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Optimal Scheduling of Forest Treatments to Reduce Fire Intensity

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By

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ABSTRACT

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National Forests, particularly in the western United States, contain substantially denser forests than those at the turn of the 19th century. Subsequently, major forest fires that fall outside the normal disturbance cycle clear the forest, threatening old growth stands and the flora and fauna that inhabit them. In order to protect these groves and habitats, the U.S. Forest Service has initiated a program to schedule treatments that aim to reduce the severity and size of wildfires by spatiotemporally scheduling various treatments that remove fuels and generally decrease the density of the forest. This document describes the model used to achieve this objective.

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Introduction

1.1. The Problem

The forests of the Western United States have increased in both density of vegetation and litter since the turn of the nineteenth century from a landscape interspersed with open areas populated with perennial grasses to one dominated by trees, undergrowth, and fuels (Gruell 2001). This increase in fuels has created conditions such that once a fire is started it burns so intensely that all life is effectively removed and what remains has the appearance of a “moonscape”. Fire suppression has also been blamed for the buildup of dead litter-based fuels as areas that experience periodic fire tend to have less severe fires and less dead or downed trees. Although the debate on the impact of fire suppression has been underway for decades, a more recent trend in forest management may also be a major contributor to large scale fire events. In the western United States, many national forests have reduced or eliminated harvesting, either by thinning or by clear cuts. Such activities tend to reduce fuels overall, create openings, reduce ladder fuels, and produce a landscape that is less prone to large severe crown fires. It is quite possible that the two trends, reduced harvesting and fire suppression, have caused a problem that will be difficult to reverse, without significant investment in fuels treatments. As National Forests have become increasingly targeted by environmentalists to serve as core habitat for threatened and endangered species, a return to large scale harvesting is unrealistic. Even large scale thinning and stand management has been discouraged.

In 1995, The “New Perspectives” approach of the US Forest Service was built around the philosophy that forests need to be managed within the natural range of variability. The goal of this approach was to allow natural processes to define the scale and level of activities in the forest so that over the long run forest health would improve, including the habitat quality of core areas, *e.g*. old growth: see “Federal Wildland Fire Management: Policy & Program Review” (United States Department of the Interior 1995).

The big conundrum is to reintroduce fire as a natural (unsuppressed) process into forests without creating ground clearing events. This tact cannot be accomplished without a concerted effort towards fuels reduction. The US Forest Service has developed a policy for fuels removal based upon the research of Mark Finney (Finney 2004; Finney 2006). His research, which will be elaborated later, tends to suggest that spatially scattered areas designated for thinning and fuels removal would reduce the size of severe fires, regardless of where they start. Based upon the results of a large number of fire simulations, the forest service has developed a fuels reduction management strategy for forest operations. As the fuels treatment plans are instituted, it is expected that fire suppression will be reduced, leading to a healthier forest.

In addition to re-integrating fire into the ecosystem after years of overgrowth and fire suppression, the Forest Service also needs to protect remnant old growth forest stand, endangered or threatened species, and lands classified as Wildland Urban Interface lands (WUI). Wildlife Urban Interface (WUI) lands, as the title implies, are lands in which humans reside or in which they are active, for instance a mountain community with cabins and commercial shops or an area that is heavily used for camping and outdoor recreation. In addition to protecting these communities, the Forest Service must also preserve forest lands for future generations' recreational and even possible industrial use supporting a sustainable base of forest products.

The biggest constraint to moving forward with plans for fuels removal is cost. Congress has often underfunded Forest Service activities by relying on income generated from logging. Since income from logging has been virtually eliminated, Congressional authorizations limit the extent to which fuels removal can be accomplished. Although it would be desirable to treat an entire forest over a short period of time with the appropriate fuels removal projects, budget limitations mean that fuels treatment plans need to be spread over decades instead of a few years. This fact alone has created a "nightmare-like" problem of prioritizing and scheduling removal activities across a forest. In fact, this scheduling problem is the core issue of this thesis.

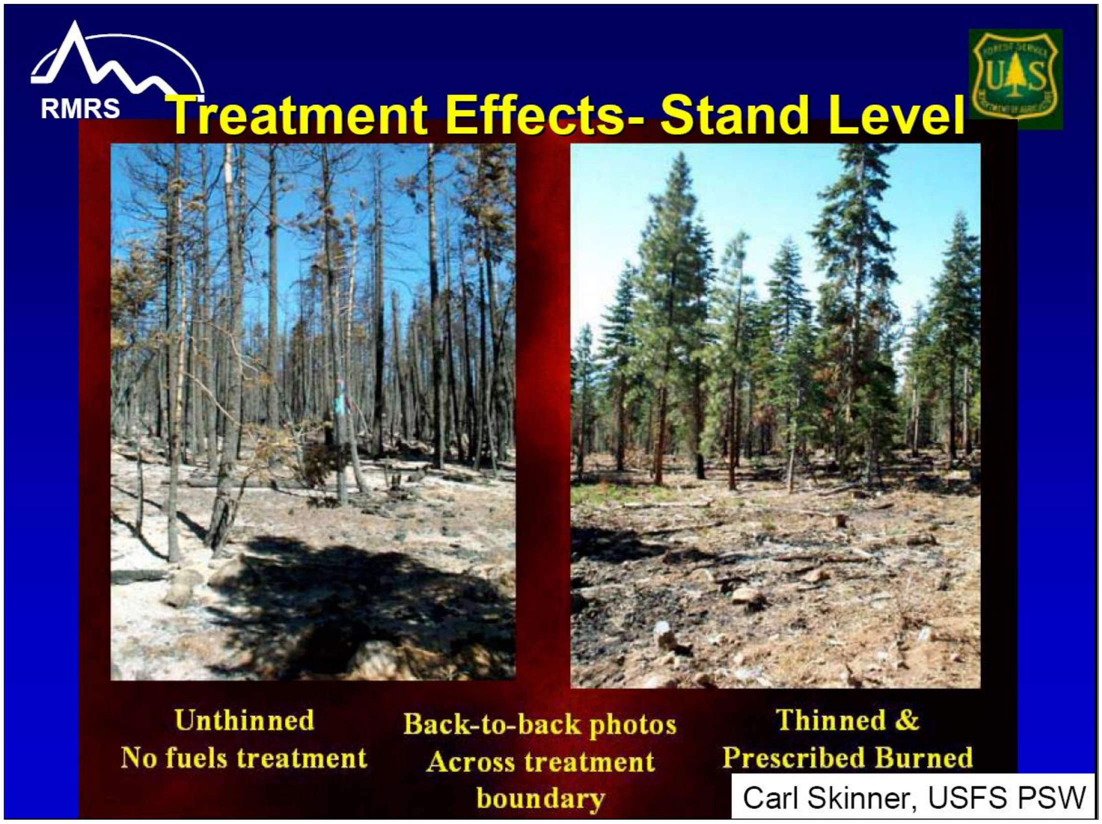
The remainder of the thesis is as follows: This chapter describes the research of Mark Finney associated with what is called the "Finney Effect", provides definitions for common terminology used by planners of the United States Forest Service, and concludes with a statement of the spatially-based scheduling problem that is the subject of this thesis. Chapter two describes the mathematical formulation of the model, variables used, the objectives, and the constraints. Chapter three describes the methods used in the approach to solve the model. Chapter four contains the results of the approaches used in the methods section. Chapter five discusses the results, and Chapter six provides conclusions.

1.2. The "Finney Effect"

The "Finney Effect" is an effect identified by Mark Finney of the United States Forest Service's Rocky Mountain Research Station in Missoula, Montana; Finney stated that by creating, "a spatial arrangement of treatments that primarily modifies fire behavior would involve area-based or dispersed patterns (Finney 2001)" which are optimally placed (Finney 2006). That is, fuel reductions such as controlled burns and thinning in *limited areas* conforming to an *optimized spatial pattern* reduces fire severity *without treating fuels in the entire forest*.

The reduction in fuels helps to confine forest fires to the ground, rather than the crowns of trees which results in areas devoid of live vegetation (See **Figure 1**). Figure 1 shows two post fire scenes, one that had been treated with controlled burn and one which had not been treated. The "post-fire scene" of the treated landscape shows that the forest was somewhat resilient as compared to the "post-fire" scene where there were no treatments. An intense fire is one that creates a moonscape and or one that grows to an extremely large size; a less intense fire would be one in which life continues to exist after the burn, such as trees and habitat in the crowns, or one that is confined to small burned areas. Finney showed through the use of a fire simulation computer program that treatments need to be dispersed, but do not need to

Figure 1 - Treatment Effects at the Stand Level



Source: Presentation by Mark Finney, September 15, 2004 in Washington, D.C.

(Finney 2004)

involve the entire forest. He identified that if approximately 28% of the forest is treated in a dispersed pattern of small treatment areas, forest fire behavior was similar to that if the entire forest had been treated with fuel removal techniques. Thus, the concept of the “Finney Effect” was borne: remove fuels in a dispersed treatment pattern covering about 28% of a forest, and fire size and severity will be substantially reduced. This concept has since been incorporated in the majority of forest management plans in California.

Unfortunately, the effectiveness of the “Finney Effect” for a given treatment lasts from approximately 15 to 20 years. This implies that areas will need to be retreated or maintained over time until the forest is in equilibrium with the disturbance due to fire. This is an issue that is still subject to debate as changes in climate may increase the occurrence of fire, and longer and extended droughts may increase tree mortality due to insects, which will increase downed litter and ladder fuels. Thus, in the near to longer term, the Forest Service may find it necessary to continue treatments (both initial and maintenance).

The US Forest Service is chronically underfunded and cannot treat even a portion of a forest without spreading the treatment activities over time. Fuels treatment plans tend to be spread over a period of 20 years. In order to fully characterize the problem of fuels treatment planning it is first necessary to define several important spatial constructs. These are constructs are covered in the next section. Given these spatial constructs, the problem of fuels reduction is then defined in section 1.4

1.3. SPLATs and PUCS

The first important term to define is the SPLAT. SPLATs are **S**trategically **Pl**aced **A**rea **T**reatments or **S**trategically **P**laced **L**andscape **A**rea **T**reatments; both breakdowns of the SPLAT acronym are used interchangeably by the United States Forest Service (USFS) and in the fire literature. When forest planners develop a fuels removal plan, the areas that have been delineated for treatment within the plan are called SPLATS. Overall, approximately 25-28% of a forest may be represented by SPLATS. Essentially, treating all SPLATS will bring the forest to the "Finney" condition.

Each SPLAT has a defined type of activity, e.g. control burns, thinning, and mechanized fuel removal. They are often placed in order to help protect nearby critical habitat and WUI lands.

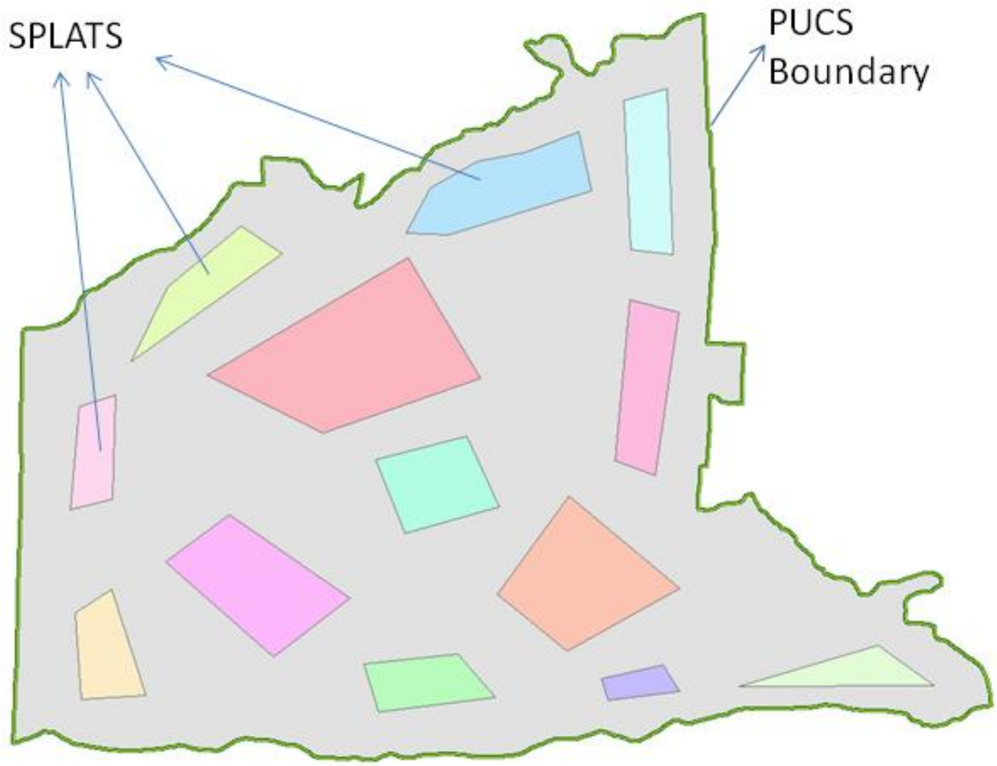
SPLATs are drawn by United States Forest Service (USFS) staff at the Ranger District level in a national forest. SPLAT boundaries are controlled in part by the forest stand and the density of fuels, by natural features, such as rivers and mountain ridges, by breaks in vegetation like forest service roads and escarpments, and by slope and aspect, as well as political boundaries, such as county lines, and other administrative boundaries. Generally, SPLAT boundaries are drawn by a group of forest service personnel who are familiar with the area and forest condition. (Kohler 2008).

SPLATs in and of themselves are quite small and are too small to consider as a project in which to contract with a company to apply the necessary treatments. Therefore, nearby SPLATs are clustered into a planning unit called **P**lanning **U**nit **C**ontaining **S**plats (PUC). A PUC contains a set of SPLATs and is considered large enough to be a project that can be contracted for fuels removal. A PUC boundary is defined by SPLATs that have been grouped, political boundaries such as county lines, and other administrative boundaries such as Ranger districts, as well as size. If all SPLATs within a PUC are treated, then it is assumed that the Finney condition will be met throughout the PUC (**Error! Reference source not found.**).

1.4. A detailed Statement of the Problem

One of the principal goals in forest management in the western United States is to reduce the intensity and size of fires. Forest management practices over the last two decades have changed considerably based upon a change in priorities. This change has resulted in moving from an emphasis on timber production to one of habitat protection. Along with this major shift in priorities has been a continued push towards fire suppression, especially in areas that are close to recreation areas. Given that fire has been suppressed, forest litter and ladder fuels have accumulated to the extent that many fires are large ground clearing events. Fire is a part of the natural regime, but fuels have accumulated to the extent that the state of a forest has changed such that a fire cannot be maintained as fires tend to be too large and intense and what replaces the forest tends to be scrub and chaparral. To remedy the outbreak of large fires and the expansion of scrub and chaparral, it makes sense to attempt to bring the condition

Figure 2 - PUCS and SPLATS



Note: In this case only the colored SPLATS would be scheduled; the gray area contains other SPLATS that are not shown because they have not been scheduled.

of the forest into a state in which naturally occurring fire events do not destroy substantial amounts of habitat, and public and private property, and reduce the expansion of scrub and chaparral land cover.

Ideally, one could treat the entire forest at the same time. However, with a limited budget one can only treat small amounts of area at a time. It thus makes sense to remove the right quantity of fuels (called fuels treatments) in optimal areas across a forest so that the forest landscape can remain viable with periodic fire events. Reducing fuels can be accomplished by a number of fuels treatment techniques, such as controlled burns, mechanical collection of litter and ladder fuels, and thinning of stands. Unfortunately most of the fuels treatment techniques involve substantial cost. Even though thinning of stands can provide revenue, it often involves smaller less valuable trees, and requires extra care so as to not damage the trees that are retained. The bottom line is that all fuels removal techniques do not generate enough revenue to cover the costs. Thus, fuels removal is constrained by available resources.

The main problem is that resources are limited to the extent that fuels treatments need to be scheduled over a relatively long planning horizon, e.g. 20 years. This is not ideal, as it means that it will take quite some time to bring a forest into a treated, more fire resistant state through the Finney effect. Given that a forest cannot be treated all at once, the locations chosen for treatments early in the schedule may play a significant role in protecting the forest and recreational areas from fires that may occur before the entire forest has been brought entirely into a treated state. Thus, the basic problem in fire intensity planning is to:

> *Select those areas (SPLATS) within the forest which are ideal for fuels removal within the context of slowing fire propagation. The number and pattern of SPLATS must be large enough in number and distributed widely across a forest, so that the pattern meets the criterion identified by Mark Finney (Finney 2001; Finney, McHugh et al. 2005).*

SPLATs are then clustered into Planning Units, called PUCS, which are of a size that makes sense within the context of contracting and project monitoring. Basically, treating a PUC means treating those SPLATs within that PUC. Since not all PUCs can be treated at the same time, the treatments must be scheduled over a 20 year period. Thus, the basic problem in fuels removal planning then is to:

> *Schedule which PUCs should be treated in each year subject to a yearly budget constraint while attempting to schedule SPLATS in areas of high priorities first and to cluster treated areas so that over time large tracts of the forest meet the Finney condition.*

This problem is called the fire intensity reduction scheduling (FIRS) problem. Though this problem has been generally defined within the context of forest maintenance and fuels reduction, it is also applicable to other spatial problems as well including allocating emergency response needs and how best to allocate aid distributed over time.

Section 2 – FIRS Model

The basic mathematical formulation of the Fire Intensity Reduction Scheduling (FIRS) model is outlined in the following pages. This model is an NP hard model that schedules PUCs (planning units containing SPLATs) over space and time. Two versions of the model were developed; the initial model is described below and then followed by the revised model and a discussion of why the model was revised.

Fire Intensity Reduction Scheduling (FIRS) model
Notation

i, j	=	indices used to represent a specific project areas, where j = 1, 2, 3, …, *n*
t	=	an index used to represent planning periods, where t = 1, 2, ,3 …, *m*
k	=	an index used to represent a specific planning area, where k = 1, 2, …, *p*
c_{jt}	=	the cost of treating project *j* in time period *t*
a_j	=	the size of treatment area in project *j* in acres
f_j	=	the total acreage of project *j* (treated and untreated)
w_j	=	the amount of wildland-urban interface acres present in project *j*
h_j	=	the number of acres of sensitive habitat present in project j
θ_j	=	the earliest time period in which project *j* can be scheduled
H_t	=	the total number of acres of habitat that can be disturbed in time period *t*
d_t	=	the discount factor for time *t*, where value is zero in time one and increases with time
B_t	=	the available budget for fuel removal projects in time period *t*
Γ_t	=	$\{j \mid \text{project } j \text{ can be assigned for treatment in period } t\}$
Ω_j	=	$\{t \mid \text{project } j \text{ can be assigned for treatment in period } t\}$
P_j	=	$\{j \mid \text{project } j \text{ is part of planning area } k\}$
E	=	$\{(i, j) \mid \text{project areas } i \text{ and } j \text{ are adjacent where } i < j\}$
s_t	=	deviation above the average yearly level of treatment area for time *t*
v_t	=	deviation below the average yearly level of treatment area for time *t*

In addition to the above notation, we will need the following decision variables:

$$x_{jt} = \begin{cases} 1, \text{if project } j \text{ is scheduled for treatment in time period } t \\ 0, \text{ otherwise} \end{cases}$$

$$u_{kt} = \begin{cases} 1, \text{if planning area } k \text{ is not assigned a project in period } t \\ 0, \text{otherwise} \end{cases}$$

$$z^0_{ijt} = \begin{cases} 1, \text{if project } i \text{ and project } j \text{ are both scheduled in time period } t \\ 0, \text{otherwise} \end{cases}$$

$$z_{ijt}^{1} = \begin{cases} 1, \text{if project } i \text{ is scheduled in time } t \text{ and project } j \text{ is scheduled in time } t+1 \\ 0, \text{otherwise} \end{cases}$$

$$z_{jit}^{1} = \begin{cases} 1, \text{if project } j \text{ is scheduled in time } t \text{ and project } i \text{ is scheduled in time } t+1 \\ 0, \text{otherwise} \end{cases}$$

Initial Model Formulation

Fire Intensity Reduction Scheduling (FIRS) model

Basic formulation

$$\textit{Maximize } \ Z_1 = \sum_{t=1}^{m} \sum_{j \in \Gamma_t} f_j x_{jt}$$

$$\textit{Minimize } \ Z_2 = \sum_{k=1}^{p} \sum_{t=1}^{m} u_{kt}$$

$$\textit{Minimize } \ Z_3 = \sum_{t=1}^{m} \sum_{j \in \Gamma_t}^{m} d_t w_j x_{jt}$$

$$\textit{Minimize } \ Z_4 = \sum_{t=1}^{m} (s_t + v_t)$$

$$\textit{Maximize } \ Z_5 = \sum_{(i,j) \in E} \left(\sum_{t=\max(\theta_i,\theta_j)}^{T} z_{ijt}^{0} + \sum_{t=\max(\theta_i,\theta_j)}^{T-1} z_{ijt}^{1} + z_{jit}^{1} \right)$$

Subject to the following:

Fire Intensity Reduction Scheduling Model

Basic formulation continued

1) $\sum_{j \in P_k \cap \Gamma_t} x_{jt} + u_{kt} \geq 1$ for each $k = 1, 2, 3, ..., p$ and $t = 1, 2, 3, ..., m$

2) $\sum_{j \in \Gamma_t} c_{jt} x_{jt} \leq B_t$ for each $t = 1, 2, 3, ..., m$

3) $\sum_{j \in \Gamma_t} h_{jt} x_{jt} \leq H_t$ for each $t = 1, 2, 3, ..., m$

4) $\sum_{t=\theta_j}^{m} x_{jt} \leq 1$ for each $j = 1, 2, 3, ..., n$

5) A)

$z_{ijt}^{0} \leq x_{it}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m$ and $j > i$

$z_{ijt}^{0} \leq x_{jt}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m$ and $j > i$

B)

$z_{ijt}^{1} \leq x_{it}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m-1$ and $j > i$

$z_{ijt}^{1} \leq x_{jt+1}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m-1$ and $j > i$

$z_{jit}^{1} \leq x_{jt}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m-1$ and $j > i$

$z_{jit}^{1} \leq x_{it+1}$ for each $(i, j) \in E$ and $\max(\theta_i, \theta_j) \leq t \leq m-1$ and $j > i$

Fire Intensity Reduction Scheduling Model
Basic formulation continued

6) $$\frac{1}{m}\sum_{t=1}^{m}\sum_{j\in\Gamma_t} a_j x_{jt} \; - \; \sum_{j\in\Gamma_t} a_j x_{jt} \; = \; v_t - s_t \qquad \text{for each } t = 1, 2, 3, ..., m$$

7) $$x_{jt} = \{0,1\} \qquad \text{for each } j = 1,2,3,...,n \text{ and } t = \theta_j, \theta_j + 1, ..., m$$

$$u_{kt} = \{0,1\} \qquad \text{for each } k = 1,2,3,..., p \text{ and } t = 1, 2, 3, ..., m$$

$$v_t \geq 0 \qquad \text{for each } t = 1, 2, 3, ..., m$$

$$s_t \geq 0 \qquad \text{for each } t = 1, 2, 3, ..., m$$

$$z^0_{ijt} = \{0,1\} \qquad \text{for each } (i, j) \in E \text{ and } t = \max(\theta_i, \theta_j), ..., m$$

$$z^1_{ijt} = \{0,1\} \qquad \text{for each } (i, j) \in E \text{ and } t = \max(\theta_i, \theta_j), ..., m-1$$

$$z^1_{jit} = \{0,1\} \qquad \text{for each } (i, j) \in E \text{ and } t = \max(\theta_i, \theta_j), ..., m-1$$

The FIRS model is a multi-objective integer-linear programming model consisting of five objectives. The FIRS model schedules projects over space and time in order to reduce fire intensity, protect WUI and sensitive habitat, by allocating a limited treatment budget over a number of years. One of the principal objectives in scheduling is to schedule neighboring PUCs in the same year if at all possible. By doing this, an even large contiguous chunk of land is brought to the “Finney” condition. Forest planners have reasoned that larger chunks of larger treated land tend to form an even greater defensive element for nearby habitat that needs to be protected. When neighboring units cannot be scheduled in the same year, then it is even considered desirable to schedule such units in subsequent years as this helps to generate a large chunk of treated land over a few years rather than in the same year. This objective is loosely called the adjacency objective, as there is an attempt to treat adjacent units in either the same year or a subsequent year.

Within the FIRS model there are five binary integer decision variables that are necessary to track: adjacency, the number of projects scheduled within a planning area (ranger district), and whether or not a specific PUCS is scheduled. They are as follows:

- The x_{jt} variables, take on the value of one if PUC project *j* is scheduled at time *t*, 0 if not;
- The u_{kt} variables, take on the value of one if planning area *k* is *not* assigned a PUC project in time period *t*, 0 if it is assigned a PUC project in time period *t*;
- The z_{ijt}^{0} variables, take on the value of one if PUC project *i* and PUC project *j* are both scheduled in time period *t*, 0 if not;
- The z_{ijt}^{1} variables, take on the value of one if PUC project *i* is scheduled in time *t* and PUC project *j* is scheduled in time $t+1$, 0 if not;
- The z_{jit}^{1} variables, take on the value of one if PUC project *j* is scheduled in time *t* and PUC project *i* is scheduled in time $t+1$, 0 if not.

The model solution is comprised of x_{jt} variables that signify when a PUC project has been scheduled, as well as u_{kt} variables which keep track of PUC projects scheduled in planning areas, and the z variables which keep track of scheduled PUC project adjacencies.

2.1. *Model Components Explained*

A. The Objective

The first objective, Z_1 or $\textit{Maximize } Z_1 = \sum_{t=1}^{m} \sum_{j \in \Gamma_t} f_j x_{jt}$, involves maximizing the total number of acres of PUC projects , over the entire planning period that is classified as meeting the Finney threshold. The second objective, Z_2 or $\textit{Minimize } Z_2 = \sum_{k=1}^{p} \sum_{t=1}^{m} u_{kt}$, involves minimizing the number of time periods t in which a given planning area k has not been assigned at least one project (u_{kt}). Planning areas are relatively large subdivisions of the forest and represent ranger districts. Since each ranger district is a somewhat independent operating unit within a National Forest, it is important to keep planning and operations staff involved in each ranger district during each time period t if at all possible. The third objective, Z_3 or $\textit{Minimize } Z_3 = \sum_{t=1}^{m} \sum_{j \in \Gamma_t} d_t w_j x_{jt}$, is an objective that is designed to minimize or maximize a discounted function of treated WUI area over time. Given a discount function it is possible to attempt to "Front-loads" or in the maximize sense "Endloads"[1] WUI acres on the schedule. In the FIRS model this objective is used maximize the treatment of PUCs within WUI areas as quickly and as early as possible. This objective is often touted as an attempt to protect cabins and other recreational facilities from the outset. It also helps to keep fire suppression costs to be lower than what would be otherwise needed to keep cabins from being destroyed in a wildfire. Scheduling PUCs containing WUI acreage as early as possible is achieved by multiplying the discount factor d_t by the amount of Wildland-Urban Interface (WUI) acres present in PUC project j (w_j) multiplied by the decision variable x_{jt} where PUC project j has been scheduled in time period t,.

The fourth objective, Z_4 $Minimize\ \ Z_4 = \sum_{t=1}^{m} (s_t + v_t)$, is the "Evenflow" objective which minimizes year to year variation in treated acres by minimizing the deviation of treated acreage above the average (s_t) and the deviation of treated acres below average (v_t) over all years. Minimizing the deviation of treated acres above and below the average level of treatment helps ensure that acreage treated from year to year does not dramatically vary. This is an objective that helps to keep workload consistent from year to year for the forest service staff. The fifth objective, Z_5 or

$$Maximize\ \ Z_5 = \sum_{(i,j)\in E} \left(\sum_{t=\max(\theta_i,\theta_j)}^{T} z_{ijt}^{0} \quad + \quad \sum_{t=\max(\theta_i,\theta_j)}^{T-1} z_{ijt}^{1} + z_{jit}^{1} \right)$$, maximizes project

[1] Front-loading attempts to schedule all WUI acreage early in the planning horizon; End-loading attempts to schedule WUI acreage late in the planning horizon. In this case we have chosen to front-load WUI acreage as it has the greatest amount of human interaction and, therefore, the greatest potential for damage by forest fire.

adjacencies in time period t (Z_{ijt}^{0}) and project adjacencies over subsequent years (Z_{ijt}^{1}). This objective was described as one of the principal objectives at the beginning of this section. Scheduling neighboring PUCs at the same time or close to the same time is considered to be very beneficial as barriers to large severe fires.

B. Simple Constraints

Constraint 1 assigns at least one PUC project, $x_{jt,}$ to each planning unit k in each time period t, or it forces u_{kt} =1. The constraint is set up such that if a PUC project j in time period t is scheduled (x_{jt} =1), then u_{kt} will take on the value of zero. In this way the u_{kt} variables tracks when a project is scheduled in a planning area (ranger district). This constraint along with the objective 2 attempts to keep each planning area, or ranger district and its personnel, within a national forest occupied with a PUC project each year. Constraint 2 forces the sum of every scheduled project x_{jt} and its associated fuels treatment cost c_{jt} to be less than the years allotted budget B_t. This constraint keeps the number of scheduled projects (PUCS) scheduled in year t to remain at or below the specified budget for year t. Constraint 3 forces every scheduled project x_{jt} and the sum of all sensitive habitats contained within it (h_{jt}) to be less than the years maximum limit on disrupting sensitive habitat. In this way, the amount of sensitive habitat that can be disturbed in a year can be kept to an amount that is deemed appropriate for each year. H_t amounts do not vary from year to year; national forest staff define this vale as a small percentage of the total amount of sensitive habitat. Constraint 4 stipulates that each project *j* can be scheduled at most once between the earliest possible time project j can be scheduled and the last year of the planning horizon.

C. Adjacency Constraints

The fifth objective of the model represents an attempt to maximize occurrences of when adjacent units are scheduled during the same year or on a successive year. This objective is designed to generate a large cluster of units that have been brought to a "Finney" treatment level. The adjacency constraints, 5A and 5B are used to track whether adjacent units have been scheduled in the same time period (5A) or split between two successive time periods (5B). The objective seeks to maximize the occurrences of when Z_{ijt}^{0} variables equal 1 or when Z_{ijt}^{1} variables equal 1. Type A constraints include the decision variable Z_{ijt}^{0}, which can take on the value of 1 only when both projects *i* and *j* are both scheduled in time period *t* (or zero if this is not the case). Note that the constraints and scheduling variables, X_{it}, are only written for time periods in which it is feasible to schedule both projects i and j. Also note that such variables X_{it} exist only when units *i* and *j* are adjacent. Type A constraints are written in groups of two, one for unit *i* being scheduled in time period t, X_{it}, and one form unit *j* being scheduled in time period *t*, X_{jt}. The value for z_{ijt}^{0} can equal 1 only when both $x_{it} = 1$ and when $x_{jt} = 1$. Thus, the objective terms of z_{ijt}^{0} will count only those occurrences when adjacent units *i* and *j* are scheduled in the same time period.

Constraints of type 5B are similar to 5A except that they capture the occurrences of when one unit, say *i* is scheduled in time *t*, and an adjacent unit, say *j*, is scheduled in time period *t+1*. It is important to note that there are several ways in which to account for when an adjacency occurs. In the above model, the constraint format is designed to t follow one developed by Balinski (1965) for a facility location model. Such constraints are considered tight constraints and tend to create facets in the model that are "integer friendly" in that they tend to force decision variables to be integer in value.

D. Treatment Constraints and Variable Restrictions

Constraint 6 tracks the treatment level in each year and computes the deviation from the average. This constraint is needed to define the level of deviation that is used to support objective 4. Constraint 7 defines the restrictions on the variables; in this case to be binary or non-negative in value.

E. iFASST and FIRS

iFASST, or the **I**nitial **F**orest **A**ctivities **S**patial **S**cheduling **T**ool, is a tool that the USFS uses to schedule initial forest treatments based upon a set of inputs and weights from which a heuristically generated solution is derived. It is based upon the FIRS model which is formulated above. iFASST can handle a maximum of five objectives and automatically assigns a weight value of one to each; these weights can be changed by the user to weight each objective before the user starts the heuristic process. The default objectives are to: 1) maximize the number of project adjacencies, 2) maximize the number of times at least one project is completed in each planning unit period, 3) maximize treated area, 4) maximize discounted WUI, and 5) attempt to even out year to year treatment levels.

Constraints that can be added include an Earliest Scheduling Time and various Budget constraints. The Earliest Scheduling Time constraint sets the earliest time period that a PUC project can be scheduled. The planning horizon that iFASST generally schedules projects is twenty years, though the user can change the planning horizon if desired. The Budget constraint sets the maximum budget available in a given time period, as well as sets an upper bound on the total amount of treatment that occurs in sensitive habitats. In this case sensitive habitats are marked by Home Range Core Areas (HRCA) and Protected Activity Centers (PACs) of the California Spotted Owl that overlap with specific SPLATS of a given PUC.

The research team at UCSB has developed the iFASST program from scratch. It uses MapObjects in order to support mapping functions and is a stand-alone decision support system. iFASST generates an initial solution utilizing a heuristic developed for the multi-dimensional knapsack. problem Once an initial solution is obtained it is added to the elite solution pool; the starting/current elite solution is modified into a "new" solution at which point the heuristic tries to reshape the "new" solution into the current elite solution using path re-linking. If a better solution is found it is added to the elite solution pool; this process is done 100 times (See **Figure 3** & **Figure 4**). A module programmed and added to iFASST as a part of this study in order to create an MPS problem file, representing a given FIRS problem. That is, a given FIRS problem instance can be set up and defined by this added functionality of the iFASST system. Using this special model file is described in greater detail below.

Figure 3 - iFASST Heuristic Routine A

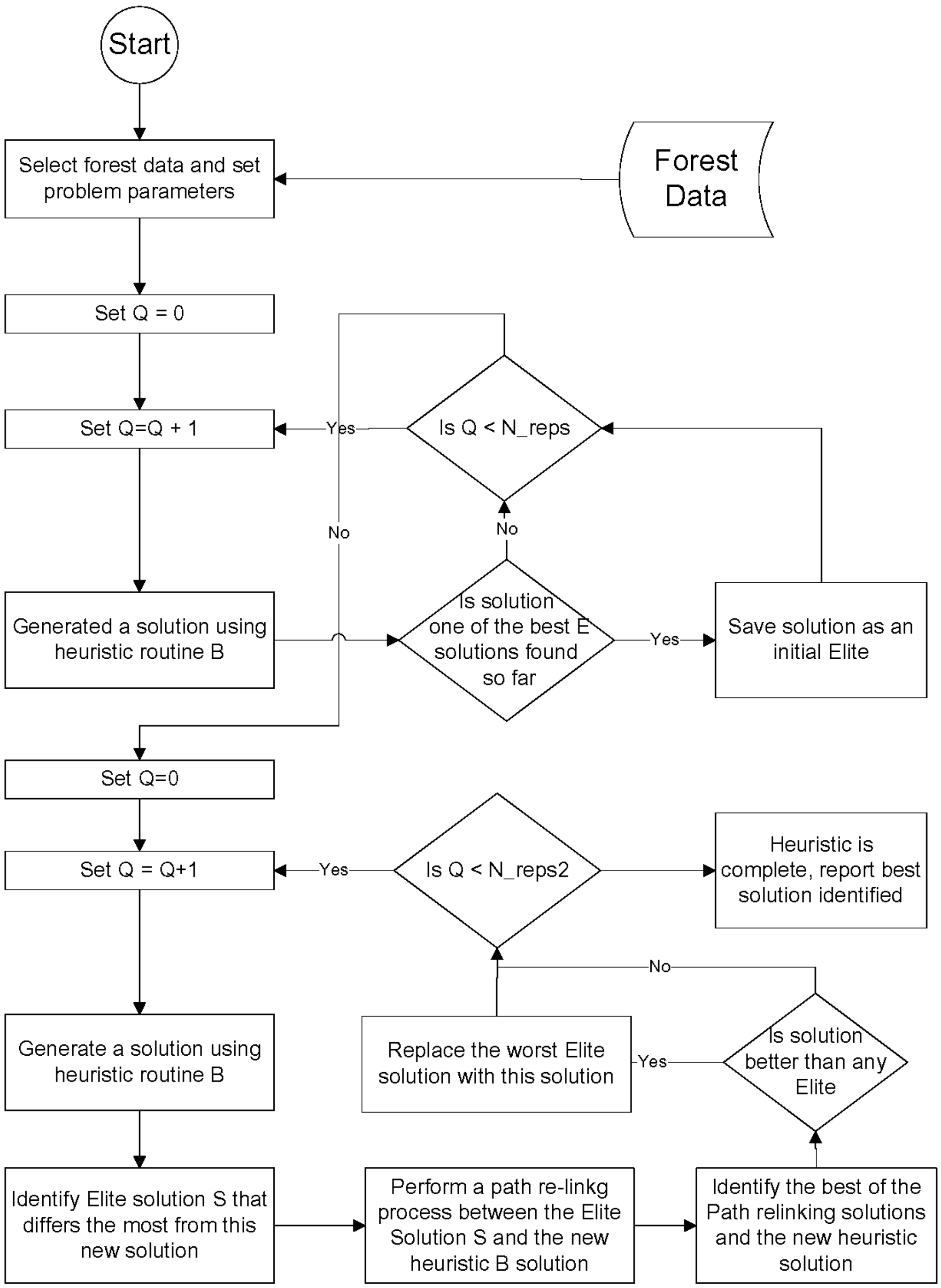
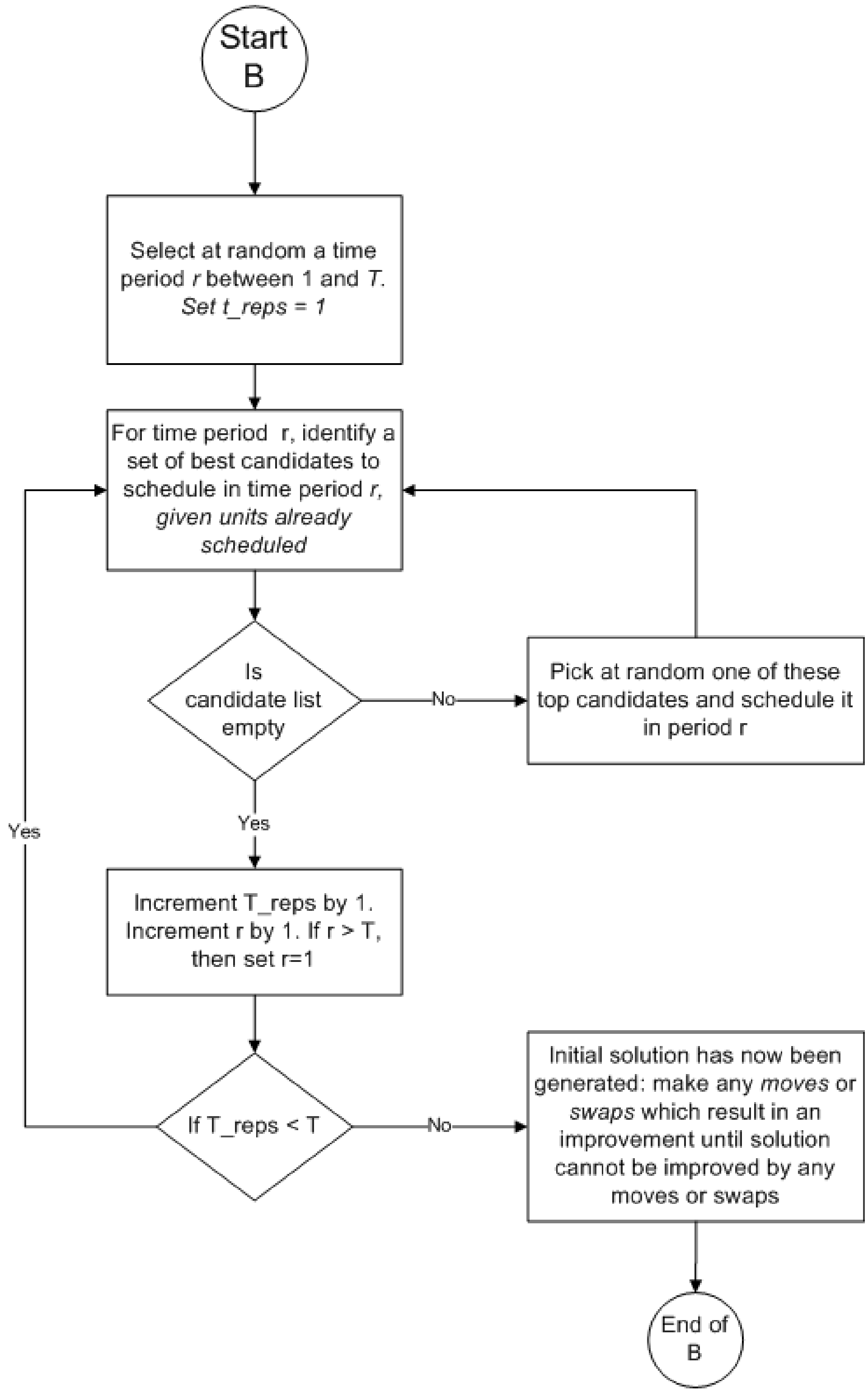


Figure 4 - iFASST Heuristic Routine B



Section 3 - Methods

Several approaches were undertaken to solve the FIRS model. This section describes those approaches and the result of their application, in order of application. Each of these approaches was run on a Sun Solaris SunBlade 2500 Workstation running the Solaris 5.8 operating system with two gigabytes of memory and two Sun Sparc 1.28GHz processors, utilizing the ILOG CPLEX 11.0.1 solver.

3.1. Running the FIRS Model

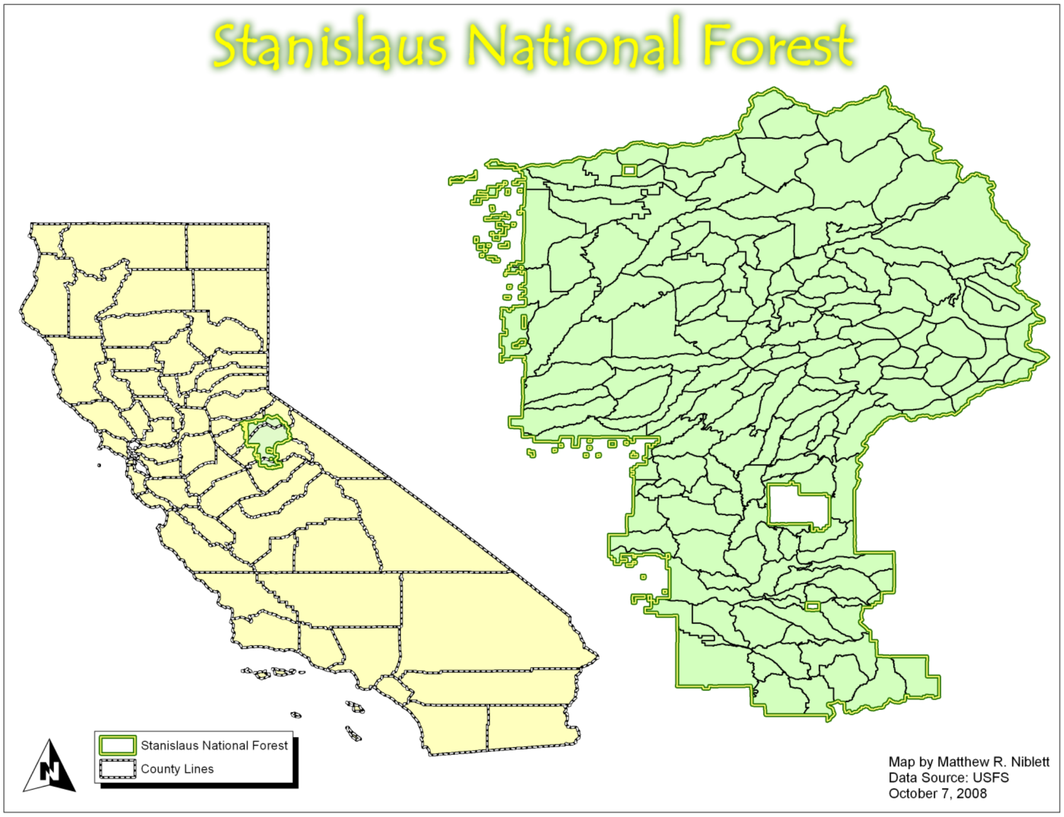
The FIRS model was setup for a given problem instance using the well-known MPS model format. This was accomplished using the module that was added to iFASST and described in the previous section. MPS format is a specific layout for specifying all components of a math programming problem and is supported by virtually all state-of-the-art general purpose optimization packages. MPS format is a generic file format and problem layout that can be used to import a given problem into an integer-linear programming solver. . This problem file was then transferred to the SunBlade 2500 workstation. The MPS model file was then read and solved by the ILOG CPLEX optimization package. Solution results for a given problem were redirected to a text file. This solution text file was then transferred to the PC running iFASST. The solution text file was then converted to a windows text file format using Notepad++, an open-source text and coding editor. A second module was added to the iFASST program so that the converted solution file could be read and processed by iFASST for display. Thus, a solution that is generated by CPLEX can be displayed on a map as well as analyzed by any of the charting routines that iFASST contains.

As solution times in solving a given problem by CPLEX can be quite large, most of the analysis reported here was concentrated on a specific, representative problem. This problem was developed by the US Forest Service for planning fuels treatments on the Stanislaus National Forest (See **Figure 5**). Stanislaus National Forest is representative of other national forests in that it involved all of the major planning objectives:

1) Maximize treated acreage,
2) minimize the number of planning periods (years) that a planning area lacks a scheduled project,
3) minimize the amount of WUI acreage scheduled in later time periods ("Front Load"),
4) minimize the variation in the amount of treatment from year to year (evenflow), and
5) maximize number of project adjacencies as described in section 2.

The objectives were respectively weighted with values of 1, 1000, 100, 10, and 1000. These weights were chosen to emphasize certain objectives over others; especially the adjacency objective. They were also representative of the relative weights that were used in the overall planning problem by forest planners.

Figure 5 – Map and general location of the Stanislaus National Forest



A. FIRS model with Balinski Constraints

The FIRS model as described in section 2 uses a particular constraint format called the Balinski constraint, first proposed by M. L. Balinski in 1965 (Balinski 1965). The Balinski constraints keep the constraints tight because they help to force the scheduling variables to be integer in value, however, the number of constraints that is needed to support this structure is high. The FIRS model utilizing Balinski constraints for the adjacency constraints for the same and subsequent years creates a total of 41,774 linear constraints. The sheer number of constraints and the lack of sufficient computer power locked up CPLEX and the run for the full model was aborted after close to two months of computer time.

B. FIRS model with Balinski and Efroymson and Ray Constraints

The second approach used was to use a form of the well known Efroymson and Ray constraints to track adjacencies. In this case, Balinski constraints were used for the adjacencies in the same time period and Efroymson and Ray type constraints were used for the adjacencies in prior and subsequent years. Efroymson and Ray constraints are constraints that were introduced by Efroymson and Ray in their 1966 paper (Efroymson 1966). These constraints are not as tight as Balinski constraints, however, they often require greater computational effort and force the solver to rely heavily on the branch and bound algorithm. The general mathematical formulation used is as follows:

Successive Years (5b constraints) – Modified Formulation

$$\left.\begin{array}{l} z_{it}^1 \le n_i x_{it} \\ z_{it}^1 \le \sum_{\substack{j \in A_i \\ j>i}} x_{j,t+1} \end{array}\right\} zi \text{ variables in the MPS model}$$

$$\left.\begin{array}{l} z_{jt}^1 \le n_j x_{jt} \\ z_{jt}^1 \le \sum_{\substack{i \in A_i \\ j>i}} x_{i,t+1} \end{array}\right\} zm \text{ variables in the MPS model}$$

In this case, the Efroymson and Ray style of constraints significantly reduce the number of constraints; total constraints went from 41,774 to 25,006 constraints. The Efroymson and Ray constraints reduced the original formulation constraint count to 59.9% of the originally formulated FIRS model. Using this approach, CPLEX was still unable to solve the model, though, it reached the same point as the model with the Balinski constraints in about half the amount of time needed for a set of all Balinski constraints. This was expected as Rosing, ReVelle, and Rosing-Vogelaar postulated that a mix of Balinski and Efroymson constraints could lead to faster solution times (Rosing 1979) for a classic location problem.

C. FIRS model with Efroymson and Ray Constraints

The third approach was to use Efroymson and Ray constraints for all of the adjacency constraints (5a and b constraints). The general mathematical formulation used is as follows:

Same Year – Modified Formulation:

$z_{it}^0 \le n_i x_{it}$ where z_{it} is the number of shared edges and n_i is the number of adjacent units j to unit i where $j>i$.

$z_{it}^0 \le \sum_{\substack{j \in N_i \\ j>i}} x_{jt}$ where N_i is the set of neighbors of j.

Successive Years – Modified Formulation

$$\left.\begin{aligned} z_{it}^1 &\le n_i x_{it} \\ z_{it}^1 &\le \sum_{\substack{j \in A_i \\ j>i}} x_{j,t+1} \end{aligned}\right\} zi \text{ variables in the MPS model}$$

$$\left.\begin{aligned} z_{jt}^1 &\le n_j x_{jt} \\ z_{jt}^1 &\le \sum_{\substack{i \in A_i \\ j>i}} x_{i,t+1} \end{aligned}\right\} zm \text{ variables in the MPS model}$$

In this case, exclusive use of the Efroymson and Ray formulation for the adjacency constraints reduced the number of constraints from 41,774 in the original formulation to 16,062 or to 38.4% of the size of the original FIRS model utilizing Balinski constraints. Solving a model with all Efroymson and Ray style adjacency constraints actually took longer than the time needed to solve the larger but tighter mixed Balinski and Efroymson and Ray constraint model to the same bound or point of convergence. Unfortunately, this model run was also aborted as it did not converge in a reasonable amount of time.

D. Tuning

Given the performance of the mixed Balinski and Efroymson and Ray constraints MPS model, it was thought that tuning the solver to solve this version of the problem could improve performance and return a solution. CPLEX 11.0.1 provides this capability and the tuning settings were saved in a parameters file. The parameters file was then loaded into CPLEX and the mixed FIRS model with Balinski and Efroymson and Ray constraints was then re-run. CPLEX was able to identify a feasible solution and reduce the bound farther than it had previous runs. However, after running for several weeks, CPLEX bogged down once again and the problem was aborted. This last approach with tuning indicated that the FIRS model could not be fully solved to optimality in any reasonable amount of computer time. We could, however, confirm that the heuristic solutions of iFASST were within 15% of optimality.

3.2. Fixing in a Percentage of a Heuristic Solution

Solving the complete FIRS problem to optimality for a realistic problem setting proved to be impossible, so another approach was attempted. The idea behind this approach uses concepts from the Lambda-Opt approach (Lin 1965). Lin developed a solution strategy for the travelling salesman problem that was based upon a swapping strategy. He suggested to take λ elements of a tour and swap them with a different set of λ elements of the tour. If this generated a shorter tour then the improved tour was now the incumbent, solution. A λ-opt solution is one that cannot be improved by and swaps of size λ. Overall, the λ-opt process starts with a feasible solution and attempts to make a swap of λ elements. If this is an improvement, it becomes the incumbent solution. The process continues until all swaps of size a λ will result in no change to the incumbent solution. In practice it has been found that the λ-opt process will find optimal or near optimal solutions with regularity when $\lambda = 1$, 2 or 3. Lin called the process λ-opt as he reasoned that if a problem has *n* elements, then when $\lambda = n$, the λ-opt heuristic would generate am optimal solution. However, in practice it usually only requires small values of λ to generate an optimal or near optimal solution. The only drawback of this heuristic in solving combinatoric problems like the travelling salesman problem or the FIRS problem is that the computational burden of making swaps for large values of λ is too high to be practical. The saving grace of this approach is that it is usually not necessary to use a high λ value.

We can employ the λ-opt approach in a rather unique and novel way for the FIRS problem. The iFASST software package employs a heuristic based upon a set of strategies, including path relinking, GRASP, and swapping. Technically it is at least as good as $\lambda = 1$. For the FIRS problem, there are *n* PUCS that can be scheduled over 20 years. In practice, not all PUCS can be scheduled as the budget is too limiting. The output of the iFASST heuristic is considered to be good, and should form the basis of a good starting solution for λ-opt approach where λ is considerably higher than 1. For the Stanislaus National Forest, there are 140 PUCs that are schedulable. A good solution involves scheduling about 120 units over the planning period. Let's suppose that we wish to test a swap of a given 15 scheduled units with another 15 schedulable units. The problem is that there are many ways in which a given 15 can be swapped with another 15 in the schedule. For example, consider the possibility of 3 units: PUC 45 scheduled in period 2, PUC 77 is scheduled in period 20, and PUC 13 is scheduled in period 5. Swapping these three amongst themselves produces several possibilities: 1) PUC 77 in 2, PUC 45 in 5, and PUC 13 in 20; 2) PUC 77 in 5, PUC 13 in 2, and PUC 45 in 20; and so on. Finding the best swap amongst these three units can be done by using the FIRS model. To show how this can be done, consider the following notation:

$\Phi = \{(j,t) \mid x_{jt} = 1 \text{ in the heuristic solution}\}$, the scheduling solution

$\Phi_s = \{(45,2),(77,20),(13,5)\}$, the swap set

The $\lambda FIRS$ model can be defined as follows:

- FIRS model (5 objectives and 7 constraint types) with the additional constraints: $x_{jt} = 1$ for each $(j,t) \in \Phi - \Phi_s$

Solving $\lambda FIRS$ to optimality using CPLEX will produce the best solution involving swaps between the swap set and between the swap set and PUCs that were never scheduled in the heuristic solution. Although FIRS is not easy to solve to optimality, $\lambda FIRS$ is a reduced problem, and considerably easier to solve to optimality. To show how we, might use this modeling construct further, consider the following set:

$$\Phi_\alpha = \{\alpha \text{ elements of } \Phi \text{ have been chosen randomly}\}$$

The set Φ_α represents a selection of a certain portion of a solution at random, to serve as the swap set. The basic idea is that once we have generated a swap set, Φ_α, We can then solve $\lambda FIRS$ to optimality to produce the optimal λ swap using the set Φ_α. The beauty of $\lambda FIRS$ is that it is identifies the best of all possible swaps within the swap set or elements without enumerating all such possibilities. For example, swapping 15 for 15 would entail at least (15 factorial permutations -1) solutions (the -1 represents the original swap set). The number of possible swaps between 15 for 15 is at least 1.307 x 10^{12} solutions. Thus, solving $\lambda FIRS$ with doing a 15 for 15 swap would represent an enormous set of possible swaps of which it would identify the best.

To use $\lambda FIRS$ to generate the best swap for 15 would involve using a Φ_{30} swap set. A size of 30 represents approximately 25% of scheduled units for the Stanislaus forest.

We have now described a new model called $\lambda FIRS$. $\lambda FIRS$ is a constrained version of the FIRS model which when solved will identify the best λ swap for a given candidate set. In many combinatoric problems, using λ = 1 or 2 yields a close to optimal, if not optimal solution when applied over the entire solution space. Because of the knapsack like constraints and the adjacency objective in FIRS, it is necessary to make λ as high as practicable. Unfortunately, it is impossible to generate all permutations of swap sets with a problem of 140 PUCs. By using a high λ value, many of these sets will overlap, negating the need to generate all possible swap sets. For the analysis reported here, we generated 1000 swap sets involving 25% of the total solution elements.

To solve $\lambda FIRS$, we begin with a starting heuristic solution $H_{0.}$ Each $\lambda FIRS$ problem represented fixing at random 75% of the solution as fixed and allowing the remaining 25% to vary. We solved each $\lambda FIRS$ problem using CPLEX where the convergence criteria was set at 1%. That is CPLEX stopped when it had solved a given problem to within 1% of optimality. The process was of solving $\lambda FIRS$ a thousand times was done in batch form. A module was added to the iFASST software package to take a heuristically generated solution and set up 1000 $\lambda FIRS$ problems associated with the heuristic solution. These problems were specified in MPS format and sent to CPLEX to solve within the 1% bound value. The results of each of the one thousand CPLEX runs were sent to a text file. The text files of each of the individual runs were then processed on the UNIX machine into two text files: one file containing all of the objectives, and the other file all of the proven bounds.

These two files were then transferred to a PC running Microsoft Windows XP and converted into the Windows text format using Notepad++. Once this was done, all of the space characters were replaced by a tab character. The text files were then opened by a specially defined program to process the objective and bound text files into a neatly sorted tab-delimited file. These processed text files were then imported into Microsoft Excel where descriptive statistics were calculated and the run containing the greatest improvement identified.

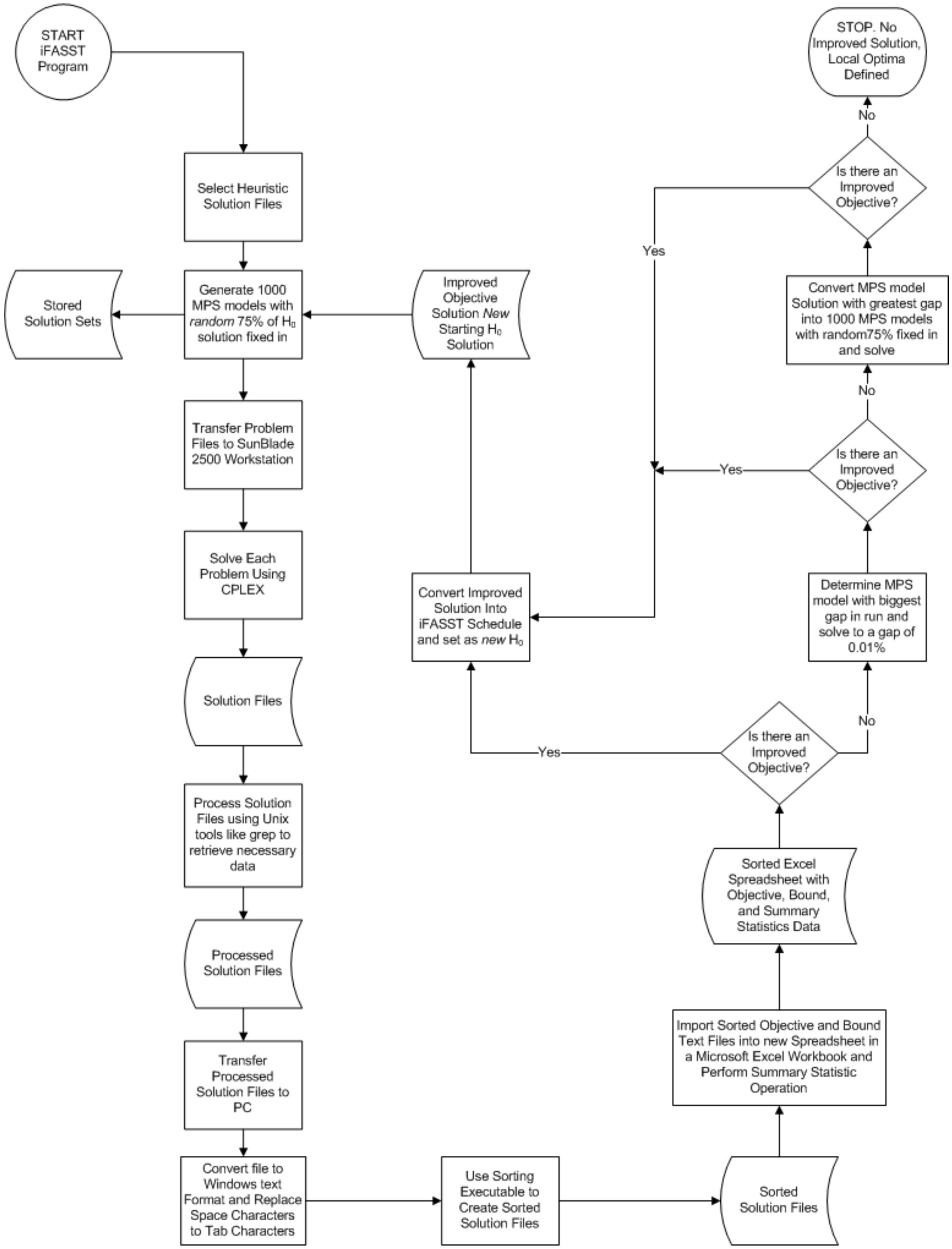
The best solution found from the 1000 $\lambda FIRS$ solutions was identified and saved. This new solution became the "incumbent" best, and the $\lambda FIRS$ process was restarted with this as the starting solution. After 1000 $\lambda FIRS$ problems were solved using this solution, the best was found and this was then designated as the new incumbent solution. This process was continued until no improvement was found in a thousand runs of $\lambda FIRS$. Note this process will monotonically converge to a stable solution. **Figure 6** depicts a flow chart of the process used in solving $\lambda FIRS$.

The basic premise for $\lambda FIRS$ is that the final stable solution is likely to be close to optimal if not optimal. Even though the original FIRS model cannot be solved to optimality, there is a high probability that $\lambda FIRS$ can converge to a solution that is within 1%.

Section 4 - Overall Results

Solving the FIRS model to optimality was impossible, though the $\lambda FIRS$ approach utilizing the concept of Lambda-Opt was successful. The first FIRS model formulation consisting only of Balinski constraints for tracking scheduled project adjacencies ran for nearly two months without even obtaining a feasible solution before it was aborted. The second FIRS model formulation using Balinski constraints for tracking adjacent projects scheduled in the same time period and Efroymson and Ray constraints for tracking adjacent projects scheduled in previous and subsequent years ran in about half the time it took to run the original FIRS model to the same

Figure 6 – Steps Used by λFIRS to Generate an Improved Solution

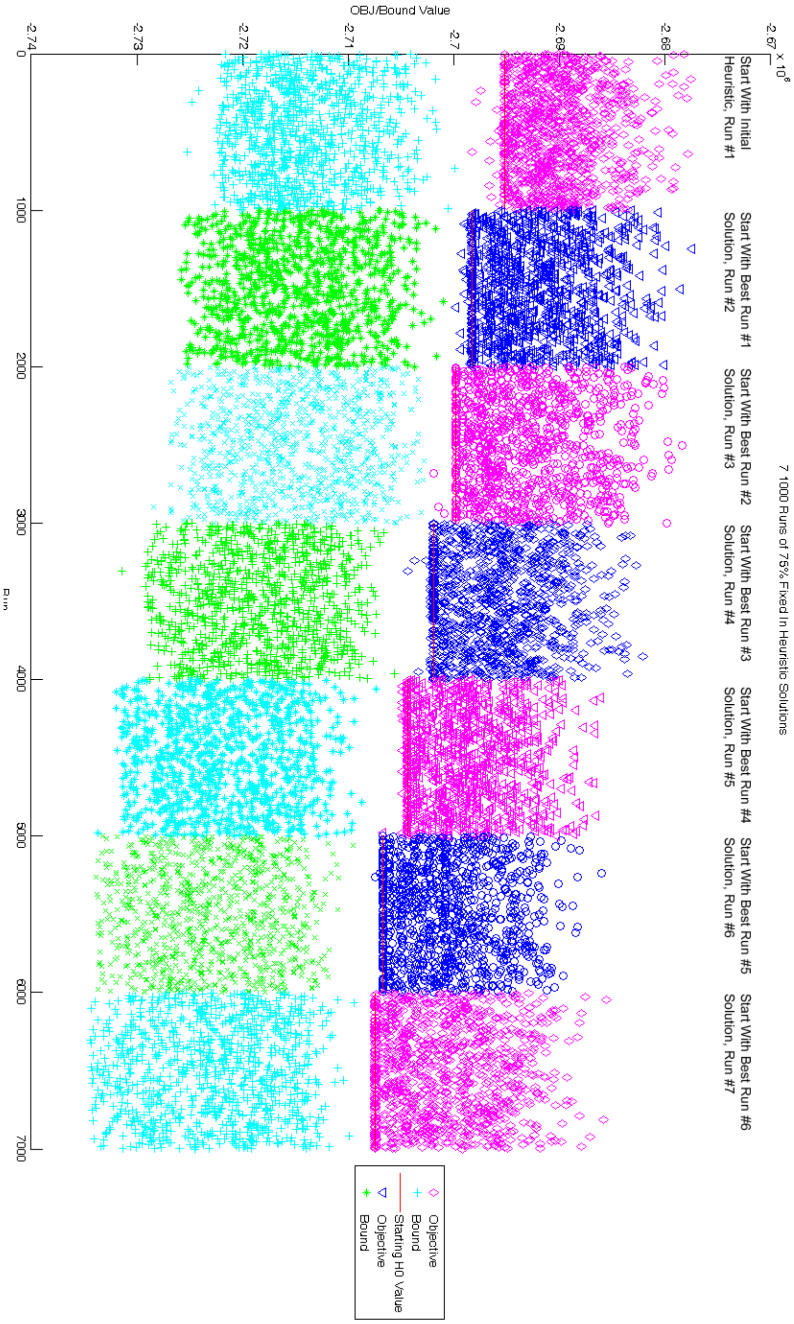


level of convergence, but was also aborted without obtaining a feasible solution. The third FIRS model formulation utilizing Efroymson and Ray constraints for tracking all scheduled project adjacencies ran for several weeks, took longer than the second FIRS model formulation, but was shorter than the first FIRS model formulation. It also failed to identify a feasible solution.

At this point tuning of the Second FIRS model formulation was attempted using the built-in tuner process of CPLEX 11.0.1. The tuning process took 50,002 seconds or nearly 14 hours. The second FIRS model formulation was then re-run with the parameters determined by CPLEX 11.0.1's tuning feature. CPLEX was able to identify a feasible solution, though still inferior to the solutions identified through the iFASST software package's heuristic approach, and identified an improved bound with a smaller gap in much less time than had been previously needed; the best bound found was -3,092,711. However, even with these improvements, CPLEX was still unable to determine an optimal solution in a reasonable amount of time and the run was aborted. This lead us to the last approach using $\lambda FIRS$ to identify an improved solution.

The results shown here are those from the $\lambda FIRS$ method. This method did indeed identify an improved solution; the $\lambda FIRS$ approach was started with a heuristically determined solution generated by iFASST. This seed solution had an objective of negative 2,695,176 and the $\lambda FIRS$ approach converged to a stable incumbent solution of negative 2,707,420 after seven complete iterations (i.e. 7 sets of 1000 $\lambda FIRS$ model runs). **Figure 7** shows the distribution of each set of $\lambda FIRS$

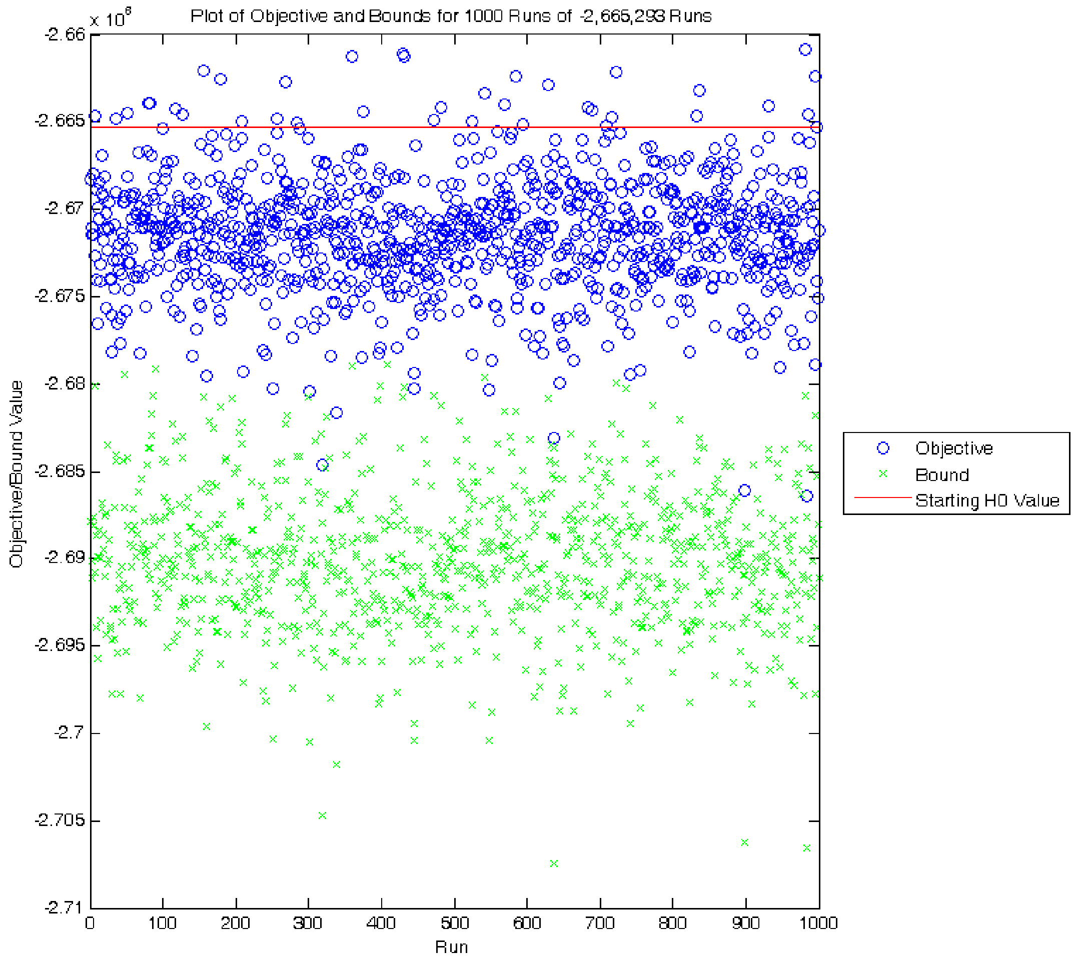
Figure 7 - Depiction of objective values, starting and best bound, associated with 7 Sets of λFIRS Runs.



runs (1000 swap models each). In each of the runs, there is a red line that shows the starting objective value (H_0) from which each of the one thousand models in a set were generated. The points that lie below this red line are improved solutions; as the number of sets of runs increases, the number of improved solutions and variation between the starting H_0 solution and the best improved solution tends to decrease. In the last run of **Figure 7** (i.e. run seven) no improvement in any of the generated 1000 swap models was found. The largest gap found in any of the solutions associated with the last set of 1000 swap models was resolved to a gap of less than 0.01%, without finding an improvement. As a final check, this solution was subjected to a $\lambda FIRS$ test of 1000 swap models with no improvement. We also tested the $\lambda FIRS$ by starting with a seed solution that was known to be inferior (but still relatively good) and subjected that solution to a $\lambda FIRS$ run of a 1000 swap models. This heuristic seed solution had an objective of -2,665,293. The result of this test involving 1000 swap models is shown in **Figure 8**.

The results of **Figure 8** indicate that an inferior seed for the λFIRS model will result in many new and better solutions being identified. Comparing Figures 7 and 8, one can see, as the incumbent seed solution improves, the likelihood of identifying better solutions through swapping tends to decrease. This type of convergence indicates that when a 1000 λ=15 swap tests fail to produce a better result the solution is stable, and unlikely to be improved regardless of the number of tested swaps. Since the swap neighborhood size is very large, results from Lin (1965) would lead to the conclusion that the final incumbent solution is not only locally optimal, but globally

Figure 8 - Results of the λFIRS Model Applied to a second heuristic solution where the initial solution seed is dominated by other solutions.



optimal. **Figure 9** displays the results of the inferior heuristic seed solution compared to the runs of those displayed in **Figure 7**. The histograms of objective values for each set of λFIRS runs is presented in **Figure 10** and also help support this conclusion, where it can be seen that as the run sequence number increases, the results of λFIRS tends to spike at the seed solution.

Table 1 shows the starting H_0 value and the most improved solution found in the 1000 models solved. The starting H_0 objective of -2,695,176 identified by the iFASST software package heuristic was improved to -2,707,420 after 6 runs of λFIRS. The seventh run resulted in no improvement. The total improvement over the 7 runs totaled -12,244 or 0.45%. The solution reduced the gap from the known best bound of -3,092,711 from 12.9% to 12.5%. **Figure 11** shows the number of improvements found, by run. The number of improved swaps found in Run 3 was quite low. The general trend in the number of solutions identified that are better than the starting solution, and the difference in objective value between the improved solution and the starting solution, decrease as the number of runs increase.

Figure 9 –Depiction of objective values, starting and best bound, associated with 8 Sets of λFIRS Runs.

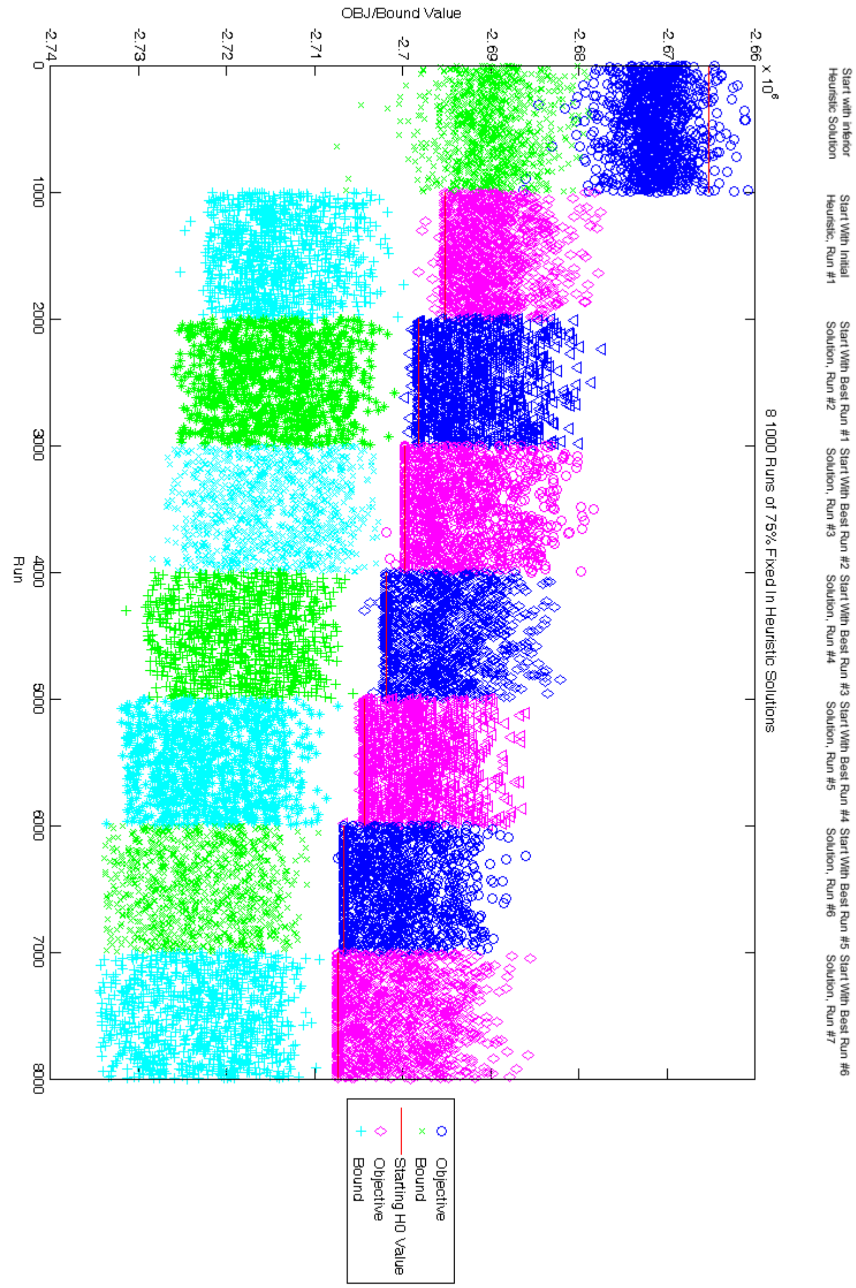


Figure 10 - Twenty bin Histogram of 8 Runs representing sets of 1000 λFIRS model solutions.

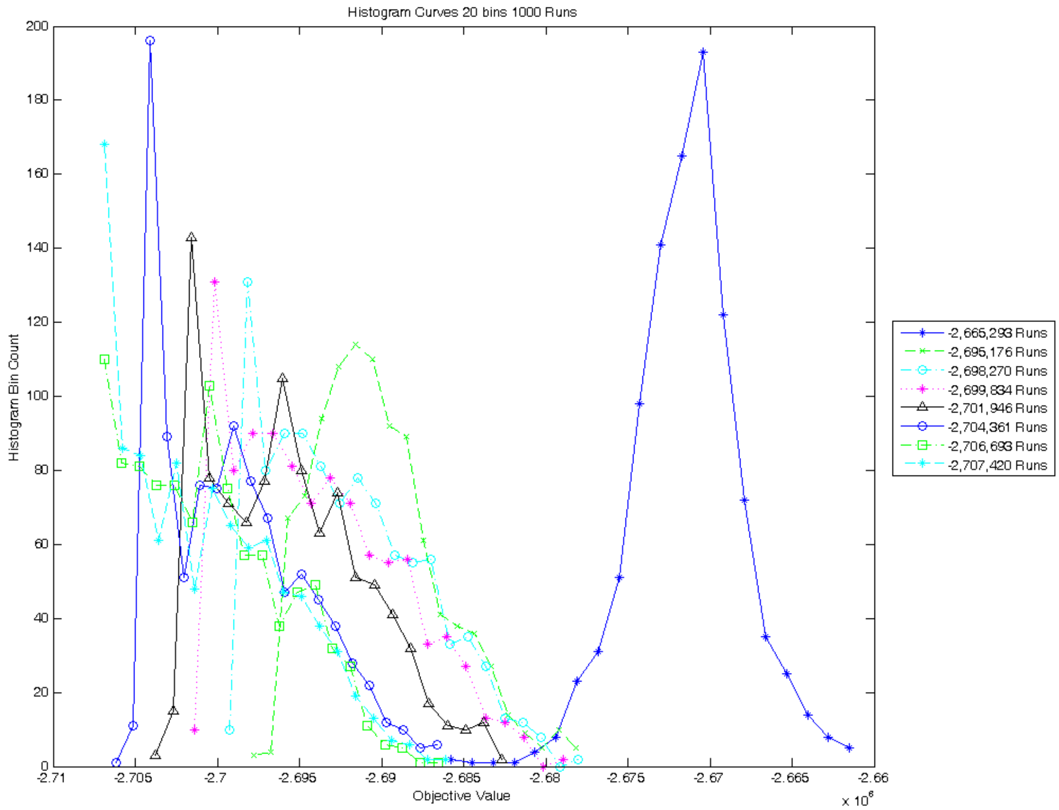


Figure 11 - Scatter plot showing the number of improved solutions as a function of sequence of λFIRS model application.

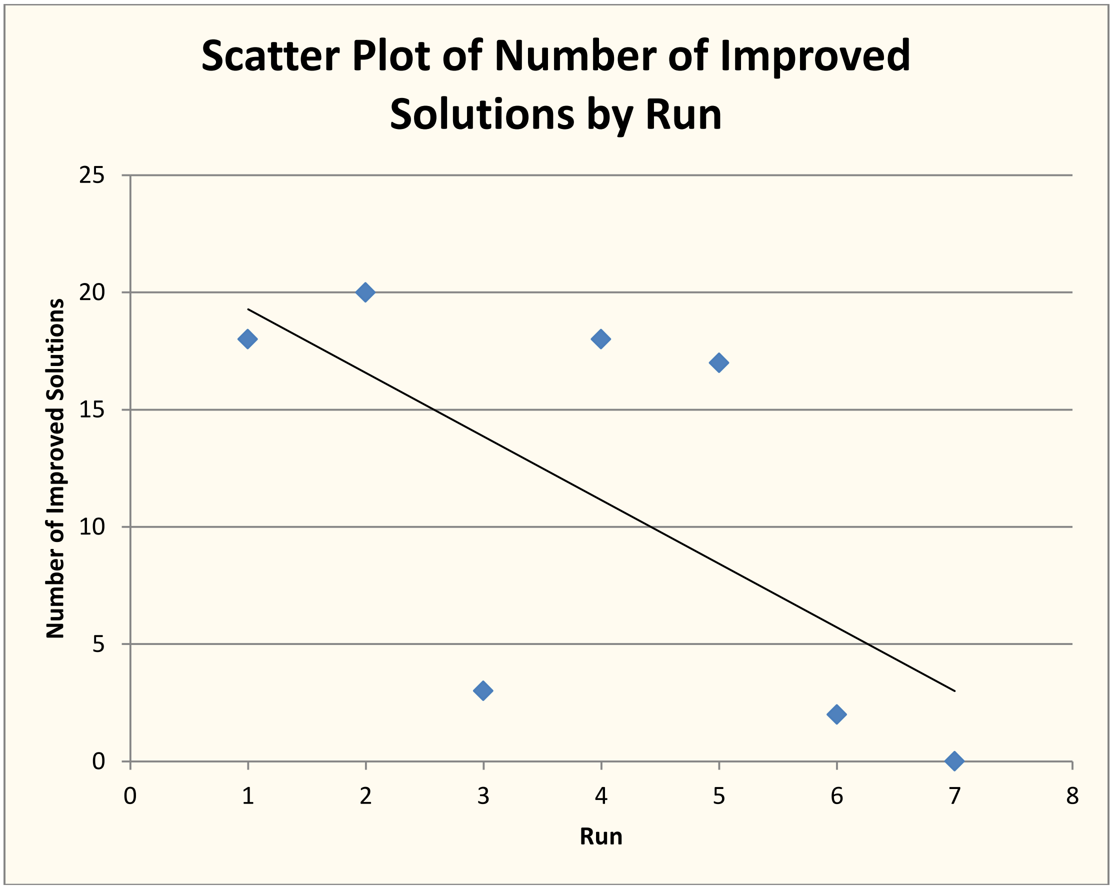


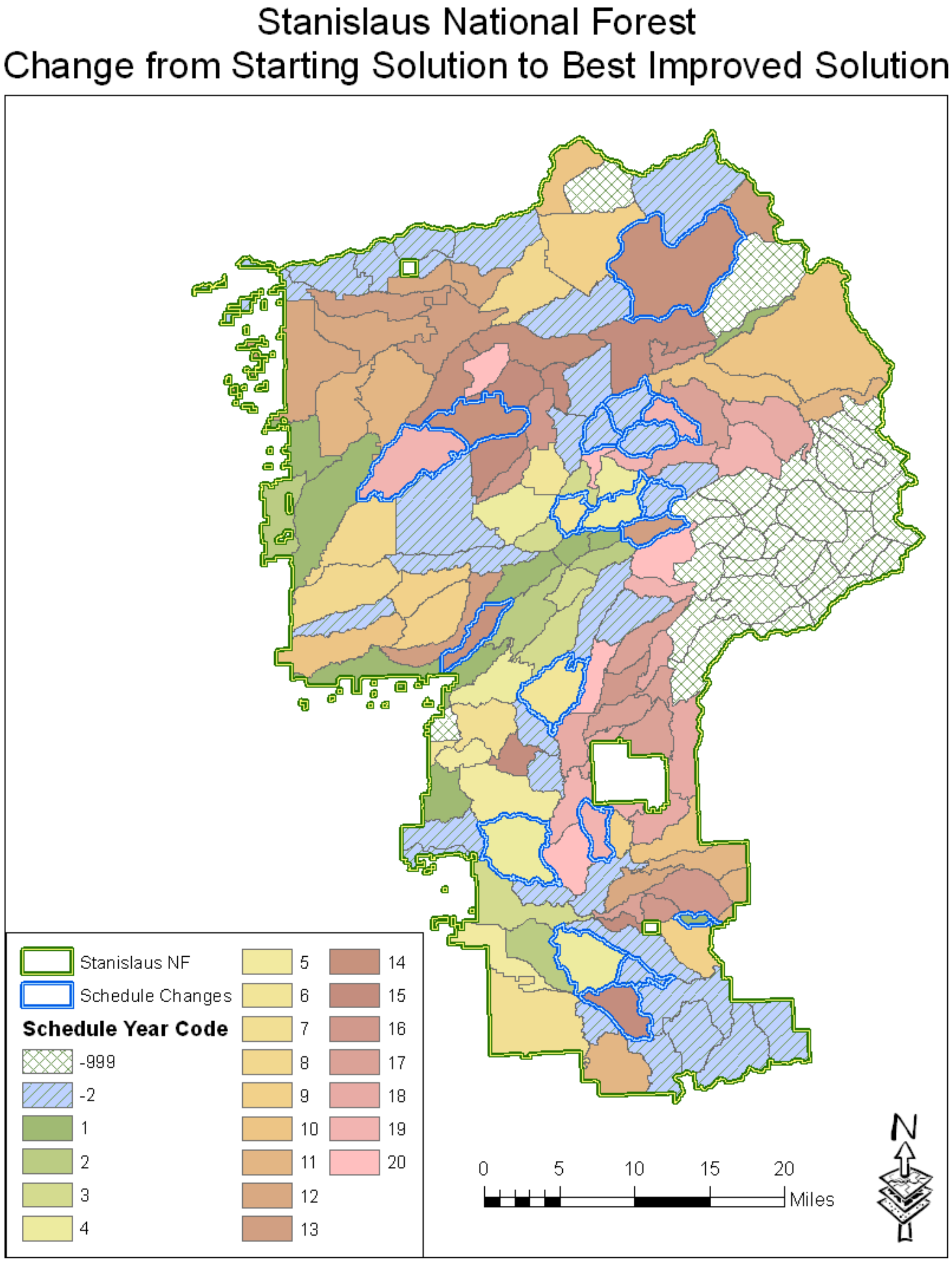
Table 1 - Results of Runs

Run	Heuristic Starting OBJ (H_0)	Most Improved Solution Objective	OBJ Difference	Number of Improved Solutions
1	-2695176	-2698270	-3094	18
2	-2698270	-2699834	-1564	20
3	-2699834	-2701946	-2112	3
4	-2701946	-2704361	-2415	18
5	-2704361	-2706693	-2332	17
6	-2706693	-2707420	-727	2
7	-2707420	N/A	N/A	0

Difference Between Starting H_0 and best solution identified in run 6 is
-12244
or 0.45%

Figure 12 shows the difference between the starting initial λFIRS seed solution based upon the iFASST heuristic and the final stable, incumbent solution generated after 7 runs of the λFIRS model. Note, the units that change are outlined in blue, and the color of the unit indicates the final schedule. In the map legend, -999 represents a PUC that did not have enough fuels to merit a fuels treatment, and -2 represents a PUC that was not scheduled for treatment. Five scheduling units (PUCs) that were not initially scheduled are now scheduled and four scheduling units (PUCs) that were previously scheduled are now unscheduled; representing a net increase of one scheduled project (PUC). This effectively increased project adjacencies through the increase in scheduling units (PUCs) that are treated and through the changing of years a scheduling unit (PUC) is scheduled to bring the scheduling of PUCS closer to large

Figure 12 **- Map display depicting the difference between the intial seed solution and the final solution generated by the λFIRS model.**



clusters of scheduled projects. **Figure 13** shows just the initial $\lambda FIRS$ seed solution, and **Figure 14** shows just the ending $\lambda FIRS$ solution shown in **Figure 12**.

Even though the final solution contains an extra scheduled unit (PUC), there is actually a decrease in the total number of acres that are effectively treated. The $\lambda FIRS$ method scheduled 108 PUCs which effectively treat 715,777.494 acres of Stanislaus National Forest. The difference in treated acreage between the starting iFASST software package heuristically generated schedule and the improved schedule found by the $\lambda FIRS$ method was only 4,045.163 acres; only a slight reduction in treated acreage. **Table 2** shows the scheduling units or PUCs that changed between the starting iFASST software package heuristic solution and the solution generated through the use of $\lambda FIRS$, and the respective change in acres protected. In addition to the decrease in acreage protected, a corresponding decrease in Treatable Acreage, and Critical Habitat acreage also occurred. The only increase was a one acre increase in the number of WUI acres treated.

Figure 13 – The initial seed solution for the λFIRS model.

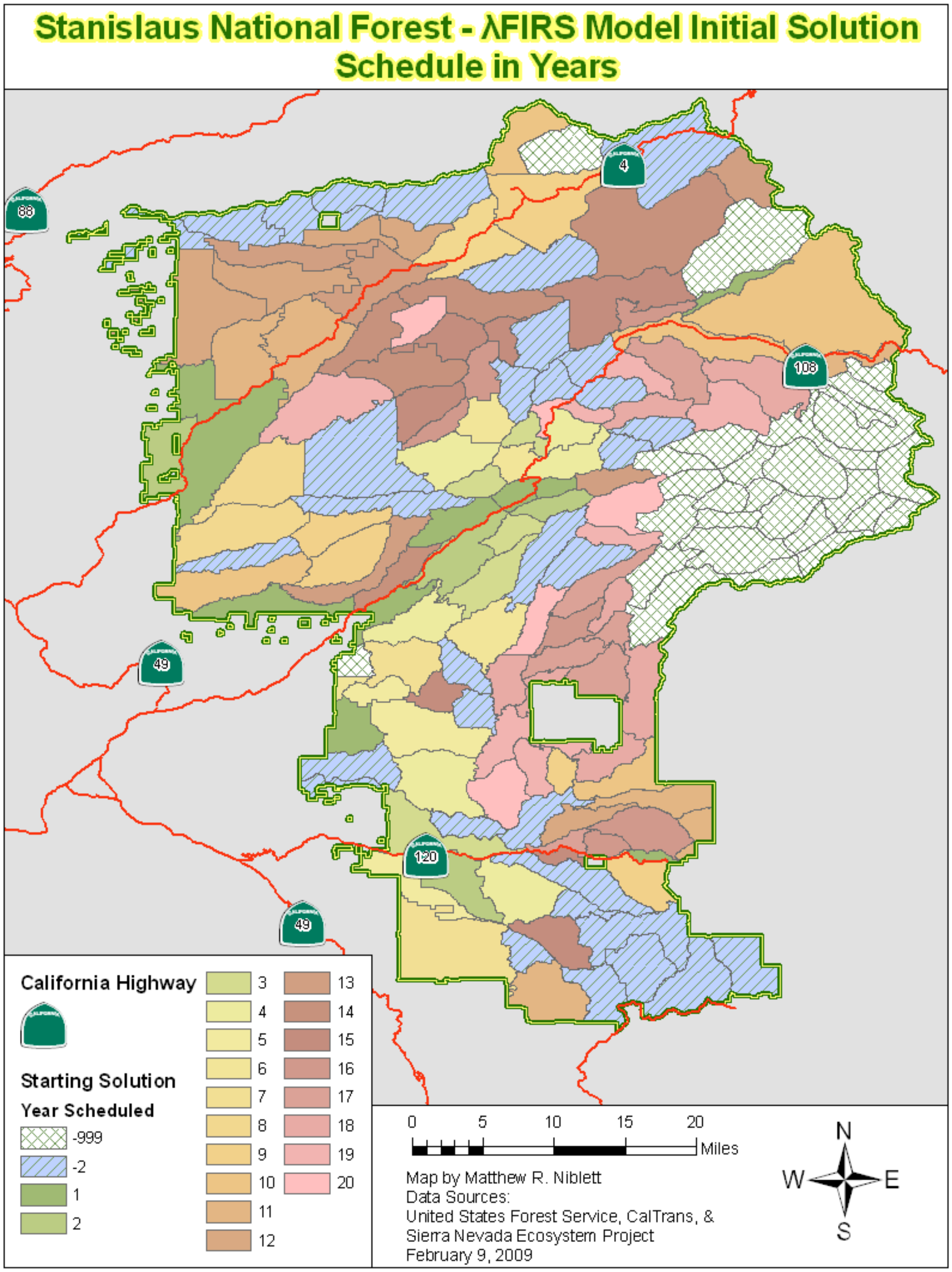


Figure 14 - The final stable solution generated by the λFIRS.

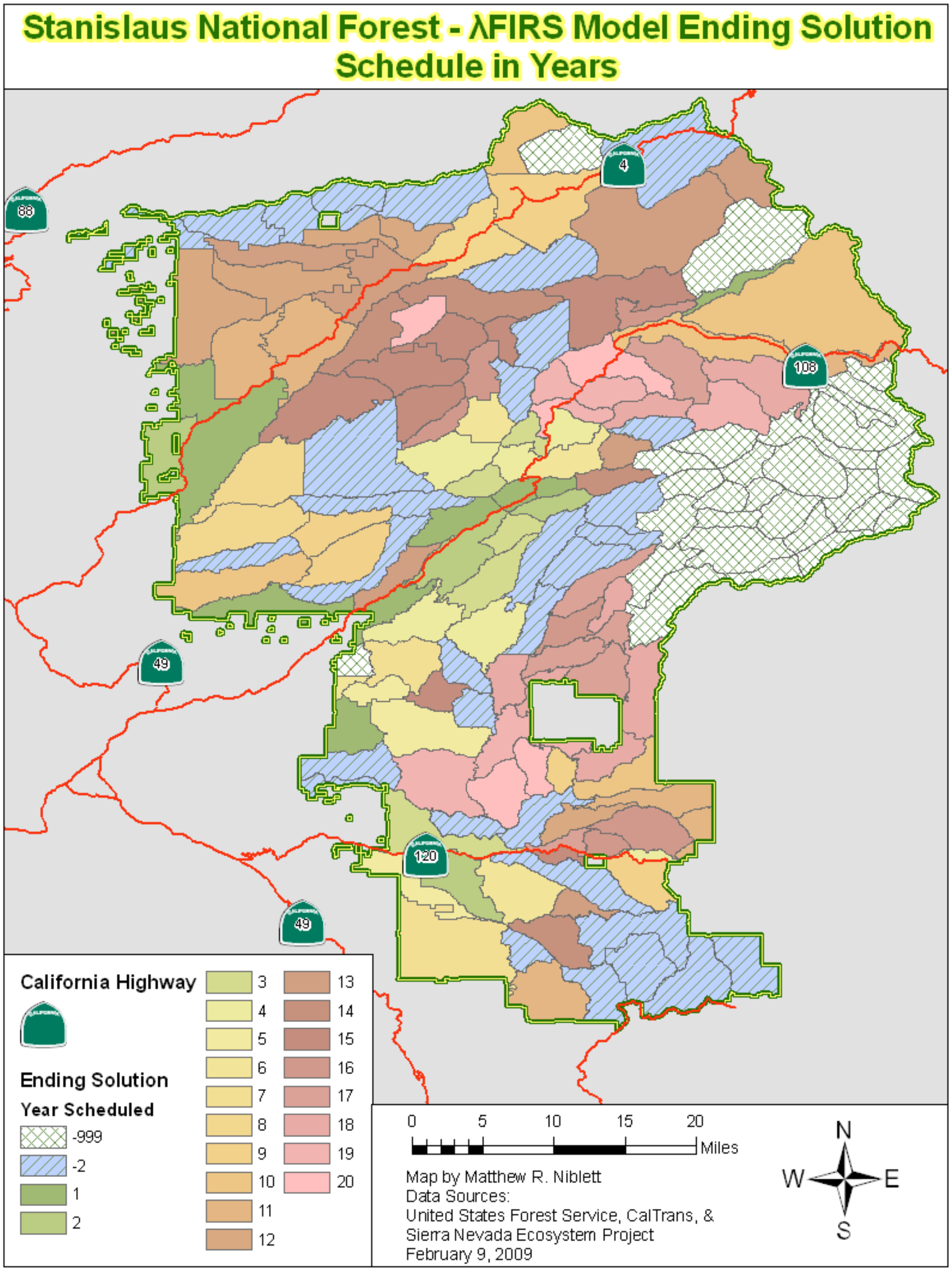


Table 2 - SUNIT Schedule

SUNIT	PUNIT	From Year	To Year	AREA in Acres	Area Start	Area Finish
7	2	14	13	26755.679	26755.679	26755.679
34	3	-2	20	4179.852	0.000	4179.852
38	2	14	15	8786.646	8786.646	8786.646
40	3	19	20	3594.607	3594.607	3594.607
44	3	-2	19	3343.437	0.000	3343.437
48	3	-2	19	4244.133	0.000	4244.133
50	2	19	15	12355.239	12355.239	12355.239
65	3	4	6	5292.342	5292.342	5292.342
66	3	-2	13	3116.419	0.000	3116.419
72	3	6	4	2971.418	2971.418	2971.418
74	3	13	14	3488.571	3488.571	3488.571
77	3	20	-2	6736.823	6736.823	0.000
96	1	13	-2	7101.280	7101.280	0.000
99	1	19	-2	3275.749	3275.749	0.000
106	1	14	13	4338.059	4338.059	4338.059
112	1	20	-2	4433.601	4433.601	0.000
116	1	6	4	8222.822	8222.822	8222.822
135	4	19	20	3688.315	3688.315	3688.315
139	1	4	19	10745.445	10745.445	10745.445
152	4	1	4	1182.771	1182.771	1182.771
157	4	4	6	8986.356	8986.356	8986.356
158	4	-2	13	2618.449	0.000	2618.449
161	4	15	14	5998.477	5998.477	5998.477
				Total =	127954.199	123909.036
				Difference =	-4045.163	

Section 5 - Discussion

The three variants of the FIRS model: the Balinski, mixed Balinski and Efroymson and Ray, and Efroymson and Ray adjacency tracking constraints, and the tuning of the mixed Balinski and Efroymson and Ray FIRS model adjacency tracking constraint formulations proved to be computationally too difficult to solve in a reasonable amount of time using ILOG CPLEX on the Sunblade workstation. The inability to generate an improved solution or confirm that the heuristic solution was optimal led to the development of the $\lambda FIRS$ method, which was able to identify an improved solution. If one needs to identify an improved solution for a complex integer programming problem in a timely manner, then this approach might be very useful. Although the λ opt approach has been used within a heuristic setting, this is the first time that such an approach has been tried through the use of an optimization algorithm.

Though the approach only found a 0.45% improvement between the starting heuristic solution and the final solution in which no improvement occurred, this is likely due to the fact that the approach encountered a local, or potential global optima. Because the λ-opt approach has been successful at generating optimal solutions to many different "hard" combinatoric problems, it is quite likely that the last improved solution generated in the 6th λFIRS model set is optimal (within a 1% bound that was used in solving all λFIRS models). An added benefit of this method is that the computational time of running of each set of 1000 swap models took on average two days. It took seven runs and approximately two weeks of computational time to final converge on a λ-opt solution.

The $\lambda FIRS$ method not only obtained an improved solution, but provided important information on how likely the heuristic solutions deviate from a known good solution. If the solution is indeed a global optima, then the starting heuristic solution is not more than 0.45% different from an optimal solution. Solving the FIRS model to optimality will ultimately determine whether this is the case, and the efficacy of this method. The solution obtained by the $\lambda FIRS$ method was interesting on its own.

Though the solution obtained by the $\lambda FIRS$ method is objectively better, the amount of effective acreage covered by the PUCs actually decreases by 4,045.163 acres. However, the schedule found by the $\lambda FIRS$ method effectively treats 715,777.494 acres or 66.3% of the entire forest area. It should be noted that not every area, or PUC, has enough fuel to necessitate a fuels treatment. For example, the eastern edge of Stanislaus National Forest is largely an alpine area and is quite rocky and rugged and not very conducive to fire. It doesn't make sense to schedule a PUC for fire treatment in these locations. If you add in these locations, which consist of 141,351.486 acres, the effective treatment level of Stanislaus National Forest as a whole increases to 857,129.000 acres or 79.4% of the forest.

The decrease in treated acreage from the iFASST software package solution and the improved solution found by the $\lambda FIRS$ method is largely due to the objective weights used. In this case, scheduling at least one project in a planning area (Ranger District), project adjacency, and WUI acreage is weighted much more than total treated area. The solution therefore is better in that it schedules more than one scheduling unit (PUCs) in a planning area (ranger district) and effectively treats areas in which human activity is likely to be greater. At the same time, it also reduces the amount of critical habitat, primarily old growth forest, which would have been impacted under the solution generated by the iFASST heuristic. In this way, the goal of restoring the forest to its natural state in which less intense fires occur is achieved by helping reduce the areas that are much more likely to have an intense fire emerge from human activity.

Section 6 - Conclusions

Though the FIRS model was not solved to optimally, an alternate model, called $\lambda FIRS$ was developed which did converge. The value of Lambda set at approximately 15, over seven times larger than what is normally used in the literature. Using a high value of lambda helps to reduce the probability that the model will not converge to an optimal or near optimal solution. The model took 7 iterations to converge to a new improved solution, better than what had ever been identified for this problem. . This solution allocates more scheduling units (PUCs) to a ranger district to reduce idle activity than previous solutions, while at the same time reduces impact to old growth forest and sensitive habitat. This is due to the weighting scheme used by the United States Forest Service to best meet the objectives they have specified. Future work should be done to determine the sensitivity of the model to the inputted weights, and if an alternative weighting scheme might better serve their needs.

However, even though there is a reduction in the total amount of treated area (4,045.163 acres), this change is quite small in relationship to the total area of the forest. Within the context of Stanislaus National Forest's total area of 1,080,027.375 acres, a difference of 4,045.163 acres in the overall solution of 857,129.000 acres is very miniscule; this is a change of less than 0.375% of the total forest area. In this case the ability to effectively utilize forest personnel, treat areas that are frequented by the public to reduce the likelihood of a severe fire outbreak, and reduce the effects of forest activities in old growth forest is an acceptable trade off.

The inability to solve the FIRS model optimally led to the development of a novel model, based on a strategy used in heuristic programming called Lambda-Opt. This is the first time in which the Lambda-Opt approach has been used inside a optimal solution routine, guaranteeing an optimal swap each time. The swap size (i.e. Lambda) was set at a very high value without significantly impacting solution times. Overall, this approach was able to demonstrate that the heuristic solution and the best $\lambda FIRS$ solution are close enough to give forest planners confidence in the use of the iFASST heuristic in solving their problems. This –modeling approach may prove successful for other difficult to solve Integer Programming problems.

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