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A REVIEW OF THE STATUS AND USE OF VALIDATION PROCEDURES FOR HEURISTICS USED IN FOREST PLANNING

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Abstract. While there exist clear methods for validating and ensuring the quality of solutions generated by forest planning heuristic techniques, the use of these methods in the literature varies from one situation to the next. Based on our experience developing and using heuristic forest planning techniques, we describe six levels of heuristic validation that are currently in use, ranging from no validation (Level 1) on one end of the spectrum, to the comparison of heuristic technique solutions with an exact solution obtained using mathematical programming methods (Level 6) on the other end. The reasons why authors may choose or reviewers may require levels of validation are proposed. We do not believe that all research papers should be subjected to the highest level of validation, but suggest that authors of papers on forest planning techniques and reviewers associated with peer-reviewed journals try to place the level of validation within the larger scientific context, then determine an appropriate level of validation. Admittedly, this is problematic for review decisions, given the fact that reviewers may differ in opinion of what is appropriate. Four brief cases are provided to help one think through these issues. Ultimately, we hope that this discussion will lead to a reasoned approach for the use of validation processes in conjunction with the presentation of heuristic techniques, rather than the current ad-hoc process that, on one hand, relies on the valuable and careful thoughts of the reviewers, yet on the other hand, may be uneven in application.

Keywords: combinatorial optimization, extreme value theory, linear programming, mixed integer programming, operations research

1 Introduction

Forest-level planning involves the development of a plan of action for a forested area that consists of the selection of management activities for timber stands, roads, or other decision units. In many cases the individual decisions can be optimized at the scale of the decision unit and they can collectively become an optimal forest plan. However, broader forest-level goals, such as wildlife habitat quality, may not be adequately considered at the decision unit scale. Therefore, in order to best meet the objectives for the broader management problem, and when viewed from the scale of the forest, some forest planning problems involve developing a collection of decisions that involve optimal or sub-optimal choices at the decision unit scale. Modern forest planning increasingly involves the accommodation of functional relationships that describe cumulative effects, maximum size of harvest units, habitat fragmentation, biodiversity, wildlife habitat, and other natural resource management concerns (Bettinger and Sessions 2003). Combinatorial optimization methods can play an important role in management decision making, since some contemporary forest plans can require a non-trivial combination of complex factors (Hertz and Widmer 2003). As a result, combinatorial optimization methods may be necessary for developing forest plans or assessing management alternatives.

In natural resource management, computational methods for addressing combinatorial optimization problems, and for accommodating spatial and temporal management goals contained in management plans, range from the traditional mathematical programming (i.e., those that can yield exact solutions) to heuristic techniques (i.e., those that produce a solution of uncertain quality). One method uses a collection of equations, and various computational methods for simultaneously solving those equations, to develop a natural resource management plan. The other method uses logic and rules to iteratively build a natural resource management plan, in a manner that is often more transparent to the decision maker. The main advantage of using a traditional mathematical programming technique is that when a solution is generated, one has confidence that it is the optimal solution to the problem being solved (or perhaps within some minor tolerance in the case of mixed integer programming). Thus the results generated are optimal unless a non-zero gap tolerance has been used. The main limitations related to the traditional mathematical programming techniques are (1) the inability to formulate complex relationships as linear or mixed integer equations, (2) the inability to solve some problems in a reasonable amount of time, and (3) a limit on the number of rows (constraints) or variables that can be included in a problem. These limitations become less of an issue as computer technology, both hardware and software, evolves, however they remain a significant problem today. What we should make clear is that traditional mathematical programming techniques are of significant value in forest planning. However, some forest planning problems preclude the use of these techniques.

The field of forest management planning continues to evolve, and there is continued interest in developing methods to optimally solve spatial management planning problems using traditional mathematical programming solution techniques (mixed integer programming, integer programming, etc.). The use of spatially-constrained natural resource management models has increased dramatically in the past 15 years (Bettinger and Chung 2004) due to a variety of reasons, including the need to adhere to regulatory and voluntary sustainability programs, and to assess the impact of potential constraints on the value of a land base (Bettinger and Sessions 2003). Lockwood and Moore (1993) were one of the first in natural resource management to recognize that solving these problems may become impractical using traditional mathematical programming methods. Although advances in mathematical programming software continue to mitigate this issue, Murray and Weintraub (2002) later illustrated a case where a significant amount of time was required to generate the constraints for a relatively small spatially-constrained problem. McDill and Braze (2001) illustrate a number of cases, however, where exact integer solutions with small tolerance gaps can be obtained in a reasonable amount of time. And while work continues in this area, Murray and Weintraub (2002) and Bertomeu and Romero (2001) suggest that it may be unrealistic to solve large or difficult problems with exact approaches, and McDill and Braze (2001) suggest that alternatives to exact approaches may still be needed.

The main emphasis of recent advances in the use of traditional mathematical techniques for natural resource planning has been on the attempt to more efficiently handle spatial restrictions through the development of constraint structures, which allow branch and bound or cutting plane algorithms to effectively solve planning problems within a reasonable amount of time using the available resources. All practical combinatorial problems in natural resource management utilize integer decision variables, many of which can be considered NP-complete or NP-hard, and thus may not be solved efficiently with exact algorithms such as mixed integer programming (Zanakis and Evans 1981). However, some instances of NP-complete problems can often be solved efficiently; the main issue is that as a problem grows in size, the computational resource requirements rapidly outgrow the algorithm's ability to solve the problem. In addition, the non-linearity that is common today among variables prevents a systematic evaluation of solution quality, such as that available in linear or mixed integer programming (McRoberts 1971). As a result, an exact method may be available but it becomes computationally unattractive as the size or complexity of the problem increases (Zanakis and Evans 1981).

As a result of these issues, we have experienced an expansion on the use of heuristic techniques in forest planning. Researchers have demonstrated that they can effectively solve complex planning problems with heuristic techniques, but concerns about quality of the results are at the forefront. The advantage of using a heuristic technique is that once developed, one may be able to quickly generate very good solutions to complex problems (Baskent and Keles 2005), if the heuristic is developed appropriately. The main limitations related to heuristics are (1) the time required to develop a method for each specific planning problem, and more importantly (2) the inability to guarantee that the optimal solution can be located and the determination of "nearness" to optimality of heuristic solutions (Hoganson and Borges 1998). In addition, heuristics are generally developed for a specific forest planning problem, and some require extensive parameterization. Often the quandary is, as McRoberts (1971) once stated:

"The provision of an indicator for the evaluation of suboptimal solutions to large-scale problems by statistical means falls into the trap of those who argue for nothing less than an exact-solution technique."

Dannenbring (1977) also suggested that questions regarding solution quality of heuristic algorithms overshadow other concerns. More than 35 years later, this is still the case as we explore the use of heuristics in forest planning.

Further complicating the assessment of heuristic quality is the idea of designing a controlled, replicated study to delve into these issues. Computational testing of optimization algorithms generally involves devising empirical studies using a set of "typical" instances, applying an algorithm and its competitors on the instances, then comparing the resulting quality of solutions (Mastrolilli and Bianchi 2005). Along these lines, several papers (e.g., Nelson and Brodie 1990, Dahlin and Sallnas 1993, Bettinger et al. 2002, Pukkala and Kurttila 2005) have illustrated computational tests of one heuristic versus others, when applied to forest planning problems. Some argue that this course of action indicates which algorithms are better, but not why they are better, and that a better course of action in assessing the quality of results generated by heuristics would be to conduct the assessment in a controlled manner (Hooker 1995).

In our experience, a more direct results-oriented validation (Lee and O'Keefe 1994) is often suggested during the peer-review of operations research papers associated with forest planning, where the performance of a heuristic technique is compared against expected (optimal) performance. However, we have noticed (after reading, writing, and reviewing over 250 papers on the subject) that the variation in heuristic validation standards is wide among the peer-reviewed forestry literature. Given the diversity of validation approaches that have been presented in the forestry literature, we make an attempt here to categorize proven approaches to validate heuristic applications. Our suggestion is that future research papers clearly identify the level of validation that was considered, and if a complete validation is not provided, describe the conditions that existed to prevent a complete validation process. Our general opinion is that a complete validation should not be required in every instance (paper) as it is often not feasible to produce such solutions. We do not intend to be prescriptive with this paper. Our intent is to promote a dialog along these lines with other interested parties. Rather than highlight the limitations of previously published work, many of our own research publications are noted to illustrate the advantages and disadvantages of the approaches described.

2 Heuristic Validation Procedures in Forest Planning

For operations research papers, Psaraftis (1994) presented review standards for operations research papers which outlined several ways to assess solution quality from heuristic techniques. The computational experience of methods presented was stressed as a critical ingredient of papers with a strong operations research component. The computational experience includes the size of the problem being solved, the type of computer being used, and the amount of time required for the generation of a solution. Computational experience can also include comparisons with solutions generated by other methods and statistical tests. In this opinion piece, we describe our approach to validating the quality of solutions generated by heuristic techniques. We outline the current status and use of validation procedures as they relate to heuristics used for natural resources planning by presenting six levels of performance standards, ranging from no performance established at one end of the spectrum to a comparison with solutions to known optimal solutions generated using exact techniques (integer or mixed integer programming) at the other end.

Level 1: *No validation or performance is established.* Validation of some forest planning models may be inherently problematic due to the size of the problem considered or the complexity of the objectives and constraints. For example, when projecting land management scenarios into the future, a number of factors that have unknown or uncertain effect, such as climate change and human population growth, can affect the accuracy of the results (Carpenter 2002). In some cases, these uncertainties are ignored, in other cases they are accommodated using stochastic processes. Alternatively, some constraints may be non-linear and not easily translated into equation form. Ultimately, there will be instances in the forest planning literature where true optimal solutions to certain forest planning problems are unknown. The evaluation of alternative scenarios with forest landscape planning models may have value, allowing one to consider a range of possibilities that a model may generate. These alternatives are typically not subject to rigorous statistical validation, but rather are tested for robustness against a set of other scenarios.

Level 2: *Self-validation is established.* This area of validation concerns the use of basic statistical approaches to assess the quality of solutions generated by heuristics. In this case, a sample set of heuristic solutions is required, which suggests that each solution generated should ideally have a different objective function value, which is easily obtained from heuristics that use stochastic processes (i.e., simulated annealing and genetic algorithms). Some heuristics, however, may not utilize stochastic processes (i.e., tabu search), therefore to adequately use some of these tests, two assumptions should be made: independence of sample solutions and a continuous distribution of samples. To achieve independence of samples, a random generation of initial starting solutions to the heuristic process can be used to induce the creation of statistically independent samples that could be validated with additional statistical tests (Golden and Alt 1979, Los and Lardinois 1982). The assumption that samples arise from a continuous distribution can be assumed even though combinatorial problems possess a discrete solution value distribution, where the number of possible solutions is finite. The number of possible solutions grows exponentially with increases in the number of decision choices, making the approximation of a continuous distribution by a discrete distribution acceptable in practice (Dannenbring 1977, Los and Lardinois 1982). However, Rosing and ReVelle (1997) suggest that sets of solutions where the objective function values have little variation may be derived from identical solution sets. With the exception of Level 2b (described below), which is appropriate whether or not a sample of heuristic solutions is collected, after making these assumptions, statistical approaches to assessing heuristic solution quality may be appropriate in many cases.

Level 2a: *Worst case performance is established.* One appealing measure of heuristic solution quality is the measure of the worst case solution. If one knows that a heuristic will never be worse than 5% of the optimal solution, for example, then one can develop a level of confidence in the algorithm. Garey et al. (1978) also suggest a performance guarantee, or worst-case performance ratio, to provide an indication (a warning) of the worst-case behavior of an algorithm. However, many worst case instances would never be implemented in practice, and they may have little value in assessing performance of a heuristic during a particular instance. Yoshimoto et al. (1994) represent one of the few cases in forest planning where worst-case solution values of a heuristic are presented.

Level 2b: *Best case performance is established.* This measure of solution quality is inherent in all papers that describe forest planning heuristics. However, if random starting solutions are assumed, or other stochastic processes are used, other measures describing the variation in heuristic technique performance should also be presented.

Level 2c. *Average performance is established.* Several researchers in natural resource management have turned to using the average solution quality as a way to describe performance. When taken in context with the value of the best solution developed with a heuristic, the average solution value may provide evidence of the repeatability of the performance of a heuristic. A number of examples of validation using this approach have been provided in the literature.

Level 2d: *Assessing the variation in solution values.* The variation in solution values, as expressed by the standard deviation or coefficient of variation, can also provide evidence of the repeatability of the performance of the heuristic process, however, the quality of the solutions can only be ascertained by subsequent comparison of solution values to other heuristics or exact methods. For example, simply to argue that heuristic procedures can produce solutions that are all within a certain range of quality of one another does not imply that they are also all of high quality. Examples of validation using this approach include Bettinger et al. (2002), Heinonen and Pukkala (2004), Pukkala and Kurttila (2005), Bettinger and Zhu (2006), Lu and Eriksson (2000), and Kurttila et al. (2002).

Level 2e: *Sensitivity analysis of heuristic parameters.* Performing a sensitivity analysis of the parameters required by a heuristic (e.g., tabu state for tabu search, or initial and final temperature and cooling rate for simulated annealing) can provide some knowledge of the behavior of the heuristic in solving a particular problem. Examples of validation using this approach include Jørgensen et al. (1992) and Martins et al. (2005).

Level 3: *Comparison with other heuristic solution values.* The comparison of solutions from the implementation of one heuristic to those from the implementation of another is useful under certain circumstances. Mainly, the comparison should involve a standard heuristic with previously proven quality. A comparison to standard heuristic techniques is useful in understanding how much of an improvement can be obtained from the previously developed straight-forward methods. However, developers of heuristic techniques should make a concerted effort to avoid the trap of spending a significant amount of time developing the new methodology, then a limited amount of time solving the same problem with a standard heuristic, which results in the standard heuristic producing lower than expected solutions often due to lack of control of the parameters used in the standard heuristic. Examples of validation where solutions have been compared with well-established heuristic techniques include Dahlin and Sallnas (1993), Brumelle et al. (1998), Hoganson and Borges (1998), Boston and Bettinger (1999), Clark et al. (2000), Lu and Eriksson (2000), Crowe and Nelson (2003), Bettinger and Zhu (2006), and Liu et al. (2006).

Level 4: *Comparison with an estimated global optimum solution.* This approach was first suggested by McRoberts (1971), and later extended by Dannenbring (1977), Golden and Alt (1979), and Los and Lardinois (1982). Los and Lardinois (1982) suggest generating as much local optima as possible, and where possible, develop estimated global optimum solution values for each problem using extreme value theory. Here, a set of solution values generated with a heuristic are described by a Weibull distribution. This is a statistically-based approach that can provide a valid point estimate of the optimal solution value (Dannenbring 1977). Applications of extreme value theory are common in the study of size effect on material strengths, the occurrence of floods and droughts, and the study of what are known as "record values" or "breaking values" (Koltz et al. 1982). The first attempt to describe how one would validate heuristic results from natural resource management planning problems was described in O'Hara et al. (1989), and used later in Bettinger et al. (1998), Falcão and Borges (2001, 2002), and Bettinger et al. (2007). However, through extensive testing on natural resource management problems, the following two situations have been recognized:

Level 4a. *A statistically significant fit of the sample data to a Weibull curve can be found, and the resulting location parameter seems to be a good indicator of the estimated global optimum solution for the forest planning problem at hand* (Bettinger et al. 1998, 2002, Falcão and Borges 2001, 2002). The "data" being the characteristics (e.g., net present value) of management plans that were developed with the same heuristic, using the same parameters.

Level 4b. *A statistically significant fit of the data to a Weibull curve can be found, however the resulting location parameter is not a good indicator of the estimated global optimum solution for the forest planning problem at hand* (Boston and Bettinger 1999, Falcão and Borges 2002). This can occur when an ineffective heuristic, such as Monte Carlo simulation (in its basic form), is used to solve spatial harvest scheduling problems, providing an estimate of the global optimum that is not as good as solutions generated by other means. Thus in these cases, the location parameter derived may be of little use in validating the performance of a heuristic.

In addition, there may arise cases where a statistically significant fit of the data to a Weibull curve is not possible. Thus even though a location parameter may be suggested when attempting to describe the data with a Weibull curve, the location parameter (as in Level 4b) is not a good indicator of the estimated global optimum solution for the forest planning problem at hand (as noticed in Boston and Bettinger 1999).

Level 5: *Comparison with optimal solutions generated for similar problems.* There may be situations where similar problems can be solved with methods that produce optimal solutions. In these cases, the problems are either relaxed (i.e., one or more constraints ignored), or the problems are optimized based on sorting functions or other rules.

Level 5a: *Comparison with a relaxed solution.* A relaxed solution implies that one or more of the constraint sets has been either ignored or adjusted to accommodate solving a forest planning problem (with techniques such as linear programming). This can allow one to establish upper or lower bounds on the optimum solution to a problem, if some of the constraints can be relaxed (Zanakis and Evans 1981). In recent published examples of natural resource management planning research, one of the most common types of relaxation technique is to remove the clearcut adjacency constraints. Boston and Bettinger (2001) and others have used this approach to assess the degree to which heuristic solution quality differs from a theoretical upper bound on certain planning problems. The difference in solution quality can be seen as the cost of the constraints if the heuristic can be argued to produce high quality solutions (i.e., solutions that are almost as good as comparable integer or mixed integer formulations of the same problem). Examples of validation using this approach include Weintraub and Vera (1991), Daust and Nelson (1993), Tarp and Helles (1997), Boston and Bettinger (1999), Barrett and Gilles (2000), Boston and Bettinger (2001), Falcão and Borges (2001), Crowe and Nelson (2003), Öhman and Lamas (2005), Martins et al. (2005), and Bettinger et al. (2007). Hoganson and Borges (1998), Borges et al. (1999), and Van Deusen (1999) also used similar approaches, and compared heuristic-derived results to unconstrained cases. In cases where one or more parameters use fuzzy sets to address inherent uncertainty in the system, the solutions can be compared to others where the uncertainty is addressed explicitly (Krcmar et al. 2001). In other cases where non-linear constraints are assumed and linear, deterministic equivalents are unavailable, linear piecewise approximation procedures have been used to develop near-optimal solutions (Hof and Pickens 1991, Hof and Joyce 1993).

Level 5b: *Comparison with deterministic simulation model solutions.* Comparisons with problems designed as deterministic simulation methods are another alternative for comparing heuristic results with those generated from other heuristic methods or traditional mathematical programming methods. Complicated and perhaps intractable models that do not contain any random components can be designed as a deterministic simulation model. As a result, deterministic simulation models can provide solutions which can be implemented directly, and can be audited and validated. The input quantities and relationships to a problem can be directly specified, and the output directly determined for systems in which no stochastic components are assumed (Law and Kelton 1991). These types of models have been used in forestry to assess systems that range in scope from harvesting productivity (Howard and Tanz 1993) to leaf area index estimation (Berterretche et al. 2005) and to large-scale wood supply sustainability (Cieszewski et al. 2004). These types of models can be used to examine various forest management scenarios and provide insight into the sensitivity of management-related assumptions. However, separate executions of these types of models are not considered independent replications, and the results are thus difficult to analyze statistically because the same inputs result in the same outputs (Willers et al. 1995). Quasi-Monte Carlo methods that use well-devised deterministic points may be useful in this regard (Tezuka 1995).

Level 6: *Comparison with a solution generated from exact techniques such as integer or mixed-integer programming, or possibly through complete enumeration.*

This is the highest order of validation since two techniques (the heuristic and the exact technique) are solving the exact same forest planning problem. Ideally, all problem instances could be solved with mixed integer programming techniques, however this is not necessarily the case with complex problems. A comparison with an exact solution, however, is one of the most commonly used approaches for heuristic validation, yet the least favorite among some researchers (Rardin and Uzsoy 2001). In this case, exact optimal solutions to a number of small instances are obtained, usually at the cost of high computation times, and the solutions from heuristics are then compared to these. In many cases, the heuristic is then applied to a dramatically larger problem of practical interest, and the performance measured on the exact-solvable case(s) is assumed to carry over to the larger problem.

The time-consuming aspect of generating mixed integer solutions is a function of the solver parameters (preferred branch, optimality tolerance, objective hurdle, variable fixing tolerance, etc.), which can be modified and assessed for their ability to produce high-quality results; a testing process may require an extensive amount of computing time. However, to understand exactly the performance of heuristics in natural resource management planning, these exact solutions may be necessary. Therefore, one disadvantage of this level of validation arises when the exact solution generated involves setting the integer programming optimality tolerance above 0.1% or so. What this implies is that the exact technique actually stops searching when it determines that the solution located is within x% of the relaxed linear programming solution. As a result, the integer or mixed-integer solution may not be the best solution that can possibly be found, but one that can be found in a reasonable amount of time. In fact, many applications of mixed integer programming assume that a solution is optimal when it is within some pre-defined optimality gap. Raising the optimality gap shortens the computation time, reducing the gap increases computation time as well as memory required (McDill and Braze 2001). Using a single planning period and a relatively small planning problem, Murray and Weintraub (2002) needed over 60,000 constraints to fully specify the problem formulation, and when solving it with a mixed integer solver, stopped the process when the tolerance gap was about 15%. However, using three time periods, McDill and Braze (2001) illustrate a number of cases where the exact solution to a problem could be found in a reasonable amount of time when the tolerance gap was about 2% or less.

Examples of validation using this approach include Weintraub and Cholaky (1991), Weintraub et al. (1994), Barrett et al. (1998), Boston and Bettinger (1999), Barrett and Gilless (2000), Rosing et al. (2002), Bettinger et al. (2002), Crowe and Nelson (2003), Bettinger and Zhu (2006) and Epstein et al. (2006). Pukkala and Kurttila (2005) also compared heuristic-derived solutions to a "true optimum" value. Many of these examples validate the quality of heuristic solutions on small to medium problems, then illustrate the use of heuristics on larger problems, noting the difficulty involved in solving the larger problems exactly, as Rardin and Uzsoy (2001) suggested. Complete enumeration is another method for determining the optimal solution to a planning problem. Complete enumeration of all possible solutions is, however, computationally intensive and has been attempted on small problems in limited cases (e.g., Nalle et al. 2002).

3 Discussion

When a heuristic technique is presented in a research paper, the question that always arises concerns the level of validation that should be required. It is our opinion one or more of the six levels of validation that we described are not necessarily required for all forest planning research papers that involve non-exact solution generation methods. Research papers that describe the use of a new heuristic model for forest planning, or describe the use of a proven model on a new problem, could address the issue of validation differently, and explain what was (or was not) attempted, and why. Depending on the heuristic or the problem being solved, it is our opinion that one or more of these levels (yet not all of them) may be appropriate. We present four brief cases to illustrate the variation in the depth of validation that might be performed.

Case I. *A well-understood heuristic technique is applied to new management problems.* Here one challenge as it relates to the use of the heuristic itself is to explain that while the heuristic technique is not novel, the problem(s) being solved may represent a novel contribution to the literature. If the problems are not necessarily novel, however, one contribution that these types of papers can make is in the analysis of alternative management scenarios. An analysis of the results from the alternative scenarios may enable one to determine the difference in value of different scenarios, without the need to focus on the performance of the heuristic. For this type of research paper, it should be sufficient for authors to cite the relative performance of the heuristic as demonstrated in previous studies. It is our opinion that an acceptable level of reporting would include a clear description of the parameters used to solve the problem. While this implies a Level 1 validation, should authors choose to select this method, they may generate a large sample of solutions for each scenario and perform a statistical analysis (Levels 2b-2d) that would be of value in assessing the robustness of the heuristic solutions generated for each scenario. It is also our opinion that the expectation of higher levels of validation should only be required when it had not been performed in earlier work.

Case II. *A well-understood heuristic technique is applied to a common or standard set of problems.* Here, authors may be describing how a well-understood heuristic behaves when applied to a standard set of management problems that have been previously presented by others. In addition, authors may have the intent of testing the effect of different heuristic parameters on solution values, and of comparing these solution values to previously-published research. Most comparisons of well-understood heuristics in the forestry literature have not used common problem sets. However, this type of cooperative effort is slowly building support in forest planning, yet is not used as widely as in the broader operations research community, where optimal solutions using exact methods are available. The mixed-integer problem library (Martin et al. 2006) is one example. To facilitate these efforts in forest planning, the University of New Brunswick hosts an Internet site (Integrated Forest Management Lab 2006) devoted to the distribution of datasets for forest planning problems. If known optimal solutions to problems are available, results of well-understood heuristics can be compared to the previously-solved linear or mixed integer models. If known optimal solutions to problems are not available, results of well-understood heuristics can be compared to the results of previously-published heuristic techniques. For these types of papers, a description of the parameters associated with the heuristic technique is needed, along with the methods used to choose the parameters. Ultimately, this type of paper could address the issue of validation by using a self-validation of solution results (Level 2), and either (a) by comparing results with other heuristic results (Level 3) or (b) by comparing results to known optimal solutions (Level 5 and 6).

Case III. *A new heuristic technique is applied to a new management problem.* In this case, authors are describing a new heuristic technique rather than a variation of a proven heuristic technique, and are applying the new heuristic technique to a previously un-reported management problem. Here, both the heuristic technique and the problem being solved are novel contributions to the literature. The purpose of this type of application is to demonstrate how a new heuristic was developed to solve a new forest management problem. If these types of problems have either a non-linear objective function, or use a multiple objective utility function, and contain non-linear or spatially-related constraints, a relaxed problem may differ significantly from the complete problem and therefore may provide little insight into the solution quality. Thus a Level 5 or 6 validation may be unobtainable. Bettinger et al. (1998), for example, performed a Level 2c and 2d assessment, where the average level of outcomes from a set of runs were presented along with the associated variation. In addition, they performed one of the first Level 4 validations of a heuristic forest planning model. Other similar work (Bettinger et al. 1997, 2003) involved complex non-linear problems along with an assessment of alternative management scenarios, where no validation was reported. In these cases, exact solutions to the problems were deemed difficult, if not impossible, to obtain. While in these cases some form of self-validation could have been developed, neither work presented average results from a set of runs, nor described the variation that might be obtained from multiple runs of the models. However, based on our knowledge of this work, a sensitivity analysis of the heuristic parameters was performed (Level 2e) but not reported, in order to develop high quality results. The emphasis of the latter two works was (a) to describe the application of a new heuristic to a new management problem, and (b) as Carpenter (2002) later suggested, to add value to the assessment of the planning procedures by evaluating alternative scenarios rather than failing to establish performance.

One goal of the validation would then be to demonstrate how the new heuristic performs by illustrating a self-validation of solution results (Level 2). It is our opinion that an adequate level of reporting in this case is to present the variation in solutions that are initiated with random starts. We believe that the use of extreme value estimation can be used, but it is not always appropriate even though the independence of starting solutions can be shown. Solving a problem exactly may be extremely costly in terms of time or resources required, and attempts to do so may require linear piecewise approximation procedures (e.g., Hof and Pickens 1991), which again leaves one to wonder how close a solution is to the global optimum. The key questions to ask here are (a) how different the heuristic is from previously published methods (i.e., what makes it new?), and (b) how different the problem is from other problems previously presented in the literature. For example, adding strategic oscillation to tabu search seems to make it a new heuristic technique, but this is a significant enhancement to the search process compared to minor variations in the way the tabu tenure is applied (dynamic vs. static). If one argues that variations in heuristic parameters are the catalyst for arriving at a "new heuristic," then results should be obtained from a basic implementation of the heuristic technique and also from a set of the enhancements, to enable a Level 3 analysis of the results. However, if the heuristic truly is "new" and unique, the full range of validation (Levels 2-3, 5-6) seems unnecessary, in our opinion, for the initial paper describing its value to science and society. One (Level 3) or the other (Levels 5 or 6) may be sufficient, while Level 2 should be encouraged at all times. Requiring high levels of validation may actually hinder the creation of new science by limiting the exposure of these new methods to the forest planning community.

Case IV. *A new heuristic technique is applied to a common or standard set of problems.* Here, authors are describing a new heuristic technique when applied to a common set of planning problems that have been used by others. As with the previous discussion (Case II), comparisons using common problem sets are not routine in the forestry literature. However, Crowe and Nelson (2003) demonstrate how one could compare a new heuristic technique to previously-published results of other heuristic techniques, as well as exact linear (relaxed) and mixed integer formulations of a problem. It is our opinion that this type of paper should address validation by using a self-validation of solution results (Level 2), and either (a) by comparing results with other heuristic results (Level 3) or (b) by comparing results to known optimal solutions (Level 5 and 6).

4 Concluding Remarks

It has been our intention to present talking points that could be used for further discussion of a rational examination of the validation of heuristic techniques used in the forest planning literature. Obviously, authors and reviewers will need to decide what level of validation is appropriate for a paper to sufficiently cover the issue of heuristic solution quality. Our insight into this type of work suggests that one specific validation rule (e.g., solve the equivalent IP solution) should not be applied to all cases. Some consideration of the complexity of the planning problem and the evolution of the heuristic technique should be acknowledged. The total contribution made by a natural resource management operations research paper should be considered before certain levels of validation are suggested. Many forest planning research efforts involve a significant amount of time and energy to develop the data and formulate the problem(s). There is value in presenting novel applications of heuristics to large, non-linear management problems even though the level of validation may seem low (e.g., Bettinger et al. 2003). We only caution that the overall contribution of a paper be considered. When new approaches for developing forest plans are presented, other factors may be important in the publication decision, such as whether a new algorithm improves the time required to generate a solution, whether a new algorithm produces higher quality results or is less sensitive to differences in problem characteristics, or whether a new algorithm is simple, has high impact, is generalizable, or is innovative (Barr et al. 1995).

The field of forest planning is rapidly changing. New management problems continually arise, and often they are combinatorial in nature or include nonlinear relationships. As a result, there is continuing need for problem identification, problem formulation, and new techniques for solving these problems effectively and efficiently. It is our opinion that all peer-reviewed research contributions in forest planning need not be burdened by the computational requirements of achieving full validation (Levels 5 or 6 described above). Although some level of validation may be necessary for papers that describe heuristic forest planning techniques, the overall contribution of the work should be considered. We have described four brief cases of problems ranging from the application of standard heuristic techniques to new problem applications to the development of innovative heuristic techniques. We believe there are appropriate levels of validation for each of these. Hopefully the structure we have provided will assist both authors and reviewers of papers in forest planning, as well as others who face similar challenges, in differentiating levels of validation for certain types of research situations. The levels of validation presented here are meant to stimulate discussion and bring to the forefront these issues. Whether these levels become a "standard" is perhaps something that a professional group such as the E4 Working Group of the Society of American Foresters, or alternatively one of the IUFRO working groups, could address.

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