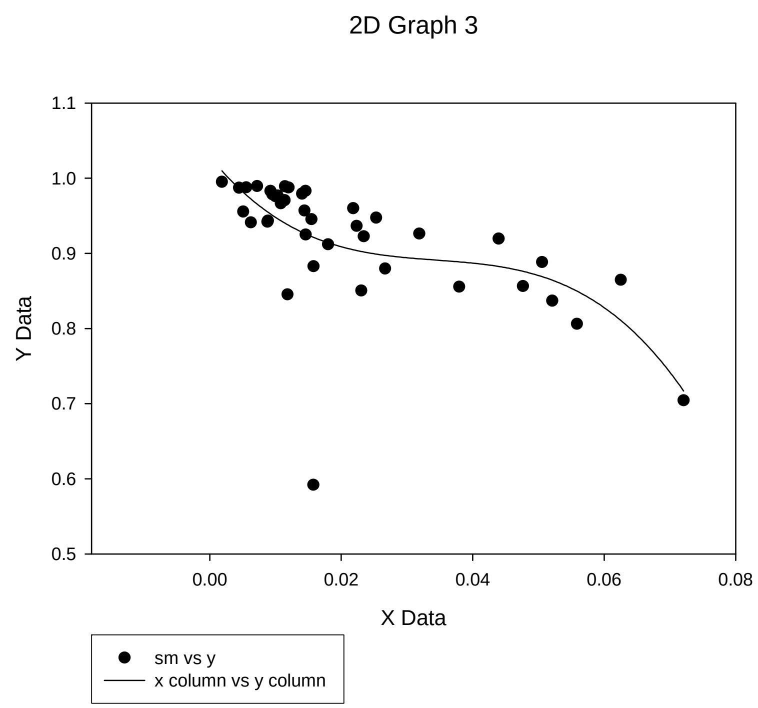


Figure 4.2 Polynomial model adopted to fit of Y on SM.

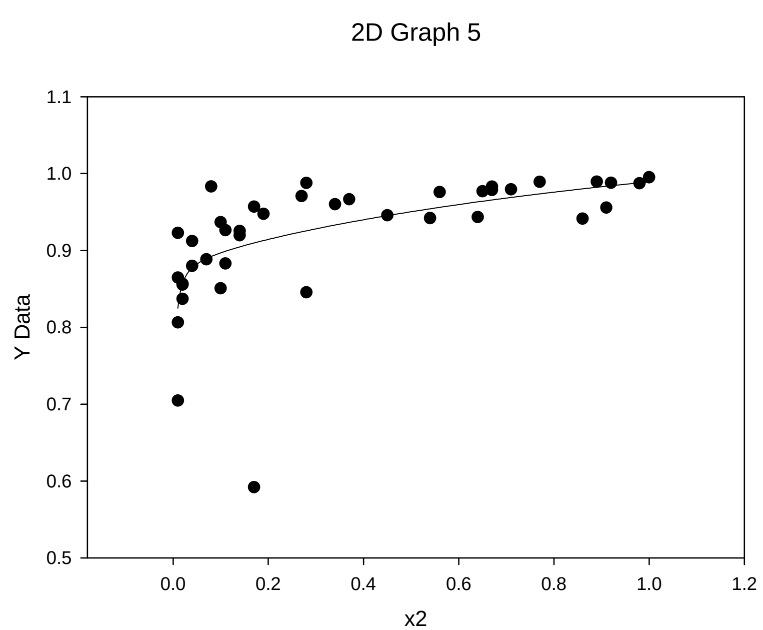


Figure 4.3 Double rectangular adopted to fit of Y on X2

The model we used to fit Y on X2:

$$Y = \frac{0.888X2}{0.001 + X2} + \frac{0.253X2}{1.475 + X2}$$

The model we finally suggest for our non-linear approach is below with RMSE 0.068:

$$Y = -30.72SM^2 + 0.95X2/(0.0004 + X2)$$

ANNs

We used mean absolute error (MAE) and root mean square error (RMSE) to compare the models we obtained. As Table 4.4 shows, the lowest MAE (0.0421) and RMSE (0.0565) occurs when we used a one-hidden layer architecture with 4 nodes. The results in Table 4.4 illustrate that with respect to RMSE, ANNs provide similar results as found with the linear regression model (0.064) and the non-linear regression model (0.061).

Table 4.4: Mean absolute error and running time on the test set

Model	MAE value	RMSE
Hidden: 4	**0.0421**	**0.0565**
Hidden: 8	0.0534	0.0695
Hidden: 50	0.0437	0.0631
Hidden: 4,2	0.0428	0.0579
Hidden: 4,4	0.0473	0.0600
Hidden: 4,8	0.0422	0.0557
Hidden: 50,5	0.0533	0.0691
Hidden: 8,4,2	0.0434	0.0594

When one plots the predicted values to the observed value, an ideal model (i.e., perfect correlation between the predicted values and observed values) would indicate a diagonal line. Figure 4.4 illustrates that the ANN model is not necessarily ideal, but a diagonal relationship is present.

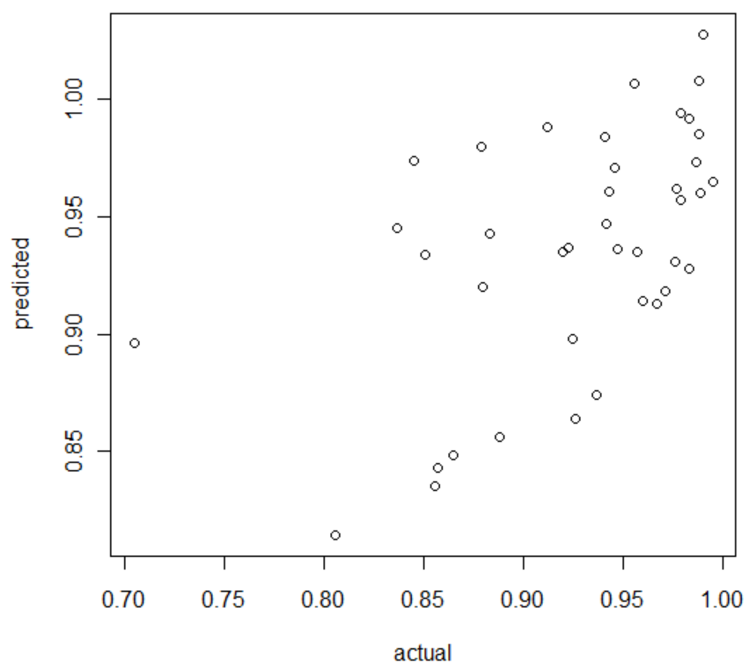


Figure 4.4: Predicted value of our best neural network compared with the actual value we located.

In this research, all three approaches provide reasonable models for a measure of heuristic quality in spatial forest planning. The multiple linear regression approach is relatively easy to implement and can reach RMSE as low as 0.064. A linear model requires the regression parameters enter into the models linearly. In other words, the model is linear with respect to the parameters, not with respect to the explanatory variables. A non-linear regression model drops the linearity assumption, and allows the parameters and explanatory variables enter into the regression function in a non-linear way. Since there is no previous theory or background for setting up a heuristic solution quality index measurement, the non-linear method seems to be the more reasonable approach.

DISCUSSION AND CONCLUSIONS

Bettinger et al. (2009b) reported six levels of heuristic validation that currently in use: no validation (Level 1), use of statistical approaches to assess the quality of heuristic solutions (Level 2), comparison with other heuristic solution values (Level 3), comparison with an estimated global optimum solution (Level 4), comparison with a relaxed solution (Level 5), comparison with a solution generated from exact techniques such as integer or mixed-integer programming or possibly complete enumeration (Level 6). As we can see, the highest level is to compare with the optimal solution. However, with the limitation of time and the increasing number of the decision variables in spatial forest planning, it may be difficult to locate the optimal solution.

In this research, three different statistical methods were applied to develop a measure of heuristic quality in spatial forest planning. RMSE is used to compare with different models. Although ANNs provide lowest RMSE, they are difficult for a novice to use and comprehend. When a new example (a new heuristic or a new problem) needs to be tested with ANNs, the best process is to add this example to a previously developed set of solutions, in order to form a new dataset, and then run the neural network process again. This process requires practitioners to obtain basic ANN knowledge, which is difficult currently since ANN is a new technology in the area of forest planning. A multiple linear regression process is relatively easy to implement, however the linearity assumption of the regression parameters is usually violated. My recommendation is to use a non-linear regression approach. However, more work should be conducted to determine whether a non-linear regression model can include different kinds of spatial forest planning problems. In the future, another heuristic-quality assessment method, probability models based on Bayesian inference, could be applied to the assessment of the forest planning solution quality (Giddings 2003). However, this may be time consuming since it has been concluded that the technique is not practical, in general, to use.

What remains to be seen is whether the non-linear relationship developed here can be transferred for use in other spatial forest planning problems. While the quality of some heuristic methods is fairly consistent when forest planning problems change (Bettinger et al. 2002), it is not unreasonable to assume that this is not a universal rule. If problems change significantly, then to use the non-linear approach described here will require the application of a number of heuristics (new and old) to a number of these significantly different problems, and also require solving exactly some of the problems. At a minimum this method should be tested against other types of spatial planning problems, with the hypothesis that the non-linear relationship is very similar to the one found here.

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CHAPTER 5

ANOTHER APPLICATION OF PARTICLE SWARM OPTIMIZATION IN FOREST PLANNING[1]

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ABSTRACT

An exploration of other opportunities to utilize PSO for the development of a typical southern forestry problem was conducted in this research. In Chapter 3, I noted that, when used alone, PSO performed rather weakly in solving a typical southern forest planning problem. Here, I am attempting to determine whether PSO, when initiated with a high-quality set of initial solutions (particles), can fine-tune and improve the overall quality of a resulting forest plan. Results indicate that PSO does improve upon the higher quality initial solutions generated by another heuristic, therefore it may play a role in forest planning by fine-tuning high quality results obtained by other methods.

Keywords: Spatial forest planning, Mathematical programming, Heuristics, Modeling techniques

INTRODUCTION

Heuristic optimization algorithms can be divided into two basic categories: deterministic and stochastic search algorithms. The deterministic search algorithms involve reasoned decisions related to changes in solutions in order to escape local optima. Tabu search is one example, and has been widely applied to a variety of forest planning problems (Bettinger et al. 1997; Boston and Bettinger 2001b; Boston and Bettinger 2006; Caro et al. 2003; Pukkala and Kurttila 2005; Richards and Gunn 2003). On the other hand, stochastic search algorithms rely on probabilistic judgments to determine whether or not search should depart from the neighborhood of a local optimum (Parsopoulos and Vrahatis 2002). For example, Simulated Annealing (SA) relies on a set of logic to iteratively adjust a solution; allocating and reallocating resources to various uses, until a very good solution to a problem has been located (Bettinger et al. 2007). SA has been used to address a variety of forest planning problems (Baskent and Jordan 2002; Bos 1993; Boston and Bettinger 1999; Chen and Gadow 2002; Crowe and Nelson 2005; Jorgensen et al. 1992; Lockwood and Moore 1993; Ohman and Eriksson 2002; Tarp and Helles 1997). Another set of stochastic algorithms are the genetic algorithms, which have also been explored for forest planning purposes (Boston and Bettinger 2002; Ducheyne et al. 2004; Lu and Eriksson 2000). Variations exist, however, such as the raindrop (RD) method which is a deterministic and stochastic search process first developed by Bettinger and Zhu (2006) to mitigate adjacency constraint violations in forest planning problems in a radiating manner.

Particle swarm optimization (PSO), is a promising new stochastic search heuristic developed by Eberhart and Kennedy (Eberhart et al., 1996; Kennedy and Eberhart 1995). The original goal of PSO was to graphically simulate the stylish but unpredictable choreography of a bird flock. Later on, from the view of evolution algorithms, it was realized that the conceptual model of PSO could be transformed to optimization problems. In this research, PSO is a stochastic search process that uses a population of feasible solutions to arrive (hopefully) at a single high-quality forest plan.

In this chapter, I will explore other opportunities to utilize PSO for the development of a typical southern forestry problem. The forest planning problem is to develop a harvest schedule that intends to achieve multiple goals, such as maximizing the total timber volume and minimizing deviations in timber volume between multiple cutting periods simultaneously. In Chapter 3, I noted that PSO performed rather weakly in solving a typical southern forest planning problem when it is allowed to operate on its own. In that instance, the initial population of solutions (particles) was randomly created, and results showed that PSO could not evolve the population very well toward superior solutions. Here, I am attempting to determine whether PSO, when initiated with a high-quality set of initial solutions (particles), can fine-tune and improve the overall quality of a resulting forest plan. The hypothesis is that PSO would be more beneficial when used in this manner then when used in the typical testing phase manner (where we begin with a poor-quality random solutions).

METHODS

PSO conceptually consists of a population of particles (individual solutions) flying through hyperspace. Each particle in PSO is represented by a velocity and a position associated with a fitness value that provides an indication of its performance in the problem space. Before evolution, the positions and speeds of particles in the swarm are initialized randomly. During evolution, each particle retains a memory of the best position it has visited and is also aware of the best position found by all other particles. PSO's advantages include that it can generally be implemented in fewer lines of computer code than other heuristic algorithms mentioned in this dissertation, it requires only primitive mathematical operators, and it has the capability of escaping local optima (Salman et. al. 2002).

The basic formulation of PSO is shown below:

$$v_{id}^{t+1} = wv_{id}^{t} + \varphi_1\beta_1(p_{id}^{t} - x_{id}^{t}) + \varphi_2\beta_2(p_{gd}^{t} - x_{id}^{t})$$
$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1}$$

Where w is the inertial weight which control the impact of the previous history of velocities on the current, φ_1 and φ_2 are constants which determine the balance between the influence of the individual's knowledge (φ_1) and that of the group (φ_2), β_1 and β_2 are uniformly distributed random numbers defined by some upper limit ($\beta_{\max}$). p_{id}^{t} and p_{gd}^{t} are the individual's previous best position and the group's previous best position. Finally, x_{id}^{t} is the current position in the dimension considered.

The standard PSO can only optimize problems in which the elements of the solution are continuous real numbers (Pugh and Martinoli 2006). I modified the standard PSO algorithm in Chapter 3 to solve problems with binary-valued solution elements. The binary equations are shown below:

$$v_{id}^{t+1} = wv_{id}^{t} + \varphi_1 \beta_1 (p_{id}^{t} - x_{id}^{t}) + \varphi_2 \beta_2 (p_{gd}^{t} - x_{id}^{t})$$

$$x_{id}^{t+1} = \begin{cases} 1 & if\ (rand() < S(v_{id}^{t+1})) \\ 0 & Otherwise \end{cases}$$

Where $S(v_{id}^{t+1})$ is the sigmoid function

$$S(v_{id}^{t+1}) = \frac{1}{1+e^{-v_{id}^{t+1}}}$$

Particles' velocities on each dimension are clamped to a maximum velocity *Vmax* which is a parameter specified by the user, and *Vmax* determines the resolution, with which regions between the present position and the target (best so far) position are searched (Eberhart and Shi 2007). A high *Vmax* means that particles might fly past good solutions, while a low *Vmax*, on the other hand, means that particles may not explore sufficiently beyond locally good regions (Eberhart and Shi 2007). An inertia weight is used to better control exploration and exploitation (Pan and Wang 2008). A large inertial weight facilitates the global exploration (searching new areas), while a small one tends to facilitate local exploration (Parsopoulos and Vrahatis 2002). The following parameters were used based on several trial and error runs of the search process on the problems for the implementation of PSO:

Swarm size: 50

Inertial weight: 0.95

Cognitive weight: 1.8

Social weight: 1.5

Velocity max: 5

Representation: integer string

In Chapter 3, the modified PSO was applied to a typical southern forestry planning problem that involves maximizing net present value of some close-to-real forest planning problem under the constraints of green-up, adjacency, and sustainable and even flow of periodic (20-year) timber harvest. Since there is a general belief that social sharing of information among the individuals of a population may provide an evolutionary advantage, an interesting question is that should PSO be used to refine “good” solutions?

RESULTS

In order to test our hypothesis that PSO could be applied to refine solutions, PSO is initialized with high-quality solutions (derived using threshold accepting (TA)). Two problems from Chapter 4 were applied here (North tract and West tract). Fifty solutions were generated to obtain the related statistics (Table 5.1). PSO does improve upon the higher quality initial solutions.

Typical testing of heuristics in forest planning involves the use of an initial random solution (or set of random solutions) to infer independence of the final solutions amongst multiple runs of a model (Golden and Alt 1979, Los and Lardinois 1982). I found earlier that PSO does not work well for a typical southern forestry problem in this regard. Informed discussions with practitioners suggested that perhaps algorithms such as these may be better suited to fine-tuning a high-quality solution (or set of solutions). Two problems from Chapter 4 were adapted to test. From this simple example, a standard PSO did improve upon the higher quality solutions generated by TA in one of the two examples (West Tract). In both examples, the mean quality increased and the variation decreased when using PSO to fine-tune the TA solutions. Therefore, what this research suggests is that PSO may be best used in a meta heuristic model, after another method like TA has been used. Until now, what we have found is that this line of inquiry (using PSO alone for forest planning) does not seem to be a fruitful endeavor.

Table 5.1 Comparisons of the objective function values for the North Tract and the West Tract between randomly started and fine-quality initial solutions.

	Maximum	Mean	Standard deviation
North Tract			
TA	26,872.60	26,545.95	148.79
PSO	26,471.54	25,515.69	653.04
PSO_TA	26,872.60	26,855.02	19.26
West Tract			
TA	99,058.91	96,461.41	1,128.04
PSO	96,907.70	92,499.94	1,981.26
PSO_TA	99,197.39	98,901.90	311.11

TA: threshold accepting

PSO: particle swarm optimization

PSO_TA: particle swarm optimization with threshold accepting as initial solution

DISCUSSION AND CONCLUSIONS

In the testing of new heuristic techniques, it is generally assumed that each instance is begun with a randomly-generated, feasible solution. Previous research (i.e., Chapter 3, Potter et al. 2009) has shown that standard and modified versions of PSO do not work well on forest planning problems that have both harvest adjacency and wood flow constraints. In practice, beginning a search with a high-quality solution may lead to very efficient forest plans. Therefore, in this work I was interested in understanding whether PSO would be able to improve upon high-quality solutions if it were included in a meta-heuristic search process.

Results indicate that PSO may be a worthwhile addition to a meta-heuristic process if it is one of the last search processes in the meta-heuristic, and is allowed to operate on a set of high-quality forest plan solutions. If PSO is allowed to operate on poor quality solutions, a meta-heuristic would be better off without it. One question that arises concerns the point at which a meta-heuristic switches to PSO. Li et al. (2010) examined numerous cases and concluded that if one could determine when the improvements in solution quality stagnate, a significant computational time savings can be made in the transition from one heuristic to another. Using PSO in a meta-heuristic also requires that a population of solutions are available when the time comes to use PSO. If threshold accepting, tabu search, or some other point-based heuristic is used prior to PSO, one would need to ensure that multiple, high-quality, diverse solutions are available once PSO begins to fine-tune the population in search of a near-global optimum.

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CHAPTER 6

SUMMARY

When an organization makes a decision to utilize a heuristic programming technique to develop a land management plan, the level of sophistication of the resulting technique will vary depending on the type of system desired and the time allowed to develop the system (Bettinger et al. 2002). Both mathematical and heuristic methods have advanced rapidly in spatial forest planning over the past 20 years. Although Bettinger and Chung (2004) conducted a comprehensive review of mathematical forest planning methods in North American scientific journals, a world-wide literature review and extensive analysis was needed to investigate the broader status, trends, and gaps related to spatial forest planning. The review presented in Chapter 2 is broader in both scope and depth (more analysis within spatial forest planning models and world-wide coverage) and more up-to-date than previously published reviews. Besides the economic and commodity production objectives, there is a noticeable increase in the proportion of ecological and social concerns in objective functions of problems. In Europe, multi-parameter objective functions now seem to be in vogue, containing little or no constraints. In the U.S., single-parameter objective functions are still common, with multiple concerns recognized as constraints. In addition to the economic and commodity production constraints, adjacency and green-up relationships have recently been considered as important constraints in many areas of the world. The literature review results also suggest that methods used in forest planning research have shifted somewhat from exact analytical solution techniques to heuristic techniques. In an effort to incorporate complex relationship into forest plans, other solution methods need to be evaluated for adoption in the planning process. Limitations in mixed integerprogramming, heuristic parameter selection processes, modification and enhancements to heuristics, and measurements of heuristic solution quality are other the gaps we have identified.

Particle swarm optimization (PSO) is a heuristic, and a member of swarm intelligence methods for solving global optimization problems (Eberhart and Shi 2001). PSO is reported to be easily implemented and computationally inexpensive, and has been proven to be an efficient method for many optimization problems (Kennedy and Eberhart 1995, Eberhart et al., 1996). Particle swarm optimization (PSO) is therefore a promising new population-based heuristic that might be useful for spatial forest planning. In my implementation of PSO to a southern U.S. forest planning problem, the algorithm gradually converged upon a final solution with some appropriate modifications, and a reasonable objective function value was reached. However, only 86% of the global optimal value could be reached, suggesting that PSO, acting alone, is not too useful for realistic forest planning problems.

Heuristic optimization algorithms seek to locate good feasible solutions to spatial forest planning problems in circumstances where the complexities of the problem, or the limited time available, do not allow the development of an exact solution. With regard to heuristics, most researchers and practitioners use various traditional statistics to assess the solution quality. Bettinger et al. (2009) reported six levels of heuristic validation that currently in use: no validation to comparison with a solution generated from exact techniques such as integer or mixed-integer programming or possibly complete enumeration. In this research, we try to assess methods whereby one can develop a relationship to assess the quality of a new heuristic (when applied to a similar planning problem) without having to locate the exact, global optimum solution to the problem. A minor goal is to propose a method one can pursue to estimate heuristic performance in the absence of an exact solution to a problem. Three different statistical methods were applied to develop a measure of heuristic quality in spatial forest planning. My recommendation is to use a non-linear regression approach to estimating heuristic solution quality in the absence of a known optimal solution, because the model fit the experimental data well, and relationships among variables were better represented. However, more work should be conducted to determine whether a non-linear regression model can be adapted to different kinds of spatial forest planning problems.

An exploration of other opportunities to utilize PSO for addressing a typical southern forestry problem was conducted in the final stage of this research. In Chapter 3, I noted that, when used alone, PSO performed rather weakly in solving a typical southern forest planning problem. When testing new heuristics, researchers generally initiate new searches with randomly-defined initial solutions to ensure independence of data (final solutions). Here, I attempted to determine whether PSO, when initiated with a high-quality set of initial solutions (particles), can fine-tune and improve the overall quality of a resulting forest plan. The high-quality solutions were developed by a point-based heuristic (threshold accepting). Results indicate that PSO can improve upon the higher quality initial solutions generated by another heuristic. Therefore it may have a role in forest planning by playing a fine-tuning role in a meta heuristic, improving results obtained by other methods.

In sum, this dissertation advances the science related to (a) the application of heuristics to forest planning problems, and (b) the assessment methods for heuristic solution quality. The literature review provided a fresh examination of the advancements in spatial forest planning. The assessment of PSO (and modified PSO), and the usefulness of PSO in a metaheuristic environment sheds light on the practical applications of the heuristic in forest planning. Finally, the solution quality assessment suggests a new approach for inferring heuristic performance when a global optimum solution is unavailable to compare against.

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