

## Abstract

The Washington State Department of Natural Resources (DNR) manages over 800,000 hectares of forested State trust lands and 20,000 kilometers of forest roads in Washington State. Forest harvest and road reconstruction decisions greatly impact the agency's cash flows and its ability to meet its fiduciary obligations. We introduce a mixed integer programming model that integrates harvest and road scheduling decisions. We show how DNR embedded the new model in its workflows and applied it to the Upper Clearwater River Landscape in the Olympic Experimental State Forest (OESF). We find that the forest valuation of the Upper Clearwater increased by \$0.5-1 million (0.4-1.1%) as a result of the new method, which allowed the DNR to concentrate capital expenditures in support of harvest and road operations in both time and space. This led to a 14.5% reduction in the size of the active road network. The Agency is now in the process of scaling the new approach to the entire forest estate.

## Introduction

Forest roads are an integral, yet expensive component of forestry (Greulich 2002). They also increase the risk of wildfires, sediment delivery (Bowker, et al. 2010, Bettinger, Sessions and Johnson 1998, Riedel 2004), and the spread of pathogens (Jules, et al. 2002) including invasive species (Gelbard and Harrison 2003). Thus, forest roads are both financial and environmental liability for timber companies. Nonetheless, practitioners generally consider road reconstruction decisions only post-optimization upon completion of harvest planning (Martell, Gunn and Weintraub 1998). As a result, road reconstruction is not coordinated with harvest scheduling, leading to higher costs and greater environmental impact.

The costs of forest road construction and maintenance are capital expenditures that do not fluctuate with time or the amount of use. Since forest roads degrade over time, however, the fixed cost of maintenance increases since last upgrade. This amount of time is in turn, a function of the harvest schedule itself, making the revenue and cost structure of the problem endogenous. Moreover, a given road segment may support timber haul from multiple locations leading to opportunities to share costs. To distinguish it from the classic fixed charge problem in operations research, we refer to this variant as the Endogenous Fixed Charge Problem (EFCP). Similar problems exist beyond forestry primarily in fleet optimization and capital investments accounting. Thus, our study is applicable to a broad segment of industry. We first summarize prior work on forest harvest and roads scheduling.

### **Harvest Scheduling and Road Access**

Forest harvest scheduling models optimize the spatiotemporal allocation of silvicultural actions such as harvests across the landscape and over time while ensuring the long-term ecological and economic sustainability of the resource. Until the mid-1970s, harvest scheduling models considered road access only indirectly or hierarchically upon completion of strategic harvest planning (Johnson and Scheurman 1977). The connection between harvest and road decisions was ignored incurring unnecessary costs. Weintraub and Navon's mixed integer programming model (1976) was one of the earliest attempts to jointly optimize harvest scheduling and road construction decisions. The authors' models were very small, however, and served only illustrative purposes. The Integrated Resource Planning Model or IRPM (Kirby, et al. 1980) was much more robust and suitable to demonstrate substantial financial savings (up to 43%) afforded by integrated decisions (Jones et al., 1991). These studies all focused on the construction and planning of new roads, not on the maintenance of an existing network.

Examples of optimization models that accounted for forest road maintenance include Bettinger et al. (1998), Karlsson et al. (2004) and Olsson and Lohmander (2005). Unlike in our case, however, the maintenance costs in the aforementioned models were assumed to be constant over time and across segments. In Karlsson et al.'s (2004) model, which optimized the transportation of raw timber to sawmills while allocating work crews and machinery to the road network, maintenance costs varied; but they did so externally by season rather than endogenously. Olsson and Lohmander's (2005) model was no different in this regard: the fixed costs associated with maintenance were not an endogenous function of the current state of the roads.

In conclusion, the endogenous nature of the cost structure of the EFCP has not been addressed. Our proposed model, called the Exogenous Fixed Charge Model (EFCM), overcomes this issue.

### **Key Assumptions of the EFCM**

There are two different types of road costs associated with harvest scheduling: reconstruction and maintenance costs. Road reconstruction costs include major repairs such as the replacement of culverts and bridges and are determined *a priori* for each road segment. Unlike reconstruction, maintenance incurs a variable cost for surfacing and minor repairs due to run-off and wear and tear. In this paper, we will assume that the latter costs are insignificant for harvest scheduling problems with long planning horizons and multi-year planning periods. Second, per forest industry standard, our model also assumes that the least-cost routes to access each **Forest Management Unit (FMU)** are available *a priori*. **FMUs are spatial units (polygons) on a forested landscape comprising a set of trees that share certain silvicultural attributes such as age or species composition that allow them to be managed as one unit. The use of predefined least-cost routes, as opposed to dynamic route assignments, is admittedly limiting and can lead to sub-**

optimal solutions by missing opportunities to share road costs. Nonetheless, it is a common industry practice and we too opted to use them instead of a “dynamic” model, which would have guaranteed optimal solutions. Existing workflows at the DNR are based on this approach and critical information about road links that are not part of any predefined least-cost route is lacking. To provide the reader with a point of reference, we also present the ideal model that determines optimal routing dynamically during optimization using synthetic road data. This model coordinates the timing of harvests and road reconstructions in such a way so that net revenue would be maximized via shared road use for hauling from multiple FMUs.

### **EFCM Formulation**

We formulated the EFCM as a mixed integer program to maximize net timber revenues while accounting for endogenously driven road reconstruction costs. The model requires that all road segments that comprise the hauling route associated with a given FMU must be reconstructed prior to the planning period in which the FMU is scheduled to be cut. Again, we assume that the least-cost hauling route for each FMU is found *a priori*.

The cost to reconstruct a road segment is determined by the cost of full reconstruction,  $\alpha$ , and parameter  $\phi_j$  that scales  $\alpha$  into  $J$  price tiers representing the decrease in cost that occurs because of recent reconstruction. If road segment  $i$  has not been used for  $J$  periods prior to the scheduled haul, full reconstruction is necessary, which incurs cost  $\alpha_i$  (and thus  $\phi_j = 1$ ). If the road segment was reconstructed in the previous period, then it requires less than the full reconstruction cost;  $\phi_1 \alpha_i$ . Similarly, if the road was reconstructed two periods prior, it requires  $\phi_2 \alpha_i$ . Because the  $\phi$  parameters are a discrete set of multipliers, we can assign any desired form of cost decrease to them as long as  $\phi_1 < \phi_2 < \dots < \phi_J$ . See Appendix I for a formal explanation.

### **Application of EFCM in Washington State**

We show how the proposed EFCM was integrated with standard workflows of the Washington State Department of Natural Resources. DNR manages over 800,000 hectares of forested State trust lands and 20,000 kilometers of forest roads in Washington State. “As a trust land manager, DNR is obligated to follow the common law duties of a trustee which include generating revenue, managing trust assets prudently, and acting with undivided loyalty to trust beneficiaries” (County of Skamania vs. State, 1984). DNR “relies primarily on net present value as the most comprehensive and direct way to measure financial returns to the trusts and evaluate investments” (PSF 2006). Scheduling decisions for forest management units regarding timber harvests and the reconstruction of forest roads for timber haul directly impacts the agency's cash flows. Currently, DNR develops harvest schedules using industry standard forest planning software, Remsoft's Woodstock (2013). Road reconstruction decisions are made only after the harvest schedules are set using Woodstock.

We show how DNR integrated EFCM in its workflows using a widely adopted commercial software package called Woodstock. DNR relies on Woodstock to generate a linear program in the so-called Model II from (Johnson and Scheurman 1977) that captures every aspect of forest planning (such as even harvest flows, ending inventory constraints and so on) except forest road reconstruction decisions (Appendix II). It specifies how many hectares of each FMU is to be cut in a given planning period. **The Model II form utilizes four sets of variables to track the management of forest stands aggregated into analysis areas with shared silvicultural characteristics such as forest type. One variable represents the acres in each analysis area that are not to cut during the planning horizon. The second and third variables represent the acres that are to be cut in a particular period for the first or last time, respectively. Finally, the fourth type of variable represents the acres to be cut in a particular period and analysis area after it had been**

cut in another period. This definition of decision variables allows for a network structure that has advantageous computational properties. We added constraints and variables to Woodstock's Model II to embed EFCM. Linking the EFCM's binary harvest indicators with the fractional harvest variables of Model II requires introducing a pair of "trigger" constraints (Appendix III, Inequalities (14) and (15)) to ensure that the binary harvest indicators from the EFCM will take the value of 1 whenever a minimum amount of area is scheduled to be harvested from an FMU. By linking the continuous harvest variables from Model II to the binary decision variables of the EFCM using the indicator variables, we create a Mixed Integer Program (MIP). The approach simultaneously maintains all the functionality of Model II while taking into account the costs of road reconstruction. Functionally, we amend the constraints and variables required of the EFCM to DNR's existing linear programming matrix. Doing so, we convert a largely aspatial model to a spatiotemporal one that not only integrates harvest and road scheduling decisions but it also allows the managers to see and control specific actions at specific locations on the landscape at specific times. And, we do this with very little computational overhead, which is why our model made its way into DNR's standard workflows.

We developed software named Builder that adds the EFCM into DNR's workflow (Fig. 1). Currently, DNR uses Woodstock to formulate the harvest scheduling models in the format of an LP matrix, which is then given to the IBM integer programming solver CPLEX. CPLEX then returns a solution to Woodstock for interpretation (Fig. 1A). Woodstock uses the solution to output a harvest plan. When using Builder, Woodstock generates the same LP matrix, but it is intercepted by Builder while being passed to CPLEX. The LP matrix is modified by adding the proposed road network and trigger constraints after being intercepted. Builder modifies the matrix (now a mixed integer program) inside the CPLEX environment for convenience. Once

modified, CPLEX solves the model and returns a solution file to Builder. Builder then creates custom outputs and prepares the solution file for interpretation by Woodstock, the same way as before (Fig. 1B).

To measure the financial benefits of the integrated EFCM on DNR trust lands, we created a control model (Appendix IV) that calculates but does not minimize road costs for each potential solution. The control model is analogue to the Model II formulation created by Woodstock in that it mimics the solution that would be gained without the EFCM. The difference is that our control model calculates the road costs automatically without having to post-process the Model II solution for road use. It establishes a benchmark net present value against which we can compare the performance of EFCM.

### **Case Study**

We applied the proposed EFCM to the Washington DNR's Upper Clearwater River landscape located on the western slopes of the Olympic Peninsula in the Pacific Northwest United States. The Upper Clearwater contains 621 operable FMUs served by an existing road network of more than 6,000 road segments, and is part of the Olympic Experimental State Forest (OESF). The management objective is to maximize net present value over a 100-year long planning horizon, divided into ten 10-year long planning periods. Managers must determine harvest regimes for each FMU to maximize NPV while meeting long-term sustainability constraints, such as even flow of revenues and harvest volumes (Appendix II, Inequalities (11) and (12)), as well as ending inventory and ending age requirements (Appendix II, Inequality (13)). Both the 100-year long planning horizon and the 10-year long planning periods are standard for the forest sector. The 10-year long periods provide sufficient flexibility for the agency to schedule harvest activities on an annual, tactical basis to make the best use of changing market conditions and in

the face of unforeseen weather events. Lastly, the minimum rotation age was set to a regionally representative 40 years.

Although the OESF is a member of a national network of experimental forests, it is a key component of DNR's commercial land-base. The right to harvest forest stands on DNR land is allocated competitively via auctions where the highest bidders get to cut and haul the designated timber. The DNR's foresters consume the optimization model's outputs one to two years before field-, and road engineering work are required to begin to prepare the timber sale for environmental review, approval, permitting and finally public auction. Using the EFCM outputs, the DNR forester designates the haul routes. The route specifications are ultimately disclosed prior to auction. The successful bidder at auction is required to improve and maintain these routes at their cost and to DNR's satisfaction.

In the next section we describe how the EFCM was parameterized and implemented on the Upper Clearwater landscape.

### **Parameterization and Data**

For the Upper Clearwater, DNR assumed that roads degrade linearly over a 30-year period. This means that a road not used for timber haul for 30 years or more requires full reconstruction, whereas a road last used between 20 and 30 years ago costs one third less and one last used between 10 and 20 years ago costs two thirds less in real terms. Under this assumption, we set  $\phi_3 = 1$ ,  $\phi_2 = \frac{2}{3}$ , and  $\phi_1 = \frac{1}{3}$ . The maximum allowable harvest,  $H_{max}$ , was set to the area of the FMUs, which places no restrictions on harvests. The minimum allowable harvest,  $H_{min}$ , was set to the equivalent of \$25,000, preventing harvests that were deemed to be unreasonably small.

Least-cost routes were found *a priori* for each FMU using GIS. The initial age-class distribution, growth estimates, and projected discounted net timber revenues of the FMUs came from the



Woodstock formulation (Model II). This formulation also included harvest flow and ending inventory constraints. Harvest flow constraints determine the maximum allowable increase and decrease in harvest volumes between adjacent periods (both 25% here). Ending inventory constraints require the area-weighted average age class of the forest at the end of the 100-year long planning horizon to be at least as large as it was in the beginning of the planning horizon. These constraints prevent over harvesting, and in conjunction with the harvest flow constraints, create a diversity of forest age classes.

To help determine the feasibility and practicality of scaling the EFCM to larger forest networks, we applied the EFCM to multiple datasets: the entire Upper Clearwater dataset (621 FMUs – “full” dataset) and three subsets of the Clearwater dataset (91, 193, and 299 FMUs: “small”, “medium”, and “large” data subsets, respectively). Each of the subsets are served by only one *mainline* (or exit node, sink node or *facility* in operations research terminology). In forest management applications, “facilities” or sink nodes often refer to paved municipal roads and “mainlines” that are maintained to standard at no cost to the timber purchaser. These roads are used to haul the timber to sawmills or to ports for processing or for further transportation (demand points). **By testing multiple network arrangements, we can be confident that the model’s solvability and benefits are not due to a peculiarity of a specific network formation.**

We solved the EFCM model and the control for all datasets using IBM ILOG CPLEX 64-bit 12.1.0 (IBM 2011) on a Dell Power Edge 510 Server with Intel Xeon CPU, X5670@2.93 GHz (2 processors) with 32 GB of RAM and the Windows Server 2008 64-bit operating system. **The control model was solved to full optimality for all datasets while the EFCM was solved to a 1% optimality gap allowing for a conservative estimation of the financial benefits of EFCM. Default values were used for all other CPLEX parameters.**

The objective function values (net present value), optimality gaps, and solution times were recorded for analyses. From the solutions, we calculated the number and the length of reconstructed road segments and converted the volume of timber to be hauled into average daily truck passes to proxy the environmental benefits of the EFCM. We also measured the spatial concentration of harvests. First, we calculated the average distance of a harvested FMU to a set number of nearest neighbor FMUs that were also harvested. For each FMU, we identified the smallest radius circle that captured the FMU centroid as well as a set number of other FMU centroids harvested in the same period. Then, we averaged the radii of the circles across all FMUs to determine the average distance to the nearest 5, 25, and 100 harvested neighbor FMUs for the full dataset. Second, we calculated the spatial concentration of harvests based the average number of truck passes per day for each road segment required for timber haul under the EFCM vs. the control model solutions for the full dataset. For each period, we summed the total harvest volumes to be hauled across each road segment. We converted these values to average truck passes per day, a common regulatory metric by using 4,800 board feet of timber as a truckload and assuming two passes per truck (one empty and one full). **These metrics help demonstrate that some of the model's benefits arise from concentrating harvests to both reduce road costs and to spatially and temporarily limit the environmental impact of logging on the landscape.**

We also investigated how the solutions respond to an unforeseen shock event related to road reconstruction costs ( $\phi$ ). These shocks emulate environmental disturbances such as massive storms that would damage or destroy parts of the infrastructure, thereby dramatically increasing reconstruction costs. The EFCM has a financial incentive to invest in road maintenance if the present value of the endogenous reductions in future reconstruction costs exceed that investment. Thus, we test the robustness of the EFCM solutions to unforeseen events that would damage the

road network thereby increasing costs dramatically. We simulate the shock to the roads by requiring full reconstruction of all road segments after the event regardless of when these segments were used previously. We then recalculate the road costs for both the EFCM and the Control Model solutions to compare their performance in the face of an unforeseen shock event.

Lastly, we built an alternative model (Appendix 1) that can determine routing dynamically during optimization instead of relying on predefined routes. We tested the alternate formulation on a theoretical landscape to assess its data requirements and computational tractability.

## Results

Table 1 lists the solution times, the number of road segments as well as total road length required for haul, the objective function values, and the optimality gaps for the three datasets for both the EFCM and the corresponding control models. We report the difference between the objective function values of the EFCM and those of the control model. When provably optimal solutions were not available, we report the difference between the upper bounds of the EFCM objective values and those of the control model to get a conservative estimate of savings.

The EFCM solved to 1% optimality gaps in reasonable time for all datasets. The most difficult instance was completed in less than three hours. While many factors, including the spatial configuration of the FMUs and the road network, might influence solution times, from the Upper Clearwater application we observed for both the EFCM and the control model that doubling the number of FMUs increased solution times by approximately a factor of ten.

In terms of objective function values, the EFCM performed better even with 1% optimality gaps than the control at full optimality. If the EFCM was run longer, the solver might improve the objective values even further. For the full Upper Clearwater dataset, the EFCM saved 10.4% on road costs, increasing overall net present value by 0.4-1.1% as compared to the control model.

The EFCM generated harvest schedules with higher objective function values and fewer required roads. In the full Upper Clearwater dataset, the EFCM reconstructed 14.9% fewer road segments than the control. In terms of the total road length, the EFCM reconstructed 14.5% less than the control. Thus, the EFCM used roads more parsimoniously in a spatially concentrated pattern. Fig. 2 shows the FMUs harvested in Period 1 and Period 10 under both the EFCM and the control model solutions. In Period 1, the spatial distribution of FMUs harvested by each model is very similar. However, by period 10, the harvest allocation is much more concentrated with the EFCM. We expect these spatiotemporally concentrated harvest patterns to lead to more spatially contiguous forest patches in similar successional stages than the less concentrated harvest patterns found in the control model solution. This expectation is supported by the result that the EFCM produced more clustered harvest patterns. The average distance from each harvest site to its nearest 5, 25 and 100 neighbors was 1,075, 3,584 and 8,680 feet, respectively for the EFCM. The same measures were 1,226, 4,161 and 10,729 feet for the Control Model. Moreover, the EFCM yielded harvest schedules with fewer road segments with a low, and more segments with a high expected number of daily truck passes compared to the Control (Table 2). The latter finding suggests that the EFCM concentrates timber hauling on a fewer number of road segments than the control model. At last but not least, we found the EFCM solutions to be more robust to unforeseen shock events related to road reconstruction costs than that of the Control Model. For a simulated network-wide shock event between Periods 1-2, 2-3, 3-4 and 4-5, the increase in road costs in the EFCM were 23.88, 13.03, 9.63 and 6.16%, respectively, whereas the Control Model resulted in 25.06, 17.59, 10.72 and 6.6%, respectively.

Finally, results from the dynamic routing formulation suggest that the model is computationally feasible, but it requires additional road data for input including network topology (previously handled in preprocessing), and would necessitate an alternate workflow for implementation.

### **Discussion and Conclusions**

As applied on the DNR-managed Olympic Experimental State Forest (OESF), DNR significantly improved the forest valuation of the Upper Clearwater River Landscape by \$0.5-1 million (0.4-1.1% greater overall net present value, roughly 15.4% of the overall road cost). This is accomplished by concentrating capital expenditures in support of harvest and road operations in time and space leading to a 14.5% reduction in active road kilometers and associated environmental hazards. Additionally, we expect higher auction revenues and increased participation as bidders notice that the new pairings of timber sales would allow them to reduce road costs by spatially and temporally concentrating harvest patterns. Since the EFCM can be easily embedded in existing workflows, we do not anticipate any changes to normal planning efforts or field operations that already leverage harvest schedules.

Although the overall improvement in NPV may seem small, it is not a completely unexpected result. The 43% improvement in NPV as demonstrated by Kirby et al. 1980 was an artifact of the construction and planning of new roads, not on the maintenance of an existing network. . We anticipate improved NPV of “pro-active adaptation” versus “no-regrets” and “no-adaptation” strategies in response to climate forcing of geomorphic process in mountainous terrain when the new roads will cost more than today’s maintenance and replacement, (Mauger et al. 2015; Chinowsky et al. 2012 and 2014). Second, the use of 5% discount rates over a large time span significantly attenuates any savings that accrue more than 30 years out. Third, and perhaps most importantly, our benchmark for comparison was the DNR’s previous best effort. Considering the agency’s mandate to use the “best available science”, we would be surprised to see very large gains “left

on the table". Lastly, it is important to point out that because of the endogenous feedback between road cost and harvests, it is impossible to make comparisons using road cost alone. Potential reductions in road costs can be offset by decreased amounts of harvest, and vice-versa. However, to help contextualize the savings, the total increase in NPV represents 15.3% of the overall road cost, which is a meaningful improvement.

As a result of these findings, DNR is currently scaling the modified workflows to the entire 110,000 hectare Olympic Experimental State Forest and in time to the entire forest estate. In collaboration with the University of Washington's Precision Forestry Cooperative, DNR organized a successful outreach to practitioners of Washington's forest industry; demonstrating Builder as a leading analytical framework that bridges a perceived gap between best available science in OR and industry's harvest scheduling workflows.

### Acknowledgments

This study was funded by the Washington State Department of Natural Resources (DNR).

### Appendix I: The EFCM

$$\text{Max} \sum_{m,t} \rho_{m,t} x_{m,t} - \sum_{i,t,j} \phi_j \alpha_i s_{i,t}^j 1.05^{(5-10t)} \quad (1)$$

Subject to:

$$\sum_j s_{i,t}^j \leq 1 \quad \forall i, t \quad (2)$$

$$\sum_{i \in S_m} \sum_j s_{i,t}^j \geq |S_m| x_{m,t} \quad \forall i, t \quad (3)$$

$$\sum_{k=1}^J s_{i,t-j}^k \geq s_{i,t}^j \quad \forall i, t, j \quad (4)$$

$$x_{m,t} \in \{0,1\} \quad \forall m, t \quad (5)$$

$$s_{i,t}^j \in \{0,1\} \quad \forall i, t, j \quad (6)$$

where the decision variables are:

$x_{m,t} = 1$  if FMU  $m$  is to be harvested in period  $t$ , 0 otherwise; and

$s_{i,t}^j = 1$  if road segment  $i$  is to be reconstructed in period  $t$  at the cost of  $\phi_j \alpha_i$ , 0 otherwise.

The sets are:

$M$  = the set of all FMUs with  $m = 1, 2, \dots, |M|$ ;

$I$  = the set of all road segments with  $i = 1, 2, \dots, |I|$ ;

$S_m$  = the set of road segments in the least-cost hauling route for FMU  $m$ ; and

$T$  = the set of 10-year long planning periods indexed by  $t = 1, 2, \dots, |T|$ . Harvests and road reconstruction activities are assumed to occur in the mid point of the planning periods.

The parameters are:

$\rho_{m,t}$  = the net discounted timber revenue associated with harvesting FMU  $m$  in period  $t$ ;

$J$  = the total number of cost tiers;

$\phi^j$  = the fraction of full reconstruction cost required for a road segment that was last reconstructed  $j$  periods earlier; and

$\alpha_i$  = the total reconstruction cost of road segment  $i$ . Parameter  $\alpha_i$  is assumed to remain constant in real value throughout the planning horizon.

The objective function (1) maximizes the discounted net revenues associated with the management of  $|M|$  units over a planning horizon of  $|T|$  planning periods. The first term accounts for the discounted net harvest revenues, whereas the second term accounts for the road reconstruction costs, assuming a 5% discount rate.

Inequalities (2) and (3) ensure that if FMU  $m$  is harvested in time  $t$ , then all road segments in the least-cost hauling route for FMU  $m$  ( $S_m$ ) must be up to regulatory standard by time  $t$ . Inequality (2) requires that only one of  $s_{i,t}^1, s_{i,t}^2, \dots, s_{i,t}^J$  can be activated in each time period. If a segment is reconstructed, only one cost is incurred. If all  $s$  variables are zero, the road segment has not been reconstructed and no cost is incurred. Inequality (3) compares the number of reconstructed segments in a unit's least-cost hauling route to the total number of road segments in the route. If any one of the road segments in the least-cost route is below regulatory standard, then  $x_{m,t}$  is forced to take the value of zero. Thus, for a harvest to occur in time  $t$ , all roads that lead to the FMU must be up to regulatory standard in time  $t$ .

Inequalities (4) represent the endogenous cost structure and control the values that variable  $s_{i,t}^j$  can take in a given period. Inequality (4) allows  $s_{i,t}^j = 1$  only if the segment has been reconstructed in period  $t - j$ . There is no restriction on variable  $s_{i,t}^J$ , however, as this variable represents the full cost of reconstructing the road segment and is used if reconstruction has not occurred for  $J$  or more periods. The cost-minimizing objective function will force the model to choose the lowest available cost tier.

Finally, inequalities (5) and (6) declare the decision variables as binary.



We also created a set of constraints that would eliminate the need for predetermined hauling routes. The model finds hauling routes dynamically given an established road network. We assume the road network can be represented by a directed graph of vertices and edges. Each road segment is defined by its starting and ending vertices with  $(i, j) \neq (j, i)$ . The model assumes that each FMU has only one access point to the road network, but multiple exit points. We connect all exit points to an additional imaginary vertex that represents the demand point outside of the system. The following constraints replace Constraint Set (3) above.

$$\sum_{i \in j_{in}} F_{(i,j),t} + \sum_{m \in U_m} x_{m,t} = \sum_{k \in j_{out}} F_{(j,k),t} \quad \forall j \in V, t \quad (3a)$$

$$\sum_{i \in V_\tau} F_{(i,\tau),t} = \sum_m x_{m,t} \quad \forall t \quad (3b)$$

$$N \sum_{\phi} s_{(i,j),t}^{\phi} \geq F_{(i,j),t} \quad \forall (i, j \neq \tau), t \quad (3c)$$

Where the additional sets and parameters are:

$U$  = the set of all FMUs;

$V$  = the set of all vertices in the road network;

$E$  = the set of edges (roads), defined by starting and ending vertices  $(i, j)$ ;

$j_{out}$  = the set of vertices that can be reached from vertex  $j$  (outflow);

$j_{in}$  = the set of vertices that lead to vertex  $j$  (inflow);

$U_j$  = the set of FMUs that use vertex  $j$  as an entry point to the network (point sources);

$V_\tau$  = the set of vertices that are considered exit points for the network;

$\tau$  = the “imaginary” vertex or demand point that all vertices in  $V_\tau$  are connected to (the sink); and

$N$  = An arbitrary large number, greater than the maximum flow that the network could incur on

any one period. To strengthen the formulation,  $N$  should be set to the smallest value that will preserve feasibility. Assuming unit-flow,  $N$  can be set to  $|M|$ , the total number of units that can be harvested.

A new decision variable is added:

$F_{(i,j),t}$  = the flow between vertices  $i$  and  $j$  in period  $t$ .

Constraint Set (3a) are the “flow” constraints. These inequalities ensure whatever flow comes into a vertex, must also exit that vertex, except for the imaginary “sink” vertex. The first term represents all the flow coming into a vertex from other vertices. The second term adds any potential point source (newly created) flow. These two terms together must equal the third term, that represents the total amount of flow leaving the vertex.

Constraint set (3b) are the “Sink constraints” that make sure all flow is exiting the system, and not getting stuck in a cycle. The first term represents all flow that makes it into the sink. The second term represents the total amount of harvest in the period. By forcing them to be equal, we ensure that all flow exits the network, and therefore, all harvests have a hauling route.

Constraint set (3c) are the “cost triggers”. These constraints trigger the reconstruction variables ( $s_{(i,j),t}^{\phi}$ ) if there is any flow on segment  $(i,j)$ . If there is flow on segment  $(i,j)$  then at least one reconstruction variable is forced to be active. The big  $N$  parameter allows the binary reconstruction variable to be always larger than the amount of flow, as long as it is greater than zero.

## Appendix II: Model II Formulation

## Model II Formulation

$$\text{Max} \sum_{l=1}^{|T|} \sum_{k=-M}^{l-Z} \sum_m A_m \rho_{m,k,l} W_{m,k,l} \quad (7)$$

$$N_{m,k} + \sum_{l=1}^{|T|} W_{m,k,l} = a_{m,k} \quad \forall m, k = -M, \dots, 0 \quad (8)$$

$$N_{m,k} + \sum_{l=k+Z}^{|T|} W_{m,k,l} = \sum_{t=-M}^{k-Z} W_{m,t,k} \quad \forall m, k = 1, \dots, |T| \quad (9)$$

$$\sum_m \sum_{k=-M}^{l-Z} v_{m,k,l} W_{m,k,l} = H_l \quad \forall l = 1, \dots, |T| \quad (10)$$

$$1.25H_t \geq H_{t+1} \quad \forall t = 1, \dots, |T| - 1 \quad (11)$$

$$.75H_t \leq H_{t+1} \quad \forall t = 1, \dots, |T| - 1 \quad (12)$$

$$\sum_m \sum_{t=-M}^{|T|} Age_t N_{m,t} A_m \geq \sum_m \sum_{t=-M}^{-1} Age_t a_{m,t} A_m \quad (13)$$

where the parameters are:

$A_m$  = the area of FMU  $m$  in hectares;

$a_{m,t}$  = percent of FMU  $m$  that is in age class  $t$  in period 1 (initial age);

$Z$  = minimum rotation age in periods;

$v_{m,t_1,t_2}$  = volume/ha in FMU  $m$  for harvests of age class  $(t_2 - t_1)$ ;

$M$  = the largest age class in the initial inventory;

$\rho_{m,t_1,t_2}$  = revenue/ha in FMU  $m$  for harvests of age class  $(t_2 - t_1)$ ;

$Age_t$  = The age of an FMU in time  $t$ ;

and the decision variables are:

$W_{m,t_1,t_2}$  =The percent of FMU  $m$  regenerated in period  $t_1$  and harvested in period  $t_2$ ;

$N_{m,t}$  =The percent of FMU  $m$  in time  $t$  that is not harvested.

Objective function (7) maximizes net present revenue across all FMUs and time periods. Inequality (8) is the first entry constraint. It makes sure that all of FMU  $m$  is accounted for, either as harvested, or not harvested. Decision variables are included in this constraint only if the age classes of the units satisfy the minimum rotation age. The first entry constraint initializes the network flow in Model II. Inequalities (9) are the network flow constraints that map the possible combinations of subsequent rotations for each time period and FMU. Again, decision variables are included in these constraints only if the age classes satisfy the minimum rotation age.

Inequalities (10) are harvest accounting constraints that sum up the harvest volumes for each period and store the value in accounting variable  $H_t$ . Inequalities (11-12) are harvest flow constraints that restrict the amount of harvest in any one period to be within 25% of the volume harvested in the previous period. Finally, Inequalities (13) is the average ending age constraint that requires that the area weighted average age class in period  $|T|$  is at least as large as the area weighted average age class of the initial inventory.

### **Appendix III Adding Trigger Constraints**

The linear programming formulation of Model II uses continuous harvest variables, however the EFCM formulation requires binary harvest indicator variables. Linking the EFCM's binary harvest indicators with the continuous harvest variables of Model II requires introducing a pair of "trigger" constraints to ensure that the binary harvest indicators from the EFCM will take the value of 1 whenever a minimum amount of area is scheduled to be harvested from an FMU:

$$\sum_{k=-M}^{t-Z} W_{m,k,t} \geq H_{min} x_{m,t} \quad \forall m, t \quad (14)$$

$$\sum_{k=-M}^{t-Z} W_{m,k,t} \leq H_{max} x_{m,t} \quad \forall m, t \quad (15)$$

where  $H_{min}$ , and  $H_{max}$  are the minimum and maximum threshold values ( $H_{max}$  is simply an upper bound on the areas of the units) to turn on or off  $x_{m,t}$ , and  $W_{m,k,t}$  is the continuous harvest variable from Model II. It is important to mention that Inequalities (14) and (15) enforce a minimum area that must be harvested within an FMU if it is to be harvested at all. If the right-hand side of Inequality (14) is greater than 0 but less than  $H_{min}$ , then the model becomes infeasible because Inequality (14) will force  $x_{m,t} = 1$  while Inequality (15) will force it to be 0.

Lastly, we also modify the revenue coefficients in the objective of the EFCM to be a function of the continuous harvest variables  $W_{m,k,t}$ .

#### Appendix IV: Control Model

To create the control model, we modify the EFCM. First, to ensure that the control model ignores the roads costs during optimization, we remove the road costs from the objective function (1) of the EFCM. Second, since the objective function of the control is not needed to minimize road costs, we must add inequalities to force the control model to use the cheapest possible  $s_{i,t}^j$  variable to rebuild a segment. Otherwise, the costs would be overestimated. To accomplish this, we add inequality (9):

$$s_{i,t}^j + \frac{1}{j-1} \sum_{p=1}^{j-1} \sum_{k=1}^J s_{i,t-p}^k \leq 1 \quad \forall i, t, j > 1 \quad (16)$$

Inequalities (16) and (4) work in concert. Inequality (4) allows, while inequality (16) forces, the use of the lowest available cost tier. In other words, these inequalities do not allow  $s_{i,t}^j$  to activate if the road segment was reconstructed fewer than  $j$  periods prior to  $t$ , and therefore qualifies for a lower cost than  $\phi_j$ . Together, these inequalities force the optimal choice of  $s_{i,t}^j$  variables without relying on a cost minimizing objective function.

Similarly, without minimizing costs, the control model could potentially reconstruct road segments that are not needed. To avoid this, we need additional inequalities that only allow  $s_{i,t}^j = 1$  if an FMU that contains segment  $i$  in its hauling route is harvested in period  $t$ :

$$\sum_{m \in I_m} x_{m,t} \geq \sum_j s_{i,t}^j \quad \forall i, t \quad (17)$$

where  $I_m$  is the set of all FMUs  $m$  that have segment  $i$  in their least-cost hauling route. These inequalities work as the counterparts of inequality (3). Inequality (3) requires that all roads in a FMUs hauling route be up to regulatory standard in the period the FMU is harvested.

Conversely, inequality (17) only allows a road to be reconstructed if an FMU that uses it is harvested.

Finally, we store the road costs in accounting variables using inequality (18). The accounting variable (*RoadCost*) simply adds up the road costs required by the harvest decisions that are found to be optimal by the control model without having any impact on the harvest schedules.

$$\sum_{i,t,j} \phi_j \alpha_i s_{i,t}^j 1.05^{(5-10t)} - \text{RoadCost} = 0 \quad (18)$$

## References

- Bettinger, P., Sessions, J., & Johnson, K. N. (1998). Ensuring the compatibility of aquatic habitat and commodity production goals in eastern Oregon with a Tabu search procedure. *Forest science*, 44(1), 96-112.
- Bowker, D., Stringer, J., Barton, C., & Fei, S. (2010). GPS and GIS Analysis of Mobile Harvesting Equipment and Sediment Delivery to Streams During Forest Harvest Operations on Steep Terrain. *Proceedings of the 33rd annual Council on Forest Engineering: Fueling the Future*, (pp. 1-17).
- Chinowsky, Paul and Channing Arndt 2012. Climate Change and Roads: A Dynamic Stressor–Response Model. *Review of Development Economics*, 16(3), 448–462, 2012.  
DOI:10.1111/j.1467-9361.2012.00673.x.
- Chinowsky, Paul S., Amy E. Schweikert, Niko L. Strzepek, and Ken Strzepek 2014. Infrastructure and climate change: a study of impacts and adaptations in Malawi, Mozambique, and Zambia. Accepted: 23 July 2014. # UNU-WIDER. Climatic Change. DOI 10.1007/s10584-014-1219-8
- County of Skamania v. State, 102 Wash. 2d 127, 134, 685 P.2d 576, 580 (1984)
- Gelbard, J. L., & Harrison, S. (2003). Roadless Habitats as Refuges for Native Grasslands: Interactions with Soil, Aspect, and Grazing. *Ecological Applications*, 13(2), 404-415.
- Greulich, F. (2002). Transportation Networks in Forest Harvesting: Early Development of the Theory. *Proceedings of the International Seminar on New Roles of Plantation Forestry Requiring Appropriate Tending and Harvesting Operations*. Tokyo, Japan: The Japan Forest Engineering Society. Retrieved April 6, 2014, from <http://faculty.washington.edu/greulich/Documents/IUFRO2002Paper.pdf>

- Hirsch, W. M., & Dantzig, G. B. (1954). *The fixed charge planning problem (No. P-648)*.  
SANTA MONICA CALIF.: RAND CORP.
- IBM. (2011). CPLEX Optimizer. IBM Corp.
- Johnson, K. N., & Scheurman, H. L. (1977). Techniques for prescribing optimal timber harvest and investment under different objectives--discussion and synthesis. *Forest Science*, 23(Supplement 18), a0001-z0001.
- Jones, J. G., Mecham, M. I., Weintraub, A., & Magendzo, A. (1991). A heuristic process for solving large-scale, mixed-integer mathematical programming models for site-specific timber harvest and transportation planning. *Proceedings of the 1991 Symposium on Systems Analysis in Forest Resources*, (pp. 192-198).
- Jules, E. S., Kauffman, M. J., Ritts, W. D., & Carroll, A. L. (2002). Spread of an Invasive Pathogen Over a Variable Landscape: A Nonnative Root Rot on Port Orford Cedar. *Ecology*, 83(11), 3167-3181.
- Karlsson, J., Rönnqvist, M., & Bergström, J. (2004). An optimization model for annual harvest planning. *Canadian Journal of Forest Research*, 34(8), 1747-1754.
- Kirby, M. W., Wong, P., Hager, W. A., & Huddleston, M. (1980). *Guide to the integrated resource planning model, Technical Report*. Berkley, CA.
- Martell, D. L., Gunn, E. A., & Weintraub, A. (1998). Forest management challenges for operational researchers. *European Journal of Operational Research*, 104, 1-17.
- Mauger, G.S., J.H. Casola, H.A. Morgan, R.L. Strauch, B. Jones, B. Curry, T.M. Busch Isaksen, L. Whitely Binder, M.B. Krosby, and A.K. Snover, 2015. State of Knowledge: Climate Change in Puget Sound. Report prepared for the Puget Sound Partnership and the



- National Oceanic and Atmospheric Administration. Climate Impacts Group, University of Washington, Seattle. doi:10.7915/CIG93777D
- McDill, M. E., Rebain, S., & Braze, J. (2002). Harvest scheduling with area-based adjacency constraints. *Forest Science*, 48(4), 631-642.
- Olsson, L., & Lohmander, P. (2005). Optimal forest transportation with respect to road investments. *Forest policy and economics*, 7(3), 369-379.
- PSF (2006), Policy for Sustainable Forests. Washington State Department of Natural Resources.
- Remsoft. (2013). Woodstock. *Version : 2012.12*. Fredricton, New Brunswick, Canada: Copyright© Remsoft Inc. 1993 - 2012 [www.remsoft.com](http://www.remsoft.com).
- Riedel, M. S. (2004). Collaborative research and watershed management for optimization of forest road best. *International Conference on*, (pp. 148-158). Raleigh, NC. Retrieved April 8, 2014, from <http://escholarship.org/uc/item/3f47q1j>.
- Sessions, J. (1987). A heurostic algorithm for the solution of the variable and fixed cost transportation problem. *Proceedings of the 1985 Symposium on System Analysis in Forest Resources*, (pp. 324-336).
- Weintraub, A., & Navon, D. (1976). A forest management planning model integrating silvicultural and. *Mangement Science*, 22(12), 1299 - 1309.
- Weintraub, A., Jones, G., Magendzo, A., Meacham, M., & Kirby, M. (1994). A heuristic system to solve mixed integer forest planning models. *Operations Research*, 42(6), 1010 1024.
- Williams, H. P. (1999). *Model building in mathematical programming*.

Figures and Tables

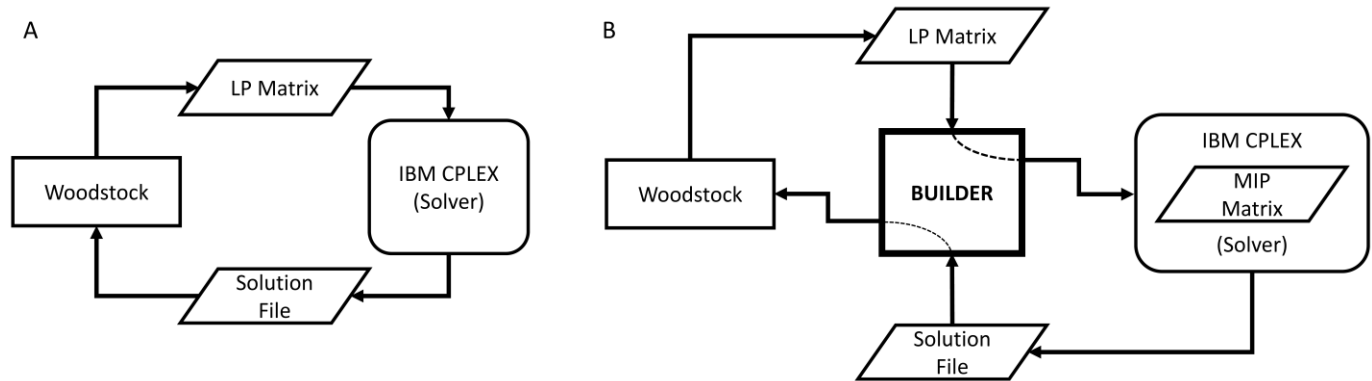


Figure 1: (A) Old DNR workflow (B) New workflow with Builder

<b>Dataset</b>	<b>Small</b>	<b>Medium</b>	<b>Large</b>	<b>Full</b>
Number of FMUs	91	193	299	621
Number of Road Segments	107	214	337	696
Number of Constraints	5917	12544	18953	41279
Number of Variables	6533	13772	20801	43271
EFCM Solve Time (s)	46	416	1077	9964
Control Solve Time (s)	2	14	34	36
EFCM Reconstructed Road Segments	517	1186	1722	3604
Control Reconstructed Road Segments	624	1336	2038	4141
EFCM Total Reconstructed Road	502,700 ft.	946,192 ft.	137,4042 ft.	2,959,438 ft.
Control Total Reconstructed Road	620,892 ft.	1,076,584 ft.	1,651,969 ft.	3,463,099 ft.
EFCM Objective Function Value	\$13,031,836	\$32,286,807	\$38,846,612	\$86,711,336
Control Objective Function Value	\$13,010,742	\$32,119,611	\$38,752,708	\$86,299,566
Minimum Difference	\$21,094	\$167,195	\$93,903	\$411,769
Upper Bound	\$13,155,500	\$32,526,500	\$39,224,700	\$87,263,600
Upper Bound on Difference	\$144,757	\$406,888	\$471,991	\$964,033

Table 1: A comparison of the performance of the EFCM and the control model.

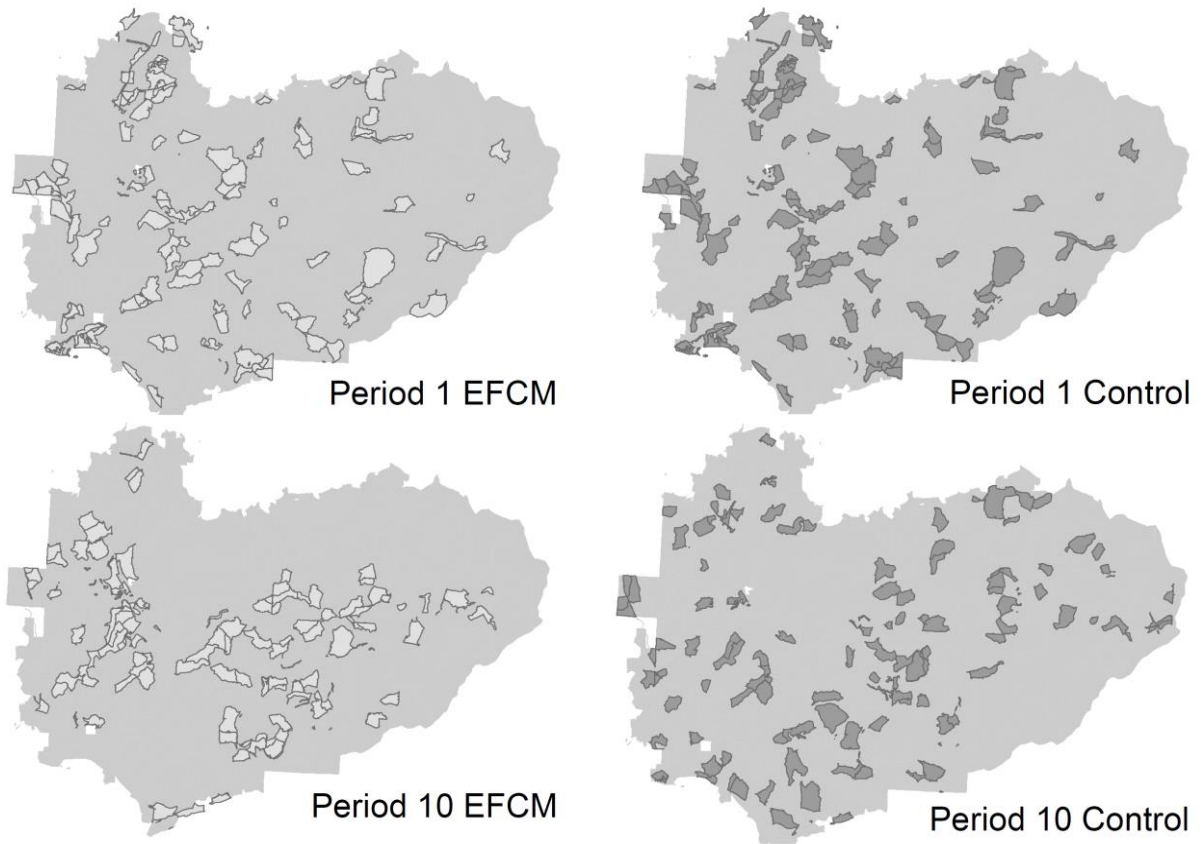


Figure 2: Comparison of FMUs harvested in Period 1 and Period 10 under the EFCM (light polygons) and control model (dark polygons) solutions.

<b>Average Number of Daily Truck Passes</b>	<b>&lt;1</b>	<b>1-2</b>	<b>2-3</b>	<b>3-4</b>	<b>4-5</b>	<b>&gt;5</b>
<b>Number of road segments (EFCM)</b>	2286	402	157	143	166	417
<b>Number of road segments (Control)</b>	2757	457	286	145	108	388
<b>Difference</b>	-471	-55	-129	-2	58	29

Table 2: Number of daily truck passes per segment expected for the EFCM vs. Control solutions