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Mountain pine beetle infested forests in the Rocky Mountain region raise complicated economic, environmental, and social impacts and pose severe forest management challenges to land managers and public and private landowners. Harvesting infested forest stands provides an opportunity to utilize otherwise wasted resources, mitigate economics losses to landowners, and generate greenhouse gas emission savings to combat climate change. Due to high operation costs and low product values, sound supply chain planning is of critical importance to the success of forest salvage utilization. However, knowledge gaps and operational uncertainties obscure the understanding of timber salvage harvest and performances of forest supply chains. In addition, lack of analytical methods and tools impedes forest operation analysis. This dissertation attempts to apply operations research to analyze post-outbreak forest salvage utilization to assist decision makers with improving the management of timber and biomass supply chain. We adopted discrete-event simulation to study salvage harvest operations to overcome analytical challenges confronted by conventional time study approach. We used multi-objective optimization to investigate trade-offs between net revenues and greenhouse gas emission savings in forest salvage utilization and compared different management scenarios. We also developed a multi-objective metaheuristic to solve large multi-objective combinatorial optimization problems for

forest supply chain management. We believe our work can provide a set of useful analytical tools for the management of beetle kill forests and post-outbreak forest salvage utilization. We also hope our work offers novel approaches to solving various challenging forest management problems for future researchers and practitioners.

Supply Chain Management of Timber and Biomass from Mountain Pine Beetle Infested Forests

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To Jessica, Meiqin, and Wenhua

Chapter 1
General Introduction

1.1 Mountain pine beetle infestation

The mountain pine beetle (MPB; *Dendroctonus ponderosae* Hopkins, Coleoptera: Curculionidae, Scolytinae) is a native bark beetle to pine forests of western North America (Cole and Amman 1980). MPB attack trees by chewing into the inner bark and phloem where they feed, mate and construct larval galleries, which disrupts the movement of photosynthate from needles to roots (Gibson et al. 2009). The beetles also introduce blue-stain fungi (*Ophiostoma montium*) that girdle the phloem and block water and nutrient transport within a tree (Ballard et al. 1984). Immature adult beetles feed on fungal spores and associated tree tissues until maturation and then emerge out to seek and attack new trees to resume such a yearly cycle (Gibson et al. 2009). The infested tree produces resin to kill the beetles and fend off the attack but such an defensive mechanism can be exhausted when there are an overwhelming number of beetles (Bentz et al. 2009). The joint attack of larval feeding and fungal colonization can kill the host tree within a few weeks (Safranyik et al. 1975). Several months to a year after the attack, infested trees begin to fade gradually from green to red, rusty brown, and finally gray (Figure 1.1) (Amman et al. 1989). Depending on environmental factors such as the weather and soil conditions, dead trees remain at the gray stage for many years where they gradually lose foliage as fine branches fall and bark flakes off the stem. Over this course, steam wood also deteriorates and becomes rotted so that standing dead trees eventually fall to the ground due to breakage or wind throw (Mitchell and Preisler 1998).

At the endemic phase, the MPB population stay at low levels and only kill older and weaker trees individually at a less than two percent annual mortality rate, resulting in patchy mortality throughout the forest (Samman and Logan 2000). When there are locally high beetle population and other favorable conditions (e.g., temperature, tree resistance, proximity to other beetle populations), eruption to an outbreak may occur and become widespread over several years that leads to millions of dead trees (Gibson et al. 2009). Outbreaks often develop in even-aged dense stands (basal area > 27.5 m^2/ha) of large (diameter at breast height > 20.3 cm), old (>80 years-old) lodgepole pines (*Pinus contorta* Douglas var. latifolia Engelmann) where more than 80 percent of trees can be killed in five to seven years (Samman and Logan 2000). Under extreme conditions or when the majority of larger-diameter lodgepole pines have been infested, beetles may also attack smaller trees or other pine species including ponderosa pine (*P. ponderosa* Laws.), western white pine (*P. monticola* Dougl.), whitebark pine (*P. albicaulis* Engelm.), limber pine (*P. flexilis* James), and Scots pine (*P. sylvestris* L.) (Gibson et al. 2009).

Figure 1.1 Forest and tress (inset) in the green stage (left), red stage (middle), and gray stage (right) following a mountain pine beetle outbreak (Photos courtesy of the U.S. Forest Service: Ron Billings, Brian Howell, and Nate Anderson).

Following its major host pine species, MPB spreads from the Pacific Coast eastward to the Black Hills of South Dakota, from northern British Columbia and western Alberta southward to northern Baja California, Mexico, and from near sea level in British Columbia, to 3,353 m in Colorado (Amman and Cole 1983). Historically, MPB outbreaks have been a regular force of natural change in western North American forests with an average return interval of 20 to 40 years (Bentz et al. 2009). Their occurrences in British Columbia, Colorado, Idaho, Montana, Wyoming and Utah have been highly synchronous, indicating the subcontinental nature of MPB outbreaks (Jarvis and Kulakowski 2015).

The recent MPB epidemic, lasting between 1990s and early 2010s, has affected a massive area of forests in North America (e.g., over 18.3 million hectares in British Columbia, Canada and 8.9 million hectares in the western United States) (Fettig et al. 2014; Corbett et al. 2015). It has been documented as the most severe and widespread outbreak throughout history in terms of intensity (killing more trees at a faster pace over a longer time period), extent (occurring concurrently in numerous forests), and extended range (beyond previously recorded north and east ranges and impacting new tree species) (Bentz et al. 2009).

1.2 MPB impacts

MPB is an integral part of the ecology of forests in western North America and it helps shaping forest structure and composition as a natural ecosystem disturbance (Klutsch et al. 2009). All forests contain a number of dead trees that provide important wildlife habitat and other ecological functions (Colorado State Forest Service. 2018). However, as forests provide considerable amounts of goods and functions of ecological, monetary, and cultural values, referred as ecosystem services (Millennium Ecosystem Assessment 2005), MPB-induced tree mortality weakens forest ecosystem services due to their high potential impact on ecosystem structure, function and composition (Seidl et al. 2016). This raises complicated economic, environmental, and social impacts and poses severe forest management challenges to land managers and public and private landowners.

1.2.1 Economic impacts

MPB outbreaks have caused enormous economic losses to the society. Volume and value losses associated with dead timber are the two main causes to the direct negative economic impacts of MPB (Snellgrove and Fahey 1977). Volume loss is the decreased amount of wood product that can be manufactured from a log or tree (Lowell et al. 2010). Because of the low moisture and sap content in dead trees, saws and chippers do not perform well compared with green timber, leading to significant increase in breakage during harvesting and handling (Byrne et al 2006). Besides, wood deterioration causes rot, shake, checks and cracks which reduce the recoverable timber product volume (Carpenter et al. 1989). Volume loss directly translates to economic loss because the amount of output product is decreased. For instance, it is estimated that between 2009 and 2054, British Columbia will witness a reduction of \$57 billion in the province’s GDP and a \$90 billion decline in economic welfare because of a loss of 731 million cubic meters (54% of total available) in merchantable pine volume due to MPB (Corbett et al. 2015). Value loss, on the other hand, refers to the reduced value of products manufactured due to product degraded type or quality (e.g., lumber grade) (Lowell et al. 2010). As MPB killed trees move from green to red to gray, the proportion of the volume of the stand decreases in higher value product categories (e.g., sawlog, post and pole) and increases in lower value product categories (e.g., pulpwood, firewood) (Loeffler and Anderson 2018). A sawlog-dominant harvest gradually transits to a pulpwood-dominant harvest, which reduces land values strikingly. Log staining of MPB timber is also considered as an apparent grade defect that reduces product values. Although blue stain does not necessarily impact mechanical properties of the wood (Byrne 2003), it has detrimental effects on the aesthetic value and market acceptability of the lumber and the volume of blue stain continues increasing along time since beetle attack (Chow and Obermajer 2006).

Forest regeneration post attacks, despite rapid stand growth, is limited in mitigating economic loss caused by MPB outbreaks. As infested trees die and more light reaches to the forest floor, advanced regeneration and understory vegetation may display enhanced growth rates, return annual wood production to previous levels quickly, and offset killed tree volume (Romme et al. 1986; Stone and Wolfe 1996; Dhar et al. 2016). However, these small-diameter young trees are not as valuable as large-diameter commercial pine forests depleted by MPB outbreaks. Moreover, extensive tree mortality can significantly influence successional pathways and forest community composition, and late successional tree species (e.g., subalpine fir) are often less commercially valuable than lodgepole pines (Gibson et al. 2009).

1.2.2 Environmental impacts

The occurrence of the MPB epidemic has undoubtedly altered stand and landscape structure (Dhar et al 2016). MPB mainly targets trees in mature, overly dense forests and allows more growing space and resources (e.g., light, water, nutrients, etc.) for understory vegetation (Stone and Wolfe 1996; Dhar and Hawkins 2011). By killing older trees and facilitating younger, more vigorous trees to grow, MPB may help forest to regenerate and proceed succession, which results in more structurally and compositionally diverse forests (Hansen 2014). Such a stand and landscape heterogeneity created by forest complexity enhances forest ecological resilience, the capacity of an ecosystem to maintain its fundamental functions and processes after disturbances (Drever et al.

2006). However, during the MPB outbreak, massive tree mortality in such short time alters the balance between living and dead portions of trees and significantly affects forest structural sustainability (Cale et al. 2016). Long-term (30 years) forest recovery from previous MPB outbreaks also shows shift in species and size composition that may have substantial impacts on forest health and ecosystem processes (Pelz and Smith 2012).

The MPB outbreak poses mixed impacts on wildlife by altering food and forage availability as well as habitat suitability (Dhar et al. 2016). Beetles are an important food supply for many avian vertebrates, and some woodpecker populations have been documented to increase in response to MPB outbreaks (Chan-McLeod 2006). However, the abundance of tree sap eaters and sapsuckers (e.g., northern flickers [*Colaptes auratus* L.], red-naped sapsuckers [*Sphyrapicus nuchalis* B.]) decreases in MPB infested stands (Walters et al. 2002). Increased tree mortality provides important nesting, roosting, and foraging habitat for wildlife that depend on snags and downed logs (Drever and Martin 2010). But coarse woody debris can adversely affect movement of big game and other wildlife (e.g., elk [Cervus canadensis] and deer [Odocoileus spp.]) (Light and Burbridge 1985). Due to defoliation of the tree canopy, cavity-nesting species and species nesting in the shrub layer respond favorably to beetle-killed forests (Saab et al. 2014), whereas species that are forest cover dependent (e.g., American marten [*Martes americana*] that prefers great canopy closure as habitat) show substantial declines in their population sizes (Steventon and Daust 2009). The variation in wildlife responses to MPB outbreaks depends on not only wildlife species and forest types (e.g., lodgepole-dominated vs. ponderosa-dominated forests), but also the severity and scale of the outbreak, time since infestation, the conditions before the outbreak, and the spatial context in which the outbreak occurs (Saab et al. 2014).

With higher percentages of tree mortality, MPB infested forest alters fuel structure in terms quantity, quality, and distribution of biomass (Harvey et al. 2014) and becomes more likely to fuel large, intense wildfires that threaten public safety, water supplies, wildlife and recreation (Colorado State Forest Service 2018). Following MPB attack, foliar moisture content in dead trees decreases gradually as time progresses (Gibson and Negron 2009). As foliage fall, canopy bulk density declines and fine surface fuels increase. As forest regrows, crown fuels recover and fine surface fuels decrease due to biomass decomposition. Coarse surface fuels increase as branches and snags fall while ladder fuels increase as shrubs and seedlings establish and surviving residual trees grow (Astrup et al. 2008). Consequently, fire behavior is modified in response to these changes in fuel characteristics. With increased surface fuel loads, surface fire behavior reaches higher rate of spread, fireline intensity, and flame length in outbreak stands than endemic stands (Jenkins et al. 2008). Torching potential also increases as a result of reduced foliar moisture in killed trees, increased surface and ladder fuel loads, and no change in canopy base height (Hicke et al. 2012b). The potential for active crown fire increases in the red stage as foliar moisture decreases, declines through the gray stage following reductions in canopy bulk density, and slowly increases again when forest regrows (Page and Jenkins 2007). Although there remains disagreement and knowledge gap in early post outbreak stages and crown fire behavior responses, higher risk and more intense wildfire potentials in MPB infested forests with a longer time lapse (>10 years) since outbreak are generally accepted (Hicke et al. 2012b).

Regarding carbon dynamics at MPB infested forests, controversial arguments have been raised. On the one hand, as dead trees decay over time, they become a net source of carbon (i.e., dead trees stop absorbing CO_2 and emit CO_2 during decomposition) and contribute to climate change (Kurz et al. 2008; Amiro et al. 2010). The carbon release legacy from bark beetle outbreaks across Western United States is estimated to continue decades into future (e.g., 2040 to 2060) as committed emissions (Ghimire et al. 2015). On the other hand, it is pointed out that residual trees show enhanced radial growth post-outbreak and rapid carbon uptake which compensates for losses due to tree mortality (Hawkins et al. 2013). Effects of increased respiration due to tree mortality and photosynthesis efficiency due to forest recovery may in fact cancel out and result in no change in net CO_2 exchange (Reed et al. 2014). MPB infestations may result in reductions in forest carbon storage, but recalcitrance of snags and coarse woody debris together with forest regrowth may recover attacked forests to net carbon sinks as quickly as 5 to 20 years (Hansen 2014). Large variability in carbon cycle responses arises from factors including time since disturbance, number of trees affected, and capacity of survival vegetation to increase growth rates post-outbreak (Hicke et al. 2012a). Despite the lack of consensus on the carbon balance between respiration and photosynthesis, the posing risks of destructive wildfires related to global warming and historical fire suppression may still keep MPB infested forests as potential large-scale carbon sources.

The MPB outbreak affects the environment in many, if not all, aspects and the impacts may be far reaching (Dhar et al 2016). Forest stand and landscape responses vary by tree species, forest composition, terrain conditions, and time since infestation. Climatic and geographical variations pose a further challenge for evaluating MPB impacts and predicting forest responses. Inconsistent conclusions from different regions suggest that it is difficult to generalize positive and negative environmental impacts of the MPB outbreak.

1.2.3 Social impacts

MPB outbreaks have negative effects on forest provisioning and regulating services, which influences local communities substantially on water supply and quality, production of timber and non-timber products, and air purification (Dhar et al. 2016). Hazardous trees also pose threats on public safety around public campsites, roads, and infrastructure (Gebert et al. 2014). In addition, live trees provide aesthetic, cultural and recreational forest values, whereas dead and dying trees decline people's landscape preference through visible damages, reduced tree density and tree size (Rosenberger et al. 2012). At wildland-urban interface, residential property values depreciate in MPB outbreak areas due to declining utility (i.e., a decrease in the level of satisfaction derived from market and nonmarket goods and services) (Price et al. 2010). At forest recreation sites, the quality of the recreation experience reduces with decreased consumer surplus and number of total visits in MPB infestation areas (Rosenberger et al. 2013), leading to reduced tourism revenues and loss of other cultural ecosystem services (Arnberger et al. 2018).

The complexity of issues and great uncertainties involved in MPB infestation area management turn the epidemic to be more of a social issue than an environmental issue (Kimmins et al. 2005). In particular, dispersed agency authorities and jurisdictional fragmentation lead to regional distinctions in how MPB infested forests are managed on public versus private lands (Scarlett and Boyd 2015). Even though the public tends to have negative views towards MPB and support measures to control it, they generally lack the knowledge of MPB and its impacts (McFarlane et al. 2006). Public education and outreach on MPB related issues can help build consensus and participation in developing land management strategies, plan and implementation in response to outbreaks (Morris et al. 2018).

1.3 Salvage utilization of MPB-kill wood and biomass

1.3.1 Salvage harvest

The primary goal of a MPB-kill salvage harvest is to utilize forest resource that is otherwise wasted and mitigate economic losses caused by the MPB outbreak (Loeffler and Anderson 2018). It provides an opportunity to contribute to local wood product and bioenergy industries (Colorado State Forest Service 2017). Affected trees can be harvested at any stage but they retain greater portion of their commercial values at the green, red, or early gray stages (Loeffler and Anderson 2018). Depending on species and extent of damage, it is estimated that beetle-attacked logs can still yield 56.1% to 99.8% values of healthy logs (Orbay and Goudie 2006). It is estimated that 0.56 billion m^3 of dead timber is available for salvage across 8.22 million hectares in the 12 western states in the US. This represents a considerable amount of revenues to recover for affected landowners in the region (Prestemon et al. 2013).

Salvage harvest removes forest overstory and eliminates the possibility of crown fire (Griffin et al. 2013), making forests more resistant to potential high-severity fires (Hood et al. 2017). Utilization of salvage timber also produces carbon benefits in various ways. At forest sites, it reduces dead wood decay emissions (Campbell et al. 2016) and increases carbon absorption by opening up the canopy to accelerate forest regeneration (Collins et al. 2010). During manufacturing, wood products normally involve less energy-intensive processes and release less carbon than their non-wood alternatives (Werner et al. 2005; Gustavsson et al. 2006). While being used, wood products serve as carbon storage, and regrowth in a sustainably managed forests is usually equal to or greater than the stored amount to offset wood product production emissions (Bergman et al. 2014). At the end of service life, wood products can be used to substitute fossil fuels as energy feedstock (Kayo et al. 2015) or continue to preserve carbon in landfill for a longer period (Ximenes et al. 2008).

Various timber harvesting equipment and systems have been developed to implement silvicultural treatments (e.g., clearcut, commercial thinning, and selective harvesting) under a wide range of vegetation and terrain conditions (Uusitalo and Pearson 2010). For MPB infested stands (Figure 1.2), residual snags and fallen stems may increase safety hazards and thus limit access for treatments (Griesbauer and Green 2006). To ensure economic efficiency and operational safety, a clearcut or patch cut with mechanized harvesting systems has become a standard salvage harvest treatment in most regions (Burton 2010).

Figure 1.2 Typical conditions of MPB infested lodgepole pine stands (left: distant observation, right: close observation) with high mortality rates showing a mix of standing, leaning, and down trees (Photos courtesy of Hee Han).

1.3.2 Forest biomass for bioenergy

In addition to timber production, degraded wood and logging residues (e.g., tree tops, branches and non-merchantable parts) from salvage harvesting can serve as feedstock for bioenergy production (Lamers et al. 2014). Compared to healthy forest stands, MPB-attacked forests represent a better source of bioenergy feedstock in terms of both quantity and quality. Because of wood degradation over time, some dead trees fail to meet the quality requirement for lumber or pulp and paper production especially when salvage harvest is delayed significantly. This results in a large amount of logging residues (Chow and Obermajer 2006). From a quality standpoint, these residues contain high woody composition and low moisture content, making it a bioenergy feedstock with high energy density (Barrette et al. 2015).

If biomass residues are loped and scattered (i.e., biomass retention slash prescription), a large amount of heavy (1,000-h) fuels are left on site (Figure 1.3) (Hood et al. 2017). To reduce fire risks and prepare harvest sites for regeneration, disposal of biomass residues by open pile burning is often used post-harvest (Stephens et al. 2012; Jones et al. 2013). However, not only does this practice produces local air pollution (Campbell et al. 2018), burn sites also create persistent openings with low tree densities even after 50 years in regenerating lodgepole pine forests (Rhoades and Fornwalt 2015). Removal of biomass residues for further utilization avoids such negative outcomes while saving costs and emissions (e.g., greenhouse gas, particulate matter) associated with open pile burning (Springsteen et al. 2011, 2015). The use of bioenergy/biofuel also reduces society's heavy dependence on fossil fuels and contributes to climate change mitigation (Panwar et al. 2011; Creutzig et al. 2015).

Figure 1.3 Site scene post-harvest when biomass residues are loped and scattered (left) or piled (right) at the landing (Photos courtesy of Hee Han and Nate Anderson).

Typically, forest biomass can be either combusted directly (e.g. hog fuel, chips) or converted to other bioenergy products, such as pellets, biochar, bio-oil, biodiesel, syngas, etc. through mechanical, thermal, chemical and/or biological conversion technologies (Sharma et al. 2013). The selection of the suitable bioenergy product is determined by targeting energy format, biomass properties, available technologies or facilities, and other economic and technical factors (McKendry 2002a, 2002b). Because biomass can be stored and used on demand for energy generation, given sound planning and management, its supply can be more consistent and predictable than other renewable energy sources, such as wind and solar (Hall and Scrase 1998).

1.3.3 Forest salvage in Colorado

Colorado's nearly 9.91 million hectares of forestland are consisted of a diverse mix of coniferous and deciduous species, where the most extensive forest types are spruce-fir, ponderosa pine, lodgepole pine, aspen and piñon-juniper[1]. Due to the complex forest types, Colorado's forests are

[1] Colorado State Forest Service https://csfs.colostate.edu/colorado-forests/

influenced by a variety of insects and diseases such as Spruce Beetle (*Dendroctonus rufipennis*), Douglas-fir beetle (*Dendroctonus pseudotsugae*), and root disease fungi. Among them, MPB infests all pine species native to Colorado and impacted more than 1.38 million hectares of forests between 1996 and 2014 (Colorado State Forest Service 2017). Tree mortality is most concentrated in lodgepole pine forests in north-central Colorado. The MPB populations now remain at endemic levels statewide with less than 360 ha of new infestation in 2017, which has been steady since 2015 (Colorado State Forest Service 2018).

In response to the massive quantity of trees killed by MPB attack, dead timber becomes the major component in Colorado's forest harvesting, which accounted for 55 and 56 percent of the total harvest volume in 2007 and 2012, respectively, more than doubling the 26 percent in 2002 (Sorenson et al. 2016). Lodgepole pine has become the leading species harvested in Colorado and accounted for 50 percent of the volume in 2012 (Sorenson et al. 2016). Throughout years, Colorado has switched from a net timber exporter (net exporting 4 million board feet [MMBF] of timber in 2002), to a net timber importer (net importing 7.3 MMBF in 2007 and 7.1 MMBF in 2012) (Morgan et al. 2006; Sorenson et al. 2016). Meanwhile, more than 90 percent of wood-based products used in Colorado are imported from out of state, representing an annual expense of $4 billion of Coloradans (Colorado State Forest Service 2016). As the majority (89 percent in 2002, 98 percent in 2007, and 99 percent in 2012) of Colorado's timber is processed in-State (Morgan et al. 2006; Sorenson et al. 2016), increasing the harvest volume contributes to wood products manufacturing and local employment, increases the market competitiveness of Colorado wood products, and benefits recreation and tourism at the same time (Colorado State Forest Service 2016).

Forest biomass utilization has also become more attractive given the recent policy enactments in Colorado, where electricity generation, thermal applications, and liquid biofuel production are considered as the most potential pathways (Eckhoff and Mackes 2010). Given the current severe wildland fire risks and concerns in dense, overgrown stands (Colorado State Forest Service 2019), biomass harvesting and utilization has gained general social acceptability to help achieve forest fuel reduction and restoration goals (Western et al. 2017).

Our study forest in this dissertation is the Colorado State Forest (16,243 ha) located in northern Colorado (40°35′59″ N, 106°00′27″ W, Figure 1.4). Elevations in the forest range from 2,570 to 2,980 m above sea level, and mean annual temperature and precipitation are 1.5°C and

75 cm, respectively (PRISM Climate Group 2012). The forest is dominated by lodgepole pine and quaking aspen (*Populus tremuloides* Michx.) with Engelmann spruce (*Picea engelmannii*) and subalpine fir (*Abies lasiocarpa*) at higher elevations. The forest was burned in the early 20th century and extensively logged in the 1940s and 1950s (Chung et al. 2017). Lodgepole pine stands have been heavily affected by MPB since 2008, resulting in a mortality rate of 47.3% across approximately 3,994 ha by 2015 (Han et al. 2018). The infested forest is located on relatively flat terrain with a stand density of 865 trees ha^{-1} and a basal area of 34.6 m^2 ha^{-1}. The average diameter at breast height (dbh) of trees is 22.4 cm and the average height is 19.6 m.

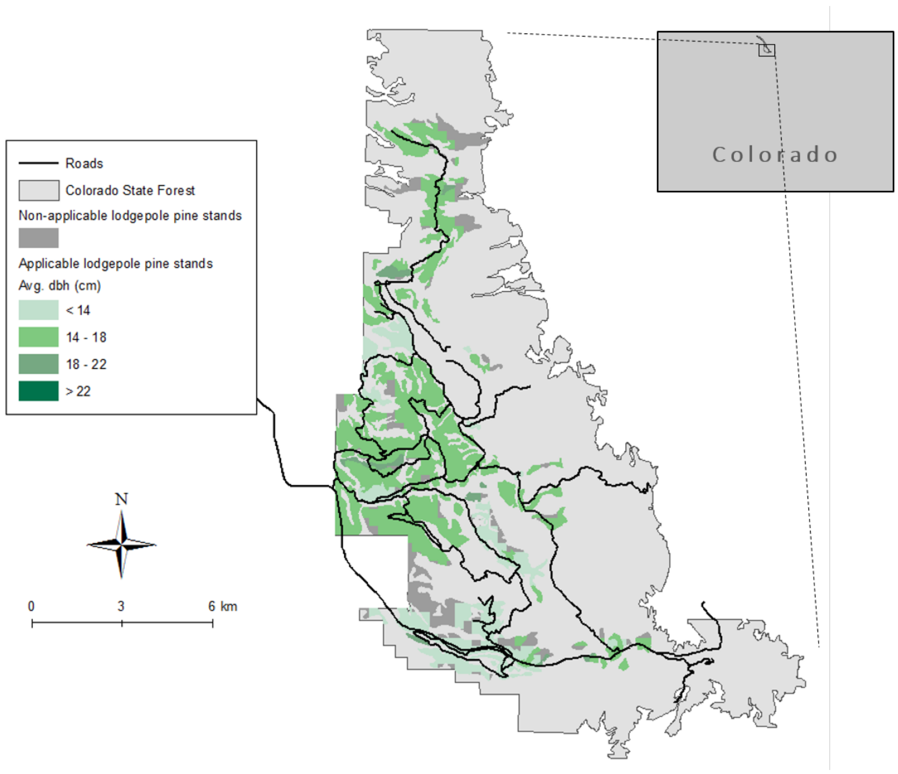

Figure 1.4 Lodgepole pine stands in the Colorado State Forest shown in diameter at breast height (dbh) classes.

The forest is currently managed for multiple uses with salvage harvest for timber production remaining a priority (Chung et al. 2017). Due to safety issues and overwhelming costs associated with harvesting on steep slope, salvage harvest in Colorado State Forest is restrained to ground-based clearcut operations in terrain with gentle slope (normally less than 30 percent), leading to 3,387 ha applicable stands. Commonly used equipment in ground-based mechanical systems are shown in Figure 1.5. Feller-bunchers are used to cut trees down. Grapple skidders transport trees or lots from stump to landing. Stroke delimbers delimb, top and buck trees. Loaders sort timber products, build log deck, and load logs onto trucks. Depending on the small-end diameter and defects, trees can be processed into three log products (i.e., saw logs, post and pole, and firewood) and sold based on dry weight to local markets located approximately 45 km from the forest. As for logging residues, potential bioenergy alternatives include hog fuels (a biomass power plant 238 km away), wood pellets (a pellet plant 45 km away), and biochar (mobile pyrolysis equipment on-site).

(a) Feller-buncher (b) Skidder (c) Delimber (d) Loader

Figure 1.5 Equipment feller-buncher (a), skidder (b), delimber (c), and loader (d) used in the ground-based clearcut salvage harvest in Colorado State Forest.

1.4 Forest supply chain management

Supply chain is the network of material flows from the source to the end-user where four business entities, i.e. supplier, manufacturer, distribution centers, and customers are involved (Beamon 1998). The management of supply chain focuses on integration of all entities so as to deliver the right amount of the right product to the right place at the right time (Feigin 2011). Forest supply chain planning focuses on producing and delivering diverse wood products from standing trees in forests to end customers in an economically viable and environmentally sound manner (Weintraub and Epstein 2005). The performance of a forest supply chain is decided by the degree of coordination and integration among entities, where various decisions are made during management to ensure the efficient flow of material and information (Sharma et al. 2013).

1.4.1 Strategic, tactical, and operational decisions

Based on the degree of significance and periods of effectiveness, decisions relevant to supply chain management fall in three levels: strategic (long-term, ten to 100 years), tactical (medium-term, six months to several years), and operational (short-term, weekly, daily or even hourly) (Huang et al. 2003). Depending on the area of MPB infested forests, amount of salvageable timber, and the time horizon of management, decisions at different levels may be involved that affect the final performance of the supply chain during forest salvage utilization.

Strategic decisions focus on the design of efficient supply chain network to increase the competitiveness and to achieve organizations overall objectives (Sharma et al. 2013). They are usually investment intensive to pursue long-term interests and may need revision after several years (De Meyer et al. 2014). The management goal is usually to determine the proper technology (e.g., bioenergy pathway), facility (e.g., number, location, and capacity), and corresponding supply chain configurations for a salvage utilization project. It is important to ensure timber and/or biomass supplies to be abundant and consistent during the entire project life cycle and comply with sustainable forest management. For example, a dedicated bioenergy combined heat and power plant is normally designed to serve more than 30 years so it should be built in a region with continuous sufficient biomass supply from nearby areas at reasonable logistic costs.

Under prerequisites to meet established strategic goals, tactical planning serves as a bridge between the long term comprehensive strategic planning and the short term detailed operational planning to ensure the subsequent operations conform to the strategic directives (D'Amours et al. 2010). Given the established infrastructure, tactical planning during forest salvage utilization focuses on improving the efficiency of resource (e.g., raw material, machine, manpower) utilization to best meet strategic goals while complying various practical constraints. This usually includes harvest scheduling among selected forest stands, material logistics control from forests to customers, and biomass pre-treatment management, etc. For example, harvesting operations are greatly influenced by the shifting weather conditions (e.g., summer fire restriction and spring thaw) so timber production (e.g., production volume, crew and machine allocation) should be planned accordingly to ensure the efficiency of the biomass supply chain.

Operational decisions concentrate on details and precise timing of operations constrained by the tactical decisions (Sharma et al. 2013). They deal with detailed production, inventory, and transportation management to ensure consistent and efficient operations of all facilities along the supply chain (De Meyer et al. 2014). In forest salvage utilization, operational decisions include harvest system configuration, bucking pattern selection, and log sorting determination, etc. For instance, daily truck scheduling and routing for hauling wood from forests to destinations is a typical operational planning problem.

1.4.2 Operations research

Operations research (OR) has long been used to develop models and solution methods to support forest management decision-making for forest industries and public forestry organizations (Rönnqvist et al. 2015). Applications include forest management planning and harvest scheduling (D'Amours et al. 2008) as well as supply chain management for forest products (e.g., wood products, paper, lumber, and biofuel) (Carlsson et al. 2008). Through modeling and quantitative analysis, a performance criterion (e.g., production cost, unit revenue, carbon emission amount) of interests is estimated to evaluate a management strategy or compare different strategies.

Simulation, defined as "an approximate imitation of the operation of a process or system" (Banks 1984), is an effective tool in industrial and manufacturing engineering to understand production systems and estimate system productivity and costs (Ziesak et al. 2004). As a simulation approach, the time study technique has been widely applied in forest operational analysis to understand the performance of individual machines as well as the entire system (Acuna et al. 2012). In general, the field data collected are used to model the productivity of individual machines based on independent variables (e.g., stand density, skidding distance, terrain slope, tree size, etc.) through regression. These regression models are then used to predict machine productivity in productive machine hours under various work conditions (Schillings 1969; LeDoux et al. 1986; Kellogg and Bettinger 1994). Because machines encounter various delays (e.g., operator break, mechanical breakdown, machine queueing), the productivity in productive machine hour is converted to the productivity in scheduled machine hours by applying the rate of machine utilization. All machine productivities in scheduled machine hours are compared to identify the bottleneck function in the system. This bottleneck productivity is then used to estimate the productivity of the entire production system and unit production costs (Gingras and Godin 1996; Han et al. 2004; Anderson et al. 2012).

Mathematical optimization, or mathematical programming, is the technique of selecting the best alternative (with regard to some criterion) from a number of candidate solutions under some restrictions. In the optimization process, the problem is formulated as a mathematical model where one or more objective functions are to be optimized (e.g., maximizing net present value, minimizing deviations in wood flow) by changing values of decision variables (e.g., harvesting system selection, production amount) while satisfying all constraints (e.g., capacity limitation, harvest area restriction) (Kaya et al. 2016). With an increasing interest in addressing sustainability in forest management, multi-objective optimization, one of the most popular multi-criteria decision making methods, has been widely applied to account for multiple, non-comparable, and often conflicting objectives simultaneously (Ananda and Herath 2009). The output is a set of "Pareto optimal" nondominated solutions, of which there is no other solution that is equal or better in all objectives (i.e., dominate this solution) (Ehrgott 2005). In any of nondominated solutions, one objective cannot be improved without sacrificing other objectives and form the Pareto front which shows trade-offs among objectives (Deb 2001). Decision makers can then select solutions that balance among objectives such as economic gains (e.g., property values), improvement on ecosystem services (e.g., water quality, wildlife habitat), and increasing social benefits (e.g., job generation, public acceptance) (Yue et al. 2013; Schroder et al. 2016).

1.4.3 Challenges of supply chain management in salvage utilizing MPB infested forests

1.4.3.1 Practical challenges

One of the biggest challenges in salvage harvest logs from beetle-killed forest stands may be the low market values of dead timber due to relatively small trees size and wood defection (Byrne et al. 2006). For this reason, the central Rocky Mountain states of Colorado, Utah, and Wyoming, which have the largest percentage volume and acreage impacts from salvable standing dead timber, would not generate profitable timber salvage at many forest stands (Prestemon et al. 2013). In addition, salvage harvest logs from natural disasters only has a narrow window (Sessions et al. 2004). Delay in salvage harvest following wildfire caused millions of dollar losses in two years (Prestemon et al. 2006). As beetle killed trees decay over time, their wood quality degrade (Lewis and Thompson 2011) and their market values continue to decrease (Barrette et al. 2015). However, at the same time, harvesting costs at beetle-killed stands continue to increase as the down tree proportion increases (Kim et al. 2017; Han et al. 2018) and salvageable volume decreases (Byrne et al. 2006). Thus ensuring the economic feasibility is of critical importance to facilitate salvage harvest of MPB infested forests.

In terms of forest bioenergy, logistics of procuring, transporting and using forest biomass can become complex and expensive, making bioenergy less competitive than other energy sources and impeding the development of bioenergy industries (D'Amours et al. 2010). The bulky shape, low energy density, and wide spread of forest biomass all cause high costs of biomass feedstock collection, handling and transportation (S. M. Wood 2003). The variation in quantity and quality of biomass by geographic locations, forest accessibility, seasonality, weather conditions, pre-processing, transportation and storage conditions, etc. contributes to increased complexity and uncertainties of the supply chain (McKendry 2002a). The interrelationship with and dependence on other forest industries also complicate the management and supply of biomass feedstock to the bioenergy sector (Bolkesj∅ et al. 2006). As logistic costs in bioenergy supply chain are estimated to account for 20 to 40 percent of total production costs (Angus-Hankin et al. 1995), a cost-efficient supply chain is important to promote the utilization of forest biomass for bioenergy.

In addition to the economic status, the potential carbon benefits associated with timber and bioenergy products are also usually considered during the supply chain management of salvage utilization of MPB-attacked forests. However, because not all timber salvage and bioenergy production are profitable (Mahmoudi et al. 2009; Prestemon et al. 2013), carbon benefits from unprofitable forest stands can only be achieved through a sacrifice in the economic status of the supply chain. Balancing the two objectives, maximizing net revenues and maximizing carbon benefits from forest salvage utilization, is important to achieve sound supply chains in practice.

Finally, multiple stakeholders, including land owners, timber producers, and bioenergy producers etc., are involved in the supply chain of forest salvage utilization (Flint et al. 2009). While their decisions and operations affect the utilization of infested forests and performance of supply chain, their management objectives are developed independently, and integration and cooperation among multiple stakeholders seldom occur. Potential misalignment in stakeholders' objectives may lead to an inefficient use of resources and an overall weak performance of the supply chain.

1.4.3.2 Analytical challenges

When modeling timber harvesting systems, regression models are often used to describe relationships between machine cycle times of individual machines and influencing factors and estimate machine productivities in productive machine hours. However, without long-term data on machine utilization rates, the use of 'standard' utilization rates of individual machines may not generate accurate estimates of machine productivity in scheduled machine hours. This issue becomes more apparent when regression models are applied beyond the range of observed data (e.g., a different skidding distance range). The time study and regression modeling approach also often fails to provide details on machine interactions and reflect site-specific operational conditions on productivity estimation. As salvage utilization of MPB-infested forests usually has narrow profit margins, more appropriate estimation on system productivity and cost of salvage harvest is extremely important. It is thus desirable to explore alternative approaches of harvesting simulation in order to provide more accurate system performance information for various management scenarios.

When both net revenues and carbon benefits need to be maximized along the supply chain of forest salvage utilization, multi-objective optimization can be employed to account for the two potentially conflicting objectives simultaneously. As the planning process involves multiple periods, multiple units, and multiple products, the planning problem becomes a combinatorial optimization problem that is NP-hard, meaning its computation complexity increases exponentially as the problem scale increases. When the problem is large, using exact methods (e.g., mixed integer programming) becomes prohibitive due to the overwhelming computation. Multi-objective metaheuristics (MOMHs) are developed as alternative methods to tackle these computationally intensive problems (Gandibleux et al. 2004). Instead of trying to find all Pareto-optimal solutions, MOMHs intend to obtain satisfactory nondominated solutions that approximate the Pareto front as much as possible within reasonable computation time (Durillo and Nebro 2011). Although many existing MOMHs demonstrate satisfactory performance (Zhang and Li 2007; Zouache et al. 2018), they often have a complex algorithm structure that involves a number of sub-processes with many parameters requiring user-inputs and fine tuning. Not only does it contribute to the algorithm computation complexity, it also complicates the parameterization process because determining parameter values itself becomes a combinatorial optimization problem. Since parameters in MOMHs are highly instance sensitive, meaning that no common values are suitable for solving all problems, a complicated parameterization process is effort-demanding and significantly restricts the algorithm adaptability and applications. It is beneficial to develop simple yet high performance MOMH algorithms that can efficiently produce nondominated solutions.

1.5 Study objectives

This Ph.D. dissertation uses OR methods to analyze the supply chain of forest salvage utilization of post-outbreak lodgepole pine stands in Colorado State Forest. The study goal is to develop and demonstrate the ability of simulation and optimization approaches in providing data-driven solutions to the management of MPB-killed stands and timber and biomass supply chain. Specific objectives are:

- Develop a stochastic discrete-event simulation model for a ground-based tree harvesting system and demonstrate the use of DES techniques in timber harvesting operations modeling.
- Develop a multi-objective optimization model to evaluate the economic and environmental objectives of the entire timber and biomass supply chain while considering options of upstream timber harvesting and residue management operations.
- Develop a new multi-objective metaheuristic algorithm to efficiently solve multi-objective combinatorial optimization problems of MPB-killed stands and biomass supply chain management.

Chapter 2

Discrete-Event Simulation of Ground-Based Timber Harvesting Operations

Abstract

Operational studies are necessary to support production and management decisions of forest industries. A time study (TS) approach is widely used in timber harvesting operations to understand the performance of individual harvesting machines as well as the entire system. However, several limitations of the TS approach include the use of generalized utilization rates, incapability of capturing interactions among equipment, and model extrapolation in sensitivity analysis. In this study, we demonstrated the use of discrete event simulation (DES) techniques in modeling a ground-based timber harvesting system, and compared the DES results with those of the TS model developed with the same observed data. Although both TS and DES models provided similar estimation results for individual machine cycle times and productivities, the estimated machine utilization rates were somewhat different due to the difference in synthesizing machine processes in each approach. Our sensitivity analysis and model expansion to simulate a hypothetical harvesting system suggest that the DES approach may become an appropriate method for analyzing complex systems especially where interactions among different machine processes are unknown.

Keywords: discrete-event; machine interactions; operational details; hypothetical systems

2.1 Introduction

Various timber harvesting systems have been developed to implement silvicultural treatments (e.g., clearcut, commercial thinning, and selective harvesting) under a wide range of vegetation and terrain conditions (Uusitalo and Pearson 2010). Involving multiple machines and operators, timber harvesting is a complex process that, if poorly designed and implemented, could become dangerous, costly or environmentally damaging. Efforts to understand harvesting system performance and the ability to identify the most suitable system for given operational conditions are essential to achieve safe, economically viable, and environmentally sound harvesting operations.

Time study (TS) techniques have been widely applied to timber harvesting operations to understand the performance of individual harvesting machines as well as the entire system (Acuna et al. 2012). In general, the field-collected data are used to model the productivity of individual machines based on independent variables (e.g., stand density, skidding distance, terrain slope, tree size, etc.) through regression. These regression models are then used to predict machine productivity in productive machine hours (PMH) in various scenarios under similar work conditions (Schillings 1969; LeDoux et al. 1986; Kellogg and Bettinger 1994). A timber harvesting system often involves multiple machines working simultaneously, and estimating the productivity of the entire harvesting system requires the productivity of individual machines in scheduled machine hours (SMH). The conversion of productivity from PMH to SMH is based on the rate of machine utilization which incorporates potential delays that may occur to individual machines. Because the entire system productivity is limited by bottlenecks in any given machine or operation, it is important to understand and accurately quantify the utilization rates of individual machines (Gingras and Godin 1996; Han et al. 2004; Anderson et al. 2012).

However, quantifying machine utilization rates is often omitted in TS techniques when the field observation period is not long enough to accurately assess utilization rates. It has been a custom to use the published machine utilization rates from past studies (Brinker et al. 2002; Bisson et al. 2015; Kizha and Han 2016), or the average values from long-term shift-level production data (Mitchell and Gallagher 2007; Pan et al. 2008b, 2008a). But either approach may not provide suitable estimates unless the harvesting system and site are similar to the ones used in the past studies, or represent the average system and work conditions. Using the published or average data becomes a larger issue when one attempts to compare different harvesting systems or system configurations. It may not be justifiable to assume the same utilization rates for machines used in different systems.

One might collect machine delay times during a detailed time study for future uses. However, due to high costs of field data collection, most detailed time studies are conducted only for a short time period (e.g., a few days) (Aedoortiz et al. 1997), and short-term data on delays might misrepresent the "normal" operational conditions as data can be biased with the presence or absence of any irregular and unpredictable events, such as machine breakdowns and adverse weather conditions. Alternatively, shift-level time studies are less costly (Olsen and Kellogg 1983) and can provide long-term delay data, but once data are averaged out, they lack detail, such as delay types and causes, and thus provide limited insights for future improvement (Olsen et al. 1998). It is also noted that some studies only reported delays longer than 15 min and included shorter delays as part of productive time (Spinelli and Visser 2008). A drawback with an arbitrary cutoff time is that this interpretation could depict system performance very differently when most delays last less than the cutoff time.

The TS approach also provides limited insights on how multiple machines interact with each other during the harvesting process. Although delay-free cycle time regression models depict the relationship between dependent and independent variables (Spinelli and Magagnotti 2010), outputs are only mean cycle time values without accounting for variation, especially variation caused by chain effects across multiple machines and tasks. When system components (i.e., individual machines) are highly interdependent, cycle time regression developed for individual machines can lead to biased productivity and cost estimates (Asikainen 1998). In addition, when one machine performs multiple tasks (e.g., a loader is used to sort and deck logs, as well as to load log trucks), it would be difficult to build a regression model representing a series of different tasks.

Simulation techniques have been widely used in industrial and manufacturing engineering as an effective tool to understand production systems and estimate system productivity and costs (Ziesak et al. 2004). When properly developed and applied, simulation techniques can be useful to overcome the aforementioned limitations of the conventional TS approach in forest operations. Discrete-event simulation (DES) models the operation of a system as a series of events occurring at discrete points in time. In DES, events are broadly defined as things that may happen and cause a change in the system's state (Karnon et al. 2012). The term 'discrete' means the system's state changes only at specific time points in response to events occurring at those time points. The simulation clock advances by jumping from one event time point to the next. No system components change in the interval between two events. As events occur in sequence, mimicking operations in practice, all operational information (e.g., processing time, wait time, queue length) is recorded to evaluate the performance of the modeled system. With DES, systems are analyzed by numerical methods rather than analytical methods (Banks 1984), which becomes an advantage when a large number of variables, parameters and functions are involved in a system, and various interactions occur among system components.

In addition, the ability of DES models to keep track of all events throughout the simulation process enables the user to build and test various operational scenarios simply by changing simulation inputs and observing the resulting outputs without disturbing the actual workflow (Banks 1984). Another attractive benefit of the DES technique is the ability to construct and examine hypothetical, unobserved systems. Production and supply systems can be studied by observing the operation of the system if the system is already in operation (Spinelli and Hartsough 2001). However, due to high costs and the laborious work of field data collection, it would be beneficial if previously collected data can be used to estimate the performance of an unobserved system. The DES model can facilitate this because with the same machines and technology, some processes and parameter values are invariant and still applicable under different circumstances. For instance, when the same machine is operated by the same operator under similar terrain and vegetation conditions for the similar harvest practice (e.g., clearcut), a skidder's empty travelling speed might not dramatically change by skidding distances or system layouts. In such cases, previously collected data may be used in designing and analyzing new systems through DES models.

DES techniques have been applied to operational studies in forestry for many years, and simulation of harvesting operations was among the first attempts. Some studies focused on the productivity and operation of individual machines (Winsauer and Bradley 1982) and others addressed interactions among harvest equipment and interactions between the harvesting system and log transportation (Bradly et al 1975, Baumgras et al 1993). These early stage models were implemented with the General Purpose Simulation System (GPSS/360, International Business Machines Corporation, Armonk, NY, USA) or programming language (e.g., FORTRAN, International Business Machines Corporation, Armonk, NY, USA), and thus required long development times especially when complex model construction was required. Later, the emergence of graphical-based simulation software development systems (e.g., Arena, Arena 15, Rockwell Automation Technologies, Inc., Milwaukee, WI, USA), AnyLogic (AnyLogic 8.3, The AnyLogic Company, Oakbrook Terrace, IL, USA), and Witness (Witness Horizon 22.0, Lanner Group Limited, Houston, TX, USA) facilitated the DES modeling process, and DES has been proved to be a reliable approach in supply chain management through various applications (Abu-taieh et al. 2007). In recent years, there were some DES applications in the fields of forest biomass supply chains where different chipping locations (Spinelli et al. 2014), equipment configuration (Asikainen 1998, 2010), trucking options (Zamora-Cristales et al. 2014), and transportation methods (Wolfsmayr et al. 2015) were examined. These studies mainly focused on supply chain logistics, comparing different systems under various circumstances in order to support operational decisions. For upstream forest harvesting operations, however, there is a dearth of studies that have employed the DES technique. Asikainen (1995, 2001) modeled mechanized harvesting systems and log transportation, incorporating the effects of random elements such as machine failures and transportation distances on the entire system. Hogg et al. (2010) simulated stump-to-mill multi-stem Eucalyptus harvesting and transport operations for system comparisons. However, none of the past studies explicitly compared DES with TS to highlight the differences between the two approaches and the potential benefits of the DES approach in analyzing the performance of harvesting systems.

In this study, we developed a stochastic DES model for a ground-based, whole-tree harvesting (WT) system, and compared it to the conventional TS approach in order to demonstrate the use of DES techniques in timber harvesting operations modeling and highlight its potential advantages in flexibility, precision, and analytical ability. We also applied the data from the WT DES model to a new DES model simulating another ground-based harvesting method called "lop-and-scatter (LS)", to demonstrate the ability of DES in analyzing hypothetical harvesting systems by reusing the previously collected data from the existing system.

2.2 Materials and methods

2.2.1 *Harvesting system and data collection*

We conducted a time study on a ground-based, whole-tree clear cut of the beetle-killed lodgepole pine (*Pinus contorta* Dougl. ex. Loud. var. *latifolia*) harvest unit located in Colorado State Forest (Figure 2.1) in northern Colorado (40°35'59" N, 106°00'27" W) (Han et al. 2018). This 1.9-ha unit was affected by the mountain pine beetle outbreak since 2008 and the mortality rate in 2015 was 47.3%. The stand density was 865 trees ha^{-1} and the average basal area was 34.6 m^{2} ha^{-1}. The mean diameter at breast height (dbh) of trees was 22.4 cm and the mean height was 19.6 m. Due to the small tree size, most trees were processed into only one piece of log. Post harvesting, we sampled 28 logs to measure small end diameter and length. These measured data were used to estimate oven dry log weight (Chung et al. 2017), resulting in 0.1185 oven dry ton (odt) per piece.

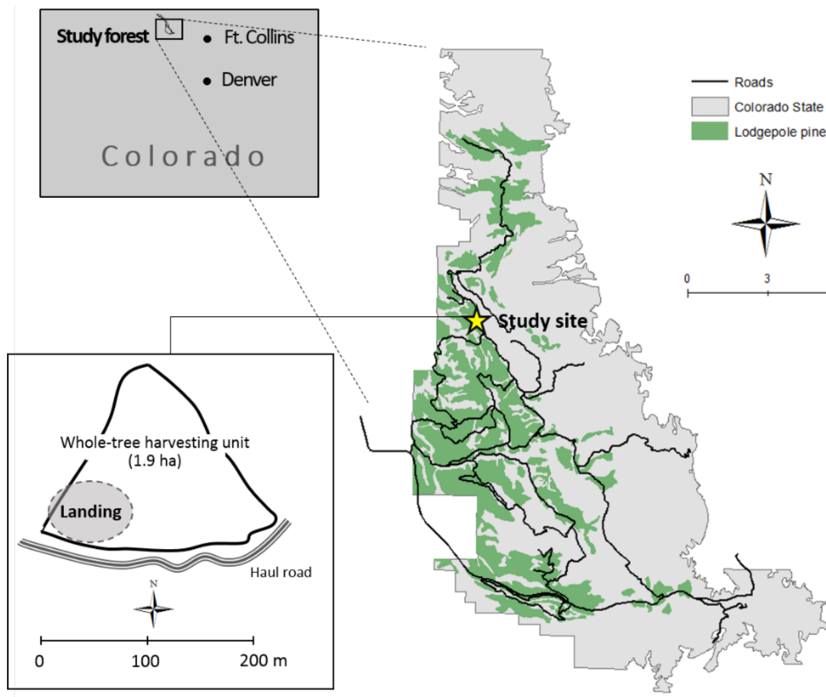

Figure 2.1 Site map showing the harvesting unit in Colorado State Forest.

The WT system consisted of one tracked feller-buncher for cutting trees down (TimberPro TL-735-B, TimberPro Inc., Shawano, WI, USA), one grapple skidder (Tigercat 615C, Tigercat Industries Inc., E. Brantford, ON, Canada) for primary transportation (i.e., from stump to landing), two stroke boom delimbers (Timberline SDL2, DDI Equipment, Whitewater, CO, USA) for delimbing and bucking, and one grapple loader (Barko 495ML Magnum, Barko Hydraulics, LLC, Superior, WI, USA) for sorting, decking, and loading logs (Figure 2.2). All equipment was operated by experienced operators and worked simultaneously on site. Cut trees were transported to the landing by the skidder in the form of whole trees. The delimbers staying close to the landing processed trees into logs. When there was a truck on site, the loader performed sorting and loading simultaneously by directly loading some logs onto the truck while placing other logs (i.e., different sorts) onto the deck. When no trucks were on site, the loader performed only log sorting and decking.

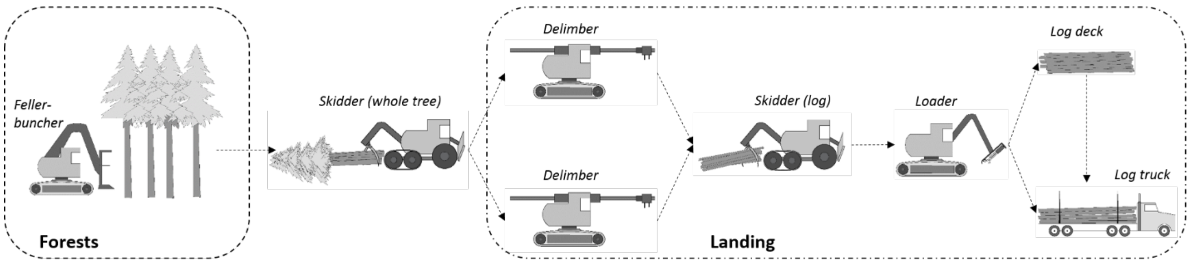

Figure 2.2 Description of the whole-tree harvesting system used in Colorado State Forest.

Following standard work study methods (Olsen et al. 1998; Acuna et al. 2012), we collected detailed time study data in December 2015 from the harvesting unit. Readers are referred to Han et al. (Han et al. 2018) for a detailed description of the WT harvest unit and field data collection. Table 2.1 shows cycle time elements and corresponding operational data for each machine and their applications in building TS and DES models. Some data were only used in the DES model because they were not related to delay-free machine cycles. Some other data were only used in the TS model because they were identified as independent variables of regression models whereas the DES model used other information to describe the same processes.

Hourly machine costs (Table 2.2) were estimated using the commonly accepted machine rate calculation method (Miyata 1980; Brinker et al. 2002). In addition to machine fixed and operation costs, we distinguished machine idle costs from operating costs to differentiate costs related to machines idling (e.g., operational delay, warm-up, etc.). This is deemed necessary because some machine operating costs, such as for fuels and lubricants, are lower during idle time. We assumed the fuel consumption rate during idle times is 10% of the productive time rate (Tigercat; Nordfjell et al. 2003).

Table 2.1 Field collected data and applications in models.

Equipment	Data	Value Range	Mean	Application
Feller-buncher	Felling time (s)	7-71	20.8	Both
	Move distance (m)	0-11.6	0.9	TS
	Number of standing trees	0-4	1.9	Both
	Number of down trees	0-2	0.1	Both
	Tree pile size	9-20	14.5	DES
	Relocation chance (0 = no, 1 = yes)	0 or 1	0.05	DES
	Relocation time (s)	11-63	46.0	DES
Skidder (Tree)	Empty travel time (s)	60-128	88.6	Both
	Positioning and grappling time (s)	12-33	20.8	Both
	Bunching time (s)	25-130	40.7	Both
	Loaded travel time (s)	58–145	86.1	Both
	Empty travel distance (m)	82.6-219.8	165.0	Both
	Loaded travel distance (m)	43.9-230.7	141.3	Both
	Number of trees	9-40	21.9	Both
Skidder (Log)	Empty travel time (s)	22-43	35.1	Both
	Positioning and grappling time (s)	5-18	8.9	Both
	Loaded travel time (s)	11-42	21.0	Both
	Empty travel distance (m)	29.0-63.7	44.3	TS
	Loaded travel distance (m)	6.7-43.6	27.1	TS
	Number of logs	9-40	22.9	TS
Delimber	Delimbing time (s)	12-104	42.3	Both
	Reposition chance (0 = no, 1 = yes)	0 or 1	0.1	DES
	Positioning time (s)	9-88	29.8	DES
	Number of live trees	0-5	0.76	Both
	Number of dead trees	0-5	0.92	Both
Loader	Sorting and decking time (s)	6-119	36.4	Both
	Loading time[*] (s)	11-115	43.7	Both
	Task (0 = sort and deck, 1 = direct loading)	0 or 1	0.30	TS
	Direct loading chance [†] (0 = no, 1 = yes)	0 or 1	0.50	DES
	Number of logs	1-14	3.3	Both

[*] Loading cycle time data include both direct loading and loading from deck. [†] Proportion of direct loading while a truck is on site. TS = time study, DES = discrete-event simulation.

Table 2.2 Estimated hourly costs of each machine in the study.

Cost component	Feller-Buncher		Delimber		Skidder		Loader	
	Operating	Idle	Operating	Idle	Operating	Idle	Operating	Idle
Sale price ($)	395,000	395,000	355,000	355,000	219,000	219,000	205,000	205,000
Salvage value ($)	59,250	59,250	71,000	71,000	32,850	32,850	61,500	61,500
Machine life (year)	5	5	5	5	5	5	5	5
Depreciation ($/year)	67,150	67,150	56,800	56,800	37,230	37,230	28,700	28,700
Interests ($/year)	26,070	26,070	24,140	24,140	14,454	14,454	14,760	14,760
Insurance ($/year)	10,428	10,428	9,656	9,656	5,781.6	5,781.6	5,904	5,904
SMH (h/year)	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
Fixed cost ($/h)	51.82	51.82	45.30	45.30	28.73	28.73	24.68	24.68
Fuel (L/h)	29.9	3.0	32.0	3.2	23.3	2.3	14.2	1.4
Fuel ($/h)	17.46	1.75	18.68	1.87	13.61	1.36	8.28	0.83
Lubricant ($/h)	6.46	0.65	6.91	0.69	5.04	0.50	3.06	0.31
R & M * ($/h)	55.96	0	39.32	0	27.92	0	19.87	0
Labor ($/h)	34.29	34.29	34.29	34.29	34.29	34.29	34.29	34.29
Operation cost ($/h)	114.16	36.68	88.29	36.85	80.86	36.16	65.50	35.42
Total cost ($/h)	165.99	88.51	144.51	82.15	109.60	64.89	90.19	60.11

* Repair and maintenance cost proportional to machine depreciation and utilization, adapted from Brinker et al. (2002). SMH = scheduled machine hours.

2.2.2 Model building

Detailed time study data were used to build both DES and TS regression models to evaluate the stump-to-truck harvesting process of the WT system. Two thirds of the cycle time data were randomly selected for model construction and the rest were used for model validation. In the DES model, time element data and other observed operational data were used to create discrete events of each machine process and corresponding input probability distributions. In the TS model, cycle time data were used as dependent variables to build delay-free cycle time equations for each machine based on independent variable values. Both models (referred to as base DES and TS models) were applied to the harvesting of 1700 trees where the average skidding distance was 152 m. The system productivity per scheduled machine hour (SMH) and the timber stump-to-truck cost estimated by both models were compared to show the differences between these two modeling approaches. The DES and TS models are described in detail below.

2.2.2.1 Discrete-event simulation models

We constructed our DES model in the Rockwell Arena simulation software (Rockwell Automation 2012), which has been widely used as a DES simulation tool for both research and practical applications (Altiok and Melamed 2010; Rossetti 2015). In the simulation, entities are used to represent objects (e.g., products, customers) that are processed by resources (e.g., machine, labor) of the modeled system. They flow through the system from one resource to another, triggered by the occurrence of events. Events themselves occur due to the arrival of entities, the completion of process tasks, random equipment failures, and other related items (e.g., break times). The model generates random realizations of these operational items from the user-defined probability distributions representing their durations. In this manner, events occur and entities move through the system over time until the simulation meets the designated terminating condition (e.g., the completion of processing of all entities, a certain length of simulation time). The DES model is normally run multiple times and provides summary statistics of the simulation results in order to account for uncertainties that may exist in the system (Kelton et al. 2009).

In our study, trees/logs were modeled as entities and machines were modeled as resources. All procedures related to the harvesting process, such as machine processing times, machine reposition probabilities, the number of trees/log pieces in a machine cycle, etc. were modeled within the simulation. To derive appropriate probability distributions for these procedures, several theoretical distributions in the form of mathematical formulations (e.g., Exponential, Gamma) were statistically "fit" to the field time study data. The quality of fit was determined by the Chi-square Goodness-of-Fit test and all proposed distributions were ranked by *p*-values from high to low. A *p*-value greater than 0.05 indicated an acceptable fit and the distribution could be used in the simulation model. If no theoretical distributions were acceptable, an empirical distribution was used, which merely divided data into groups with values representing proportions of data in each group. For example, the number of trees that were delimbed in a delimbing cycle followed an empirical distribution, and the time used for delimbing one tree was drawn from an Erlang distribution. The final fitted distributions of all modeled processes are listed in Table 2.3. Events were connected by logical links developed to form the structure and logic of the DES model (Figure 2.3). A simulation run began as the feller-buncher started cutting trees. Trees/logs were then processed by each machine following the order in practice. For a feller-buncher cutting cycle, the model first determined if a machine relocation was necessary prior to cutting based on the machine relocation probability. If yes, the model randomly drew a relocation time from the relocation time distribution and added it to the machine cycle time. The model then generated the number of trees cut for the cycle and assigned a cutting time randomly drawn from the cutting time distribution. After completing one tree-cutting cycle, the feller-buncher was ready for the next cycle and trees were stacked in a pile waiting to be transported by the skidder.

Table 2.3 Fitted distributions for each event of machine operations.

Equipment	Event	Distribution	Arena Expression*	*p*-value
Feller-buncher	Relocation chance	Empirical	DISC (0.95, 0, 1, 1)	-
	Relocation time	Empirical	CONT (0.00, 10.50, 0.29, 23.50, 0.64, 36.50, 0.86, 49.50, 1, 63.50)	-
	Down tree cycle chance	Empirical	DISC (0.94, 0, 1, 1)	-
	Down tree cycle time	Beta	11.5 + 31 × BETA (1.57, 1.47)	0.30
	Cycle cut piece	Empirical	DISC (0.22, 1, 0.85, 2, 0.96, 3, 1, 4)	-
	One-piece felling time	Erlang	4.5 + ERLA (2.57, 4)	0.37
	Two-piece felling time	Erlang	7.5 + ERLA (2.4, 5)	0.09
	More-piece felling time	Gamma	12.5 + GAMM (3.25, 3.37)	0.17
	Tree pile size	Weibull	8.5 + WEIB (6.73, 2.06)	0.06
Delimber	Reposition chance	Empirical	DISC (0.90, 0, 1, 1)	-
	Reposition time	Erlang	8.5 + ERLA (10.7, 2)	0.36
	Cycle cut piece	Empirical	DISC (0.53, 1, 0.87, 2, 0.94, 3, 1, 4)	-
	One-piece delimb time	Erlang	11.5 + ERLA (4.96, 5)	0.23
	Two-piece delimb time	Gamma	12.5 + GAMM (7.67, 4.13)	0.17
	More-piece delimb time	Beta	27.5 + 54 × BETA (1.36, 1.59)	0.12
Skidder	Empty distance ratio †	Triangular	TRIA (0.55, 1.15, 1.57)	0.14
	Loaded distance ratio	Triangular	TRIA (0.09, 0.77, 1)	0.49
	Empty speed	Triangular	TRIA (1.41, 1.91, 2.27)	0.27
	Loaded speed	Triangular	TRIA (0, 1.27, 2.44)	0.06
	Skid log trip	Triangular	TRIA (49.5, 67, 88.5)	0.44
Loader	Loading piece	Poisson	POIS (2.88)	0.74
	Direct loading chance	Empirical	DISC (0.51, 0, 1, 1)	-
	Loading time	Beta	13.5 + 69 × BETA (1.27, 1.91)	0.36
	Sort and deck piece	Poisson	POIS (3.45)	0.31
	Sort and deck time	Erlang	5.5 + ERLA (7.35, 4)	0.24

* In Arena expression, DISC (CumP1, Val1, …, CumPn, Valn) and CONT (CumP1, Val1, …, CumPn, Valn) are empirical distributions showing pairs of cumulative probabilities and associated values. For other distributions, input values are parameters specified according to distribution mathematical forms. More details on Arena's probability distribution can be found in Kelton et al. (2009). † The skidder empty travel distance in each trip was estimated to be proportional to the average skidding distance. In the same trip, the skidder loaded travel distance was estimated to be proportional to the empty travel distance

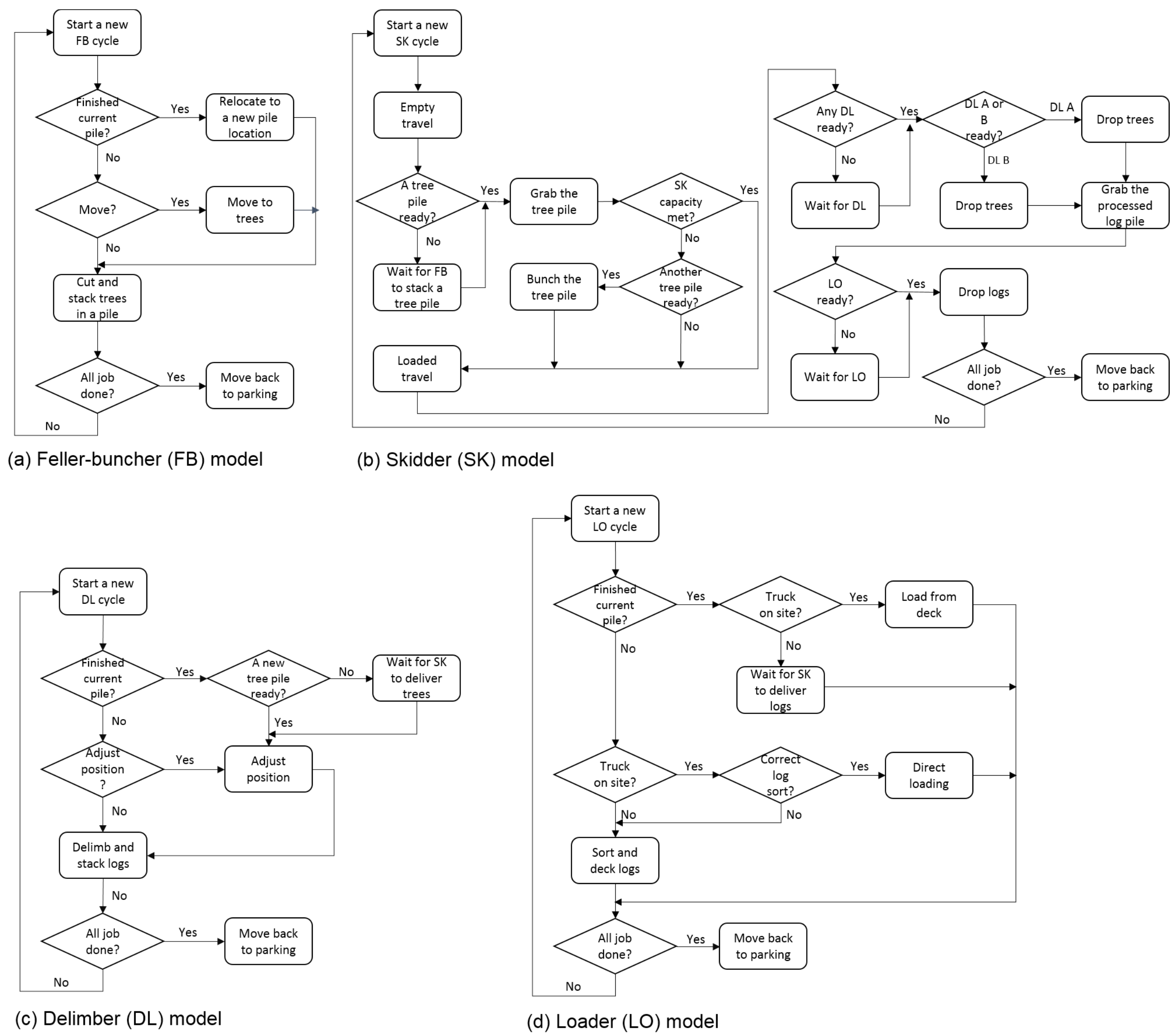

Figure 2.3 The DES model logic developed for the feller-buncher (FB, **a**), skidder (SK, **b**), delimber (DL, **c**), and loader (LO, **d**) in the whole-tree harvesting system.

The skidder started a new cycle with an empty travel from the landing to a tree pile. Travel time was estimated using travel distance and speed that were randomly drawn from the user-defined distance and speed distributions. When the skidder arrived at a tree pile, the skidder operator checked if the pile was ready for transportation; if not, the operator had to wait for the feller-buncher to finish cutting trees and completing a tree pile. The skidder grabbed a tree pile otherwise, and then sought another tree pile to combine if the capacity was not met yet. As the skidder travelled loaded towards the landing, the operator checked if any of the two delimbers had completed processing of the previously delivered trees. If no delimber was available, the skidder waited until one delimber was ready, and then passed the trees onto the available delimber. The skidder then grabbed the processed logs and skidded them to the loader. Similarly, the operator checked the loader's availability before passing logs.

The delimber operator started a new cycle by checking if the previous tree pile had been finished. If there was no tree to delimb, the operator stayed idle and waited for the skidder to deliver trees. If there were trees from the previous pile, the model determined if the delimber needed to adjust machine position before delimbing. If yes, it added a reposition time. The model then randomly generated the number of trees and delimbing time to complete the delimbing cycle. Processed logs were stacked in a log pile and readied for pick up by the skidder that delivered a log pile to the log deck at the landing.

The loader had different tasks depending on the availability of log trucks and sorted logs. When the skidder delivered logs and a truck was available on site, the loader operator simultaneously sorted logs and loaded the requested sort onto the truck ("direct loading"). When a truck was available but there were no more logs to sort, the loader loaded the previously sorted and decked logs onto the truck ("load from deck"). When no truck was available at the landing, the loader operator sorted logs and stacked them on the deck ("sort and deck"). When neither logs to sort nor trucks were available, the loader stays idle.

Because long-term shift level information was not available, assumptions were made during the simulation in order to setup work shifts and machine breakdowns. A work day was assumed to be 10 SMH with a 45-min machine warm-up period in the morning and 45-min machine maintenance work at the end of day. Five trucks were scheduled to visit the harvest site to haul logs and their inter-arrival time was assumed to be normally distributed (i.e., NORM (60, 15) in Arena). For all equipment, machine failures might occur at any time. The failure rate and repair times were assumed to follow an exponential distribution with parameters of 1,000 and 30 min (i.e., EXPO (1000) and EXPO (30) in Arena), respectively. For each machine, time spent on operation, warm-up and maintenance, idle state, and other disturbances (e.g., repair, personal delay) were categorized as utilization, scheduled delay, operational delay, and other delays. Scheduled delays included machine warm-up and scheduled maintenances, while operational delays were mainly caused by machine interactions (i.e., time spent to wait until other machines finish their cycles). When all harvested logs were delivered to the landing, all the machines except for the loader stopped working and returned to their parking spots. The loader continued working until all harvested logs were loaded onto trucks. Once all logs were loaded, a single simulation run was considered completed. In this study, a total of 100 simulation runs were made.

2.2.2.2 Time study regression models

We adopted the multiple least-squares linear regression models in Han et al. (2018) for most machines in our TS models except for the skidder. In this study, we developed two separate regression equations (R Statistical Software version 3.4.0 (R Core Team 2017)) for the skidder to estimate delay-free cycle times of two different tasks: skidding trees to the delimbers at the landing, and skidding logs from the delimbers to the loader. A tree skidding cycle included empty travel from the landing, grabbing trees, bunching trees, loaded travel and dropping trees. A log skidding cycle included empty travel to a processed log pile, grabbing logs, loaded travel to the loader, and dropping logs.

For each machine, the average values of independent variables were used to predict the mean delay-free cycle times. Combined with the average processed log volume in each machine cycle, hourly productivities in PMH were calculated for all equipment. Because TS models were static, machine interactions and different types of delays could not be captured by the model. Instead, machine productivities in PMH were converted to productivities in SMH by applying the following empirical utilization rates (Brinker et al. 2002; Han et al. 2018): 60% for the feller-buncher, 65% for the delimbers, 60% for the skidder, and 65% for the loader. A machine with the lowest SMH productivity became the system bottleneck and its productivity was used for the entire system productivity. As the result, unit production costs, resulting machine utilization rates, and unutilized machine times (categorized as delay) were estimated.

2.2.3 *Sensitivity analysis*

The average skidding distance normally has a large influence on the skidder's cycle time, productivity, interactions with other machines, and ultimately the performance of the entire system. We conducted a sensitivity analysis to evaluate the impact of the average skidding distance on both the DES and TS models. Different average distances were used ranging between 50 and 600 m with an increment of 50 m. The results from the DES and TS models are compared in terms of system productivity, unit production cost, and machine utilization rates.

We also examined the sensitivity of the DES model to truck availability to assess how the harvest system responds to different number and frequency of trucks. In our studied system, the loader serves as a link between in-woods harvesting operations and truck transportation. Different trucking schedules likely affect the loader's work pattern and its interactions with other machines. Truck scheduling has been traditionally dealt with as a separate problem from stump-to-landing operations in forest operations analysis, but it may become an important factor for operational efficiency when harvesting units have limited space for landing and log decking. Using the DES model, we varied the number of trucks on site from 0 to 10 trucks per day and examined its influence on the loader's utilization, time used for different tasks, and truck on-site time. We were not able to estimate the impact of different truck schedules using the TS approach because TS regression models were static and the loader's interactions with trucks were impossible to model with our limited data. Therefore, we did not make comparisons between the DES and TS models for varying truck schedules.

2.2.4 *Hypothetical systems*

To demonstrate the potential advantage of DES models in analyzing hypothetical systems, we built a new DES model to simulate another ground-based harvesting system called lop-and-scatter (LS) (Han et al. 2018). The LS system employs the same machines as the WT system, but with differences in the delimbing location and the order of operations (Figure 2.4). In LS, the delimber processes trees at the stump instead of at the landing, leaving limbs and tree tops in the woods. The skidder then forwards the processed logs to the loader at the landing.

For the DES model developed for the LS system (hereafter referred to as LS DES), we used the same discrete events and input probability distributions as those used in the previous DES model developed for the WT system (hereafter referred to as WT DES). A new additional event required for the LS DES model was a delimber's in-woods movement from tree pile to pile. For this, we used a delimber's reposition time distribution as a substitution. Logical links were developed to connect sequential events necessary for the LS system (Figure 2.5). In this system, the delimbers directly interact with the feller-buncher, while the skidder transports only processed logs from stump to landing.

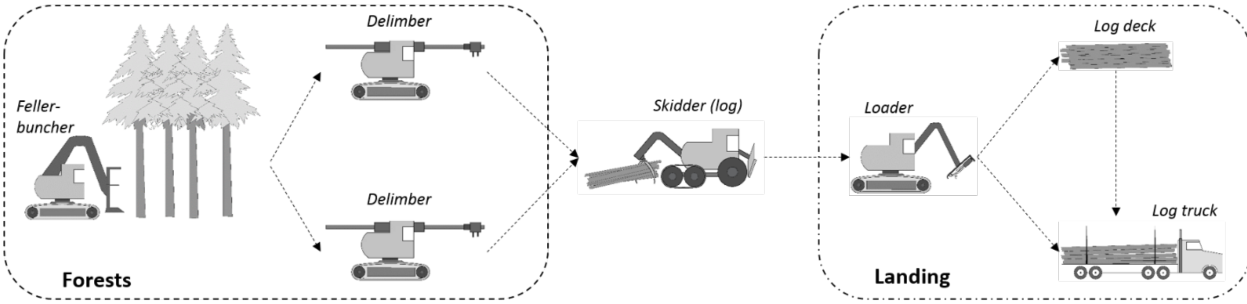

Figure 2.4 Description of the lop-and-scatter system used in Colorado State Forest.

The LS DES model was run under the same harvesting conditions used in the WT DES model. The results were then compared with our independent data obtained from the LS operations conducted in the same unit in Colorado State Forest for model validation (Han et al. 2018).

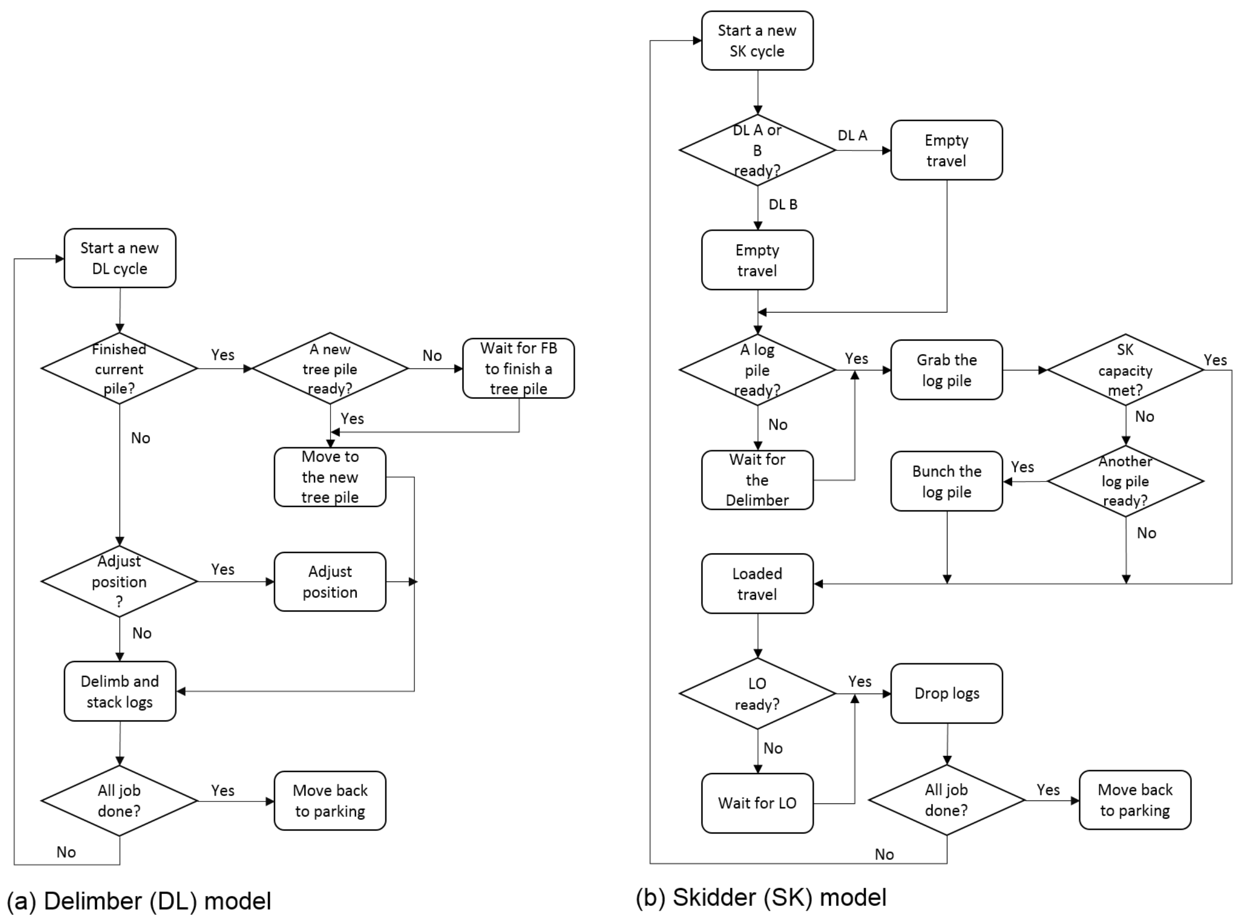

Figure 2.5 The DES model logic developed for the delimber (DL) (**a**) and skidder (SK) (**b**) in the lop-and-scatter system. The feller-buncher (FB) and loader (LO) have the same work patterns as in the WT DES model (Figure 2.3a, d), and thus are not presented here.

The field LS data were also used to develop a new TS model for the LS system (LS TS). We compared the results of the LS TS model with the LS DES model. For further analysis, we used two sets of machine utilization rates when converting machine productivities in PMH to those in SMH. The first set is the general utilization rates (Brinker et al. 2002) used in the WT TS model. The other set is the utilization rates resulting from the LS DES model. Estimations from these two approaches are referred to as LS TS_conventional and LS TS_adjusted, and are compared with the outputs from the LS DES model in terms of system productivity in SMH and unit production cost to further highlight the importance of machine utilization rates in system performance evaluation.

2.3 Results

2.3.1 *DES and TS models for whole-tree harvesting*

The results of 100 simulation runs of the base WT DES model are presented in Table 2.4. Individual machine process productivities ranged from 17.08 to 145.01 odt/PMH with log processing by delimber B having the lowest productivity and log skidding by the skidder having the highest productivity in the system. The utilization rates were fairly even among the individual machines except for the feller-buncher that had the lowest rate of 51.7%. The entire system productivity was 20.16 odt/SMH and unit production cost was estimated at $29.71/odt. The coefficient of variation (i.e., the ratio of standard deviation to the mean) was less than 7% for all the machines, indicating the simulated machine processes were not variable among simulation runs.

Table 2.4 Performance metrics of individual machines and the entire system of whole-tree harvesting generated by 100 simulation runs of the DES model. Standard deviations are shown inside parentheses.

Machine	Cycle Time* (s)	Productivity (odt/PMH)	Utilization (%)	Sys. Prod. (odt/SMH)	Unit Cost ($/odt)
Feller-buncher	20.5 (1.5)	41.83 (0.66)	51.7 (4.2)	20.16 (1.71)	29.71 (1.92)
Delimber A	42.5 (3.0)	17.14 (0.35)	61.6 (6.1)		
Delimber B	42.9 (3.0)	17.08 (0.40)	56.3 (6.0)		
Skidder (trees)	256.0 (3.1)	39.86 (1.71)	64.5 (5.2)		
Skidder (logs)	71.3 (9.1)	145.01 (4.49)			
Loader (loading †)	42.2 (3.0)	29.43 (1.86)	66.9 (4.5)		
Loader (sort and deck)	36.4 (3.0)	40.17 (1.31)			

* Delay free cycle time. † Loading includes both direct loading and load from deck. odt = oven dry ton, PMH = productive machine hours

Table 2.5 presents the delay-free cycle time regression models used in this study for the TS approach. Each regression model was tested for assumptions of normality, independence and equal variance in order to ensure the validity of regression analysis. No serious violations were identified, and all models were significant (p < 0.05). The TS model predicted the system productivity and unit production cost to be 18.67 odt/SMH and $30.21/odt, respectively (Table 2.6). The skidder became the system bottleneck due to its lowest productivity in SMH after conversion using the generalized utilization rate. The feller-buncher was predicted to have the highest productivity and therefore the lowest utilization in the system.

Table 2.5 Delay-free cycle time regression models for individual machines used in whole-tree harvesting (adopted from Han et al. (2018)).

Machine	Average Cycle Time Estimator (s)	SE	t	p-value	Adj. R^2	Model p-value
Feller-buncher	= 10.140	0.614	16.50	<0.01	0.4329	<0.01
	+ 3.709 × No. of standing trees	0.296	12.54	<0.01		
	+ 13.082 × No. of down trees	0.870	15.04	<0.01		
	+ 0.301 × move dist. (m)	0.025	12.29	<0.01		
Delimber	= 30.765	1.522	22.22	<0.01	0.1898	<0.01
	+ 6.624 × No. of live trees	0.913	7.25	<0.01		
	+ 5.729 × No. of dead trees	0.961	5.96	<0.01		
Skidder (trees)	= 25.125	47.53	0.529	0.603	0.5976	<0.01
	+ 0.192 × empty travel dist. (m)	0.099	1.944	0.066		
	+ 0.145 × loaded travel dist. (m)	0.073	1.983	0.061		
	+ 1.881 × No. of trees	0.984	1.913	0.070		
Skidder (logs)	= 42.290	6.964	6.073	<0.01	0.2625	<0.01
	+ 0.890 × No. of logs	0.312	2.850	0.010		
Loader	= 22.006	1.892	11.629	<0.01	0.2033	<0.01
	+ 3.739 × No. of logs	0.471	7.937	<0.01		
	+ 8.248 × loading activity (1 or 0)	1.794	4.597	<0.01		

Table 2.6 Performance metrics of individual machines and the entire system of whole-tree harvesting predicted by the TS model.

Machine	Cycle time* (s)	Productivity (odt/PMH)	Utilization (%)	Sys. Prod. (odt/SMH)	Unit cost ($/odt)
Feller-buncher	19.5	41.83	44.6	18.67	30.21
Delimber A	41.1	17.53	53.3		
Delimber B	41.1	17.53	53.3		
Skidder (trees)	237.5	39.33	60		
Skidder (logs †)	62.6	148.29			
Loader (loading §)	42.5	28.89	48.8		
Loader (sort and deck)	34.3	42.94			

* Delay free cycle time. † Calculated by assuming equal number of skidding tree process and skidding log process. § Calculated with the assumption that loader spends 30% and 70% of its times on direct loading, and sorting and decking, respectively.

The comparisons of machine productivity between the estimated values and the field-observed values in the validation data set show that the estimated average machine productivities of all equipment by both models deviate less than 9% from the observed values (Table 2.7). The DES model has better estimates of productivity for the feller-buncher, skidder and loader, while the TS model has better estimates for the delimbers. The biggest difference was found with the loader "sort and deck" process where the TS model overestimated the productivity by 8.6%. As for machine utilization, the two models reported similar rates for all machines but the loader (Figure 2.6). For the feller-buncher, delimbers and skidder, the minor differences in machine utilization rates by the two models mainly came from the differences in estimated machine productivities and the system productivity. In the DES model, Delimber A had a higher utilization than Delimber B because during the simulation it was assigned as the primary resource, which means Delimber A is used first if delimbers were available. In the TS model, the two delimbers were equally treated. For the loader, the difference in the reported utilization is apparent. The TS model reported lower utilization because it only included "direct loading" and "sort and deck" whereas the DES model also considered "load from deck" processes. The occurrence of this last process depends on the status of the loader (i.e., no log pile to sort and load) and the truck (i.e., available on site). The TS model could not assess this situation so that it overestimated loader productivity and underestimated the loader utilization.

Table 2.7 Comparison of the estimated mean machine productivities obtained from the WT DES and TS models with the field-observed productivities for whole-tree harvesting.

Machine	Observed Productivity (odt/PMH)	Difference * (%)	
		DES	WT
Feller-buncher	42.75	−2.1	−2.2
Delimber A	17.30	−1.0	1.3
Delimber B	17.30	−1.3	1.3
Skidder (tree)	37.30	6.9	5.4
Skidder (log)	153.18	−5.3	−3.2
Loader (load)	27.78	5.9	4.0
Loader (sort and deck)	39.54	1.6	8.6

* Percentage difference between model estimates and the observed values. WT = whole-tree harvesting, DES = discrete event simulation, TS = time study.

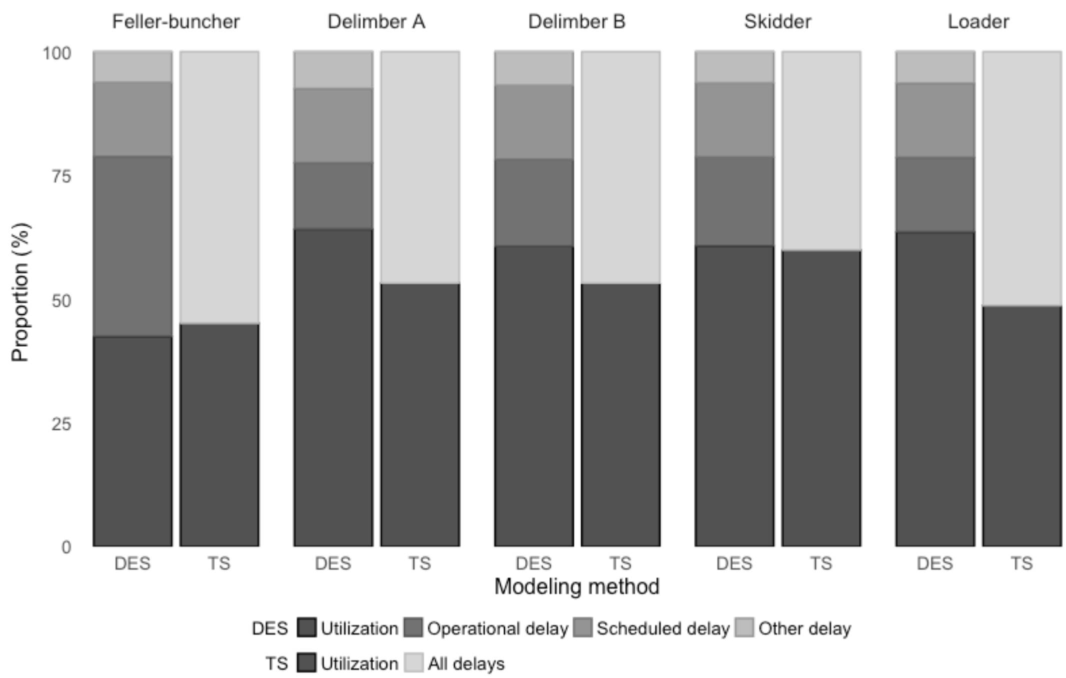

Figure 2.6 Machine utilization and delay proportions estimated by the WT DES and WT TS models.

The DES model was also able to provide both delay type and quantity of each machine. The amount of scheduled delays and other delays were similar across all machines, while the feller-buncher had the largest proportion of operational delay because of its high productivity and interactions with lower productivity machines. Due to the variation of operations and interdependencies among machines, there was no "absolute" system bottleneck and all other machines experienced a certain amount of operational delays. The TS model was able to estimate only the overall utilization of individual machines based on their published empirical utilization rates (or long-term utilization rates) and the bottleneck machine's productivity. The feller-buncher had the largest overall delays as well in the TS model due to its high productivity compared to the other machines. The skidder was the system bottleneck and its utilization rate was estimated to be equal to the empirical rate.

2.3.2 *Sensitivity analysis*

2.3.2.1 Skidding distances

The utilization rates of individual machines changed with different skidding distances (Figure 2.7). The results show that operational delays of individual machines varied widely across different skidding distances, while the proportions of scheduled and other delays were relatively constant over the range of skidding distance. A longer skidding distance increased the skidder's cycle time and utilization, and decreased its operational delay, while it increased operational delays of all the other machines. This indicates the skidder becomes the system bottleneck causing the delimbers and the loader to wait for the skidder to supply logs. As skidding distance increases, the feller-buncher appears to experience increased operational delay because it has to spend a longer time waiting for the other machines. The TS model shows similar patterns of changes in total delays but with more abrupt transitions as skidding distance increases. This is because the utilization rate of the bottleneck machine is assumed to be constant.

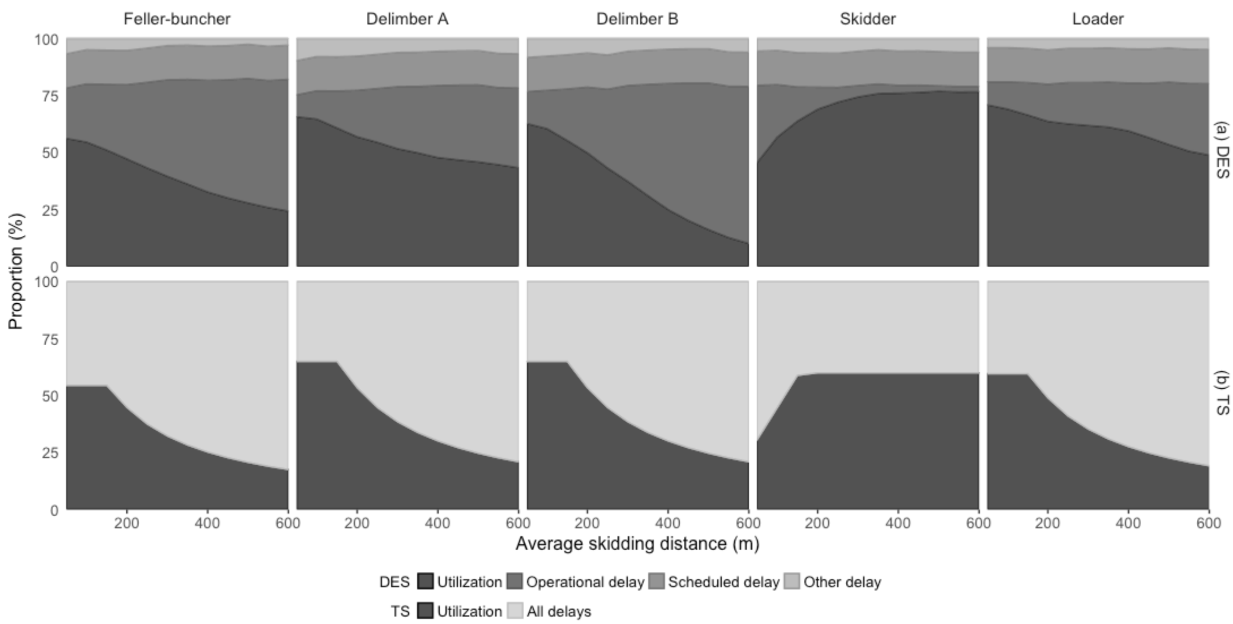

Figure 2.7 Changes in machine utilization and delay proportions over different skidding distances estimated by the WT DES model (**a**) and the WT TS model (**b**).

The productivity of the entire system and its unit production cost also change in response to different skidding distances (Figure 2.8). Overall, the estimated system productivity decreased and the unit cost increased as skidding distance increased in both models. However, when skidding distances were relatively short (i.e., less than 100 m), the TS model estimated the system productivity and unit cost to be constant, whereas the DES model showed gradual changes. This is because for the short skidding distances the delimber was the system bottleneck and skidding distance does not influence the system cost nor the productivity in the TS model. The DES model, however, was able to capture changes in skidder efficiency caused by different skidding distances and incorporate them into system productivity and cost estimation.

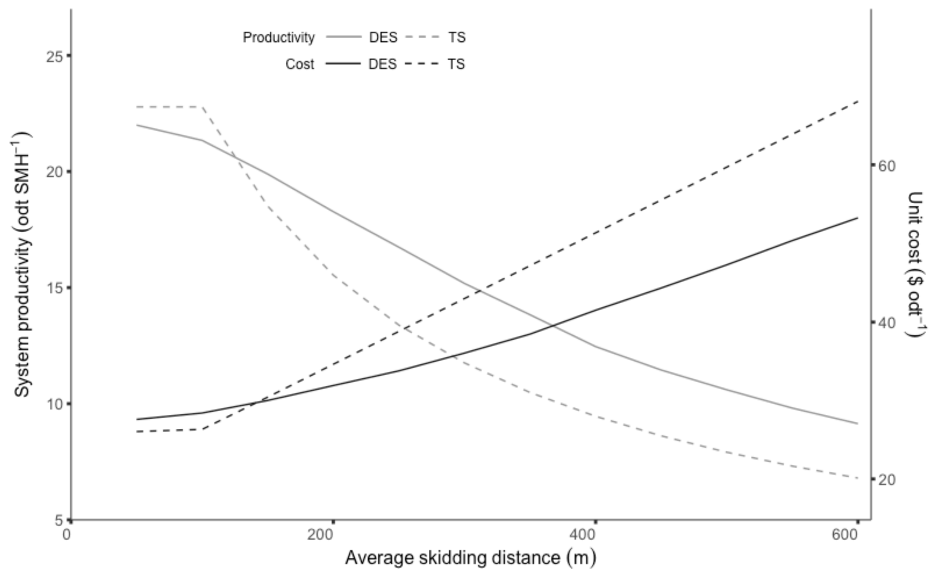

Figure 2.8 Changes in system productivity (left y-axis) and unit production cost (right y-axis) over different skidding distances estimated by the DES and TS models.

2.3.2.2 Trucking schedules

The DES model estimated the utilization rate of the loader at about 55% when no trucks were scheduled (Figure 2.9). The utilization rate increased by approximately 2% per truck as more trucks were scheduled to pick up the logs. The results show that the loader spends an increasing amount of time in "direct loading" as more trucks are scheduled. On the other hand, the truck on-site time, which includes truck waiting time in queue and truck loading time, increased due to higher chances of queueing. When the scheduled truck number was less than four, the truck on-site time had an average of 60 min and a standard deviation of 15 min. Beyond that, the on-site time increased quickly in both the average and standard deviation. With 10 trucks visiting the harvesting site per day, the loader would spend about 30%, 25% and 25% of its productive times on "direct loading", "load from deck", and "sort and deck", respectively, with a total utilization rate of approximately 80%. But the truck on-site time had an average of 177 min and a standard deviation of 35 min.

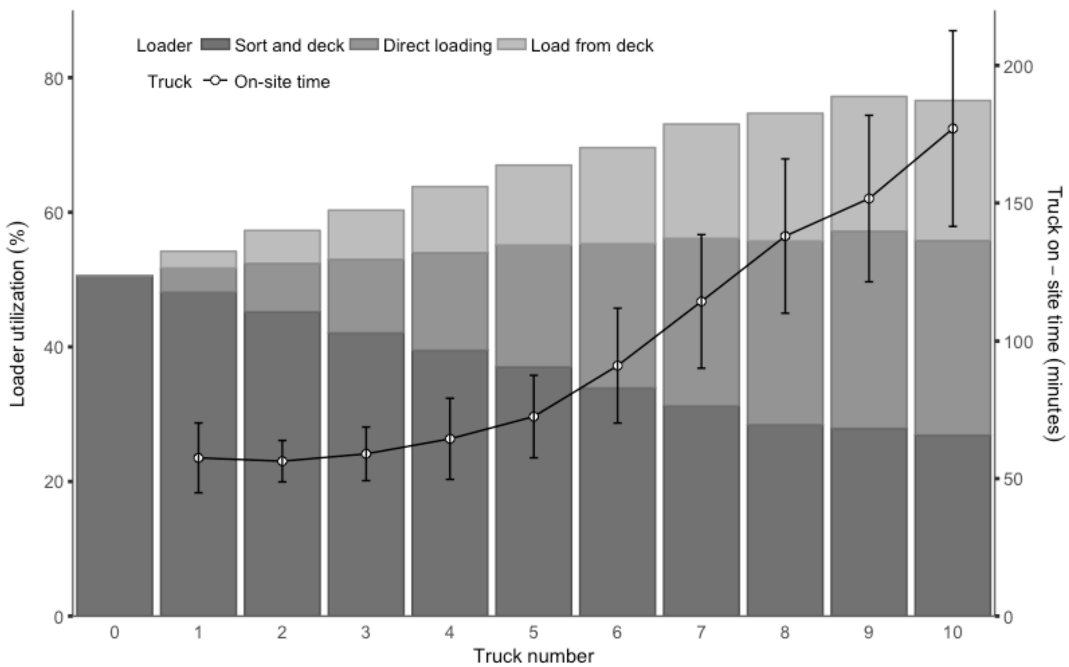

Figure 2.9 Loader utilization with task proportions (left y-axis) and truck on-site time (right y-axis) under different trucking schedules.

2.3.3 *DES model for the lop-and-scatter system*

The results of the DES model built for the lop-and-scatter harvesting system using the whole-tree harvesting data show that the estimated machine productivities for individual machines were similar to the field-observed productivities (Table 2.8). The biggest difference was with the skidder. The model underestimated the skidder productivity by 9.7% with the observed value being about two standard deviations from the mean estimate. This difference might be attributed to the intrinsic differences between transportation of trees and logs (e.g., turn size). Our comparisons of the LS DES model with the two LS TS models (i.e., TS conventional and TS adjusted) show that the LS DES model estimates were similar to those of TS adjusted, but somewhat different from TS conventional in terms of system productivity and unit production cost (Figure 2.10). This indicates that both the DES and TS models assess the performance of individual machines similarly when the same, scenario-based machine utilization rates are used as inputs. The results of the TS conventional model were different (15.7% and 10.7% difference in productivity and cost estimates, respectively) because of the published machine utilization rates used in the analysis.

Table 2.8 Comparison of the estimated mean machine productivities obtained from the LS DES model with the field-observed productivities for lop-and-scatter.

Machine	Productivity (odt/PMH)		Difference* (%)
	Observed	DES	
Feller-buncher	41.35	41.88 (0.60)	1.3%
Delimber A	13.20	13.81 (0.35)	4.6%
Delimber B	13.20	13.72 (0.40)	4.0%
Skidder	41.07	37.10 (2.02)	−9.7%
Loader (load)	28.40	29.16 (3.98)	−3.4%
Loader (sort and deck)	40.98	39.60 (1.76)	2.7%

* Percentage difference between model estimates and the observed values.

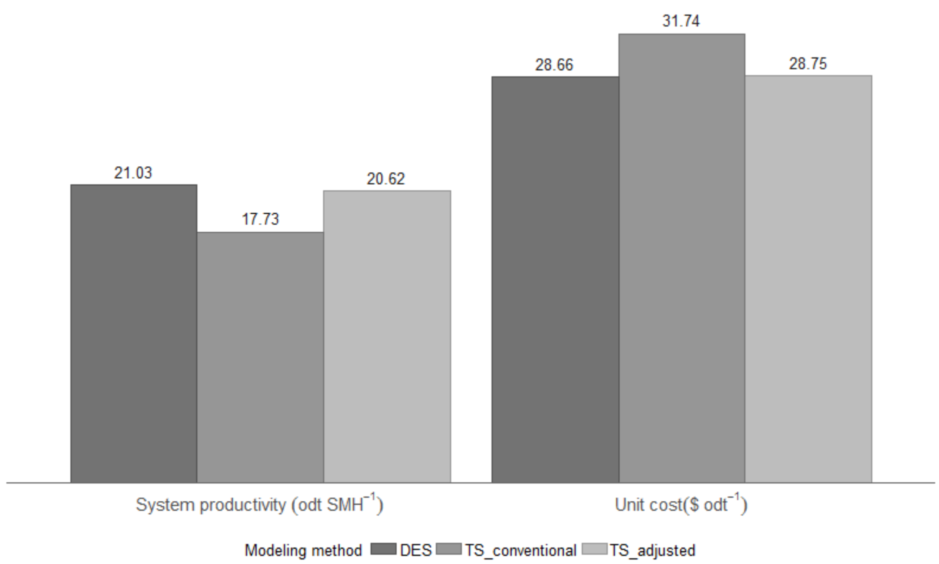

Figure 2.10 LS system performance estimated by the DES, TS conventional and TS adjusted models.

2.4 Discussion

2.4.1 *Process synthesis and model resolution*

Comparing the WT TS and DES model results, the TS model estimated the system productivity to be 7.4% lower and the unit cost to be 1.7% higher (Tables 2.4 and 2.6). The differences were mainly caused by the synthesis procedure for machine processes of the two modeling approaches. The TS model does not track the material flow in the system and thus determines the system productivity as the lowest machine SMH productivity, whereas the DES model is able to keep track of material flow and machine activities as a series of events. As Asikainen (1998) noted, static, deterministic models, such as the TS model, generate satisfactory results when the studied system is simple and unbalanced (i.e., apparent bottleneck) but may lead to biased estimates for complex systems.

The ability of capturing operational details in DES modelling is of great value for system improvement. In this study, the TS model was not able to provide information on machine utilization in enough detail to understand the system dynamics (Figures 2.6 and 2.7). The DES model, however, could capture machine interactions more precisely by mimicking the actual work pattern and machine-to-machine wood flows. The DES model was able to not only quantify the amount of operational delays but also identify the cause of delays (e.g., the skidder's operational delays were caused by other "bottleneck" machines, such as the delimber or the loader). While scheduled and other delays are unavoidable in machine operations, the amount of operational delays depicts the efficiency of the harvesting system, and understanding the cause-and-effect of delays can greatly help improve system balance and thus overall efficiency (Spinelli and Visser 2008).

2.4.2 *Sensitivity analysis*

When TS regression models are applied to a wide range of independent variable values, model extrapolation always becomes a concern. In the TS approach, coefficients in a regression model only infer associations between the dependent and independent variables in the given data set, not necessarily cause-and-effect relationships in general. For example, estimating skidding cycle times based on a linear relationship may produce unreasonable results when the coefficient is applied beyond the original observation range (Figures 2.7 and 2.8). The DES approach has a similar restriction because input probability distributions are produced from site-specific data. However, in DES models, a full machine cycle is broken into multiple processes that can be estimated independently. Grappling time, dropping time, skidder empty and loaded traveling speed are still likely to be the same across a wide range of skidding distances, whereas skidder travel times is a direct function of skidding distance. This separate estimation of process times makes the DES models more applicable to a wider range of independent variable values than the TS models. The more gradual changes shown in the DES model outputs from the current study confirmed this benefit (Figures 2.7 and 2.8).

The results of our sensitivity analysis on truck availability shows that loader operations and log transportation mutually affect each other. With very few trucks scheduled, the loader has to spend time for “sort and deck” and later “load from deck”, handling logs twice. Increasing the number of scheduled trucks increases the loader “direct loading” time and loader utilization, but too many trucks on site increases the average and variability of truck queue time. This leads to decreased trucking efficiency and increased transportation cost. In a forest supply chain, efficient wood flow from the harvesting system to transportation is critical in reducing logistics costs (Beck and Sessions 2013). The strength of the DES in capturing changes in machine interactions is particularly beneficial to scenario analysis on trucking schedules (Spinelli et al. 2014; Zamora-Cristales et al. 2014). Our DES model shows the potential tradeoff between loader utilization and truck on-site time (Figure 2.9) and can be used in operational planning to balance harvesting and transportation efficiency for optimal outcomes.

2.4.3 *Analysis of hypothetical systems*

In harvesting operations, delay times may vary significantly by system design, as well as stand and terrain conditions (Spinelli and Visser 2008). Our study shows that the use of general machine utilization rates in evaluating new harvesting systems (e.g., TS_conventional) may not be appropriate because such utilization rates do not reflect system-specific work conditions, such as machine interactions, that may be caused by a new composition or arrangement of machine processes (Figure 2.10). A discrete-event simulation of wood flow through a series of machine processes seems more appropriate for new system evaluation because of its ability to address potential machine interactions and precisely estimate the utilization of individual machines. Our finding is consistent with a previous study (Asikainen 2010) that compared a DES model with a deterministic spreadsheet model developed for stump crushing and truck transportation.

2.4.4 *DES model drawbacks*

While the DES approach has many advantages, there are also drawbacks. Special skills are required to build DES models, and the modeling process can be expensive and time-consuming (Banks 1984). DES model construction also requires a considerable amount of data, such as time elements of individual machines and their probability distributions, and it is often the case that sufficient data are not available in forest operations to make DES modeling feasible. Although modern data acquisition technologies (e.g., auto-video recording, GPS tracking, sensors) can help access operational data more easily and frequently (Mușat et al. 2015; Contreras et al. 2017; Borz et al. 2018), long-term field data collection is still necessary to obtain a representative sample of field operations and thus ensure quality output. Also, the large amount of random inputs in DES modeling can make it difficult to interpret the output in simple terms, especially for highly complex systems (Sharma 2015).

2.5 Conclusions

Our comparison of the TS and DES approaches in modeling a ground-based timber harvesting system indicates that the DES approach may be a more appropriate method for analyzing complex systems especially where interactions among different machine processes are unknown. Randomness and uncertainties can be considered in DES throughout the modeling process to account for variations of operations. Replications of DES model runs enable the user to show a comprehensive picture of the system performance in terms of both average and variability. In addition, the ability of DES to reuse the previously collected data provides an opportunity to evaluate alternative or hypothetical systems that have not been tested in field. Although model construction and output interpretation can be complex and expensive, we believe the potential benefits of the DES approach to provide more comprehensive and precise information that can help identify problematic areas and improvement opportunities in forest operations planning, surpass its potential drawbacks.

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Chapter 3

Economic and Environmental Optimization of Forest Supply Chain for Timber and Bioenergy Production from Beetle-killed Biomass in Northern Colorado

Abstract

In the northern Colorado Rocky Mountains, harvesting mountain pine beetle infested forest stands provides an opportunity to utilize otherwise wasted resources and generate net revenues and greenhouse gas (GHG) emission savings. While sound wood from beetle-killed stands can be still used for traditional timber products, degraded wood and logging residues can provide a feedstock for bioenergy. However, timber and bioenergy production are commonly managed separately, and their integration is seldom considered. In addition, due to the relatively low market value and high harvesting cost of beetle-killed wood, the GHG emission saving benefit is often realized only at the expense of compromises in net revenues during salvage harvest. In this study, we compared two decision-making scenarios of managing the supply chain of salvage utilizing beetle-killed forests. In the Sequential scenario, timber and bioenergy production was managed sequentially in two separate processes, where salvage harvest was conducted without considering influences on or from bioenergy production and then biomass availability was assessed as outcomes from timber production managed for bioenergy production. In the Integrated scenario, timber and bioenergy production was managed jointly in one process, where collective decisions are made on salvage harvest, residue treatment, and bioenergy product selection and production. We applied a multi-objective optimization approach to integrate the economic and environmental objectives measured by the total net revenues and the total net GHG emission savings, respectively, through the use of timber and bioenergy products. The results show that distinctive decisions are made for harvesting system selection and residue treatment by the two scenarios. When the optimization is fully economic-oriented, 49.6% more forest areas are harvested under the Integrated scenario than the Sequential scenario, generating 12.3% more net revenues and 50.5% more net GHG emission savings. Comparison of Pareto fronts also indicates the Integrated scenario provides more efficient trade-offs between the two objectives and performs strictly better than the Sequential scenario in both objectives.

Key words: Multi-objective optimization, beetle-killed biomass, forest supply chain, scenario comparison

3.1 Introduction

The recent mountain pine beetle (*Dendroctonus ponderosae* Hopkins, MPB) epidemic has affected a massive area of forests in North America (US Department of Agriculture Forest Service 2017). Between 1996 and 2013, Colorado has severely suffered from MPB infestation where more than 1.38 million ha of forest lands were affected (Colorado State Forest Service., 2016). This has caused enormous economic costs to landowners and local communities due to degradation in wood quality (Lewis and Thompson 2011), reduction in timber production (Romme et al. 1986), and loss of long-term stability of wood supply in the region (Corbett et al. 2015). Negative influences are also reported on non-timber values including landscape preference (Arnberger et al. 2018), recreation (Rosenberger et al. 2013), and housing depreciation in the outbreak areas (Price et al. 2010).

On the environmental side, increased tree mortality not only weakens forest ecosystem services (Dhar et al. 2016), but it also affects wildlife species to various extent (Saab et al. 2014) and alters forest fuel structure and fire behavior (Hicke et al. 2012b; Harvey et al. 2014). As dead trees decay over time, they become a net source of carbon (i.e., dead trees stop absorbing CO_2 and emit CO_2 during decomposition) and contribute to climate change (Kurz et al. 2008).

Salvage harvest of dead trees provides an opportunity to utilize forest resources that are otherwise wasted, contributing to the economies of rural areas and local wood product industries. It is estimated that beetle-killed logs can still yield 56.1% to 99.8% values of healthy logs depending on extent of damage (Orbay and Goudie 2006). Prestemon et al (2013) reports that there are 0.56 billion m^3 of dead timber available for salvage across 8.22 million hectares in 12 western states. This represents a considerable amount of revenues for affected landowners to mitigate economic losses. On the other hand, usage of salvage timber creates carbon benefits by reducing carbon emissions from dead wood decay in the infested forests (Campbell et al. 2016). Replacing non-renewable resources that require more energy intensive manufacturing than timber products is another benefit of utilization of dead wood (Werner et al. 2005; Gustavsson et al. 2006). Timber products can also serve as carbon storage while in use (Bergman et al. 2014) and substitute fossil fuels as energy feedstock (Kayo et al. 2015) or continue to preserve carbon in landfill (Ximenes et al. 2008) at the end of service life.

In addition to timber production, degraded wood and logging residues (e.g., tree tops, branches and non-merchantable parts), which are a byproduct of salvage harvesting, can serve as feedstock for bioenergy production (Lamers et al. 2014). Because of wood degradation over time, some salvaged trees might fail to meet the quality of lumber or pulp and paper production especially when salvage harvest is delayed significantly (Barrette et al. 2015). This leads to a great amount of biomass residues as potential high-quality bioenergy feedstock with high woody composition and low moisture content (Chow and Obermajer 2006). Further utilizing them for bioenergy production avoids costs and emissions (e.g., greenhouse gas, particulate matter) associated with open pile burning (Springsteen et al. 2011, 2015) that is often required to reduce fire risks and prepare harvest sites for regeneration (Stephens et al. 2012; Jones et al. 2013). It also reduces society's heavy dependence on fossil fuels and contributes to climate change mitigation (Panwar et al. 2011; Creutzig et al. 2015).

Because MPB-infested stands often have high harvesting costs due to complicated stand conditions (Kim et al. 2017) and low product values due to wood defects (Byrne et al. 2006), timber salvage often only has narrow profit margins or may even be unprofitable in some forest area (Prestemon et al. 2013). Besides, high costs of comminution and transportation of biomass have been an obstacle to the wide utilization of beetle-killed wood for bioenergy (Anderson and Mitchell 2016). Therefore, although producing timber and bioenergy products from beetle-killed forests have a potential for reducing GHG emissions, such an environmental benefit is sometimes realized at the expense of economic compromises. Understanding the trade-offs between economic and environmental benefits of beetle-kill resource utilization would be important in decision-making on salvage harvest operations and supply chain management.

To achieve sound forest supply chain management, mathematical optimization is frequently used to support the decision-making process (D'Amours et al. 2008; Rönnqvist et al. 2015). If there is only one stakeholder managing all resources in the forest supply chain, bioenergy can be treated as a byproduct from timber production and included as part of the optimization (Carlsson and Rönnqvist 2005; Kong et al. 2012; Feng et al. 2013). In a fragmented supply chain that involves multiple stakeholders, however, until now most studies have exclusively dealt with either timber products (Bredström et al. 2004; Dems et al. 2017) or bioenergy feedstocks (Rentizelas et al. 2009; Gunnarsson et al. 2004), whereas the linkage between the two products has not been thoroughly investigated yet. Such a gap is caused by the fact that timber production is at much greater scales in amounts and values than bioenergy production so that the latter has minimal influences on the former. As a result, timber supply chain studies sometimes neglect the treatment of biomass residues (Richards and Gunn 2000; Karlsson et al. 2004; D'Amours et al. 2008) whereas bioenergy supply chain studies (Kanzian et al. 2009; Ghaffariyan et al. 2013) often assume biomass residues become available at the landing in a ready-to-use form at free of charge. The decision-making process is thus decoupled, where decisions regarding timber and bioenergy production are made separately and sequentially. Nevertheless, not only technical and economic feasibility of biomass feedstock logistics, but also conventional silvicultural treatments and harvesting methods often become barriers of producing and utilizing forest biomass for bioenergy. When utilizing MPB-infested forest resources, due to lower values of timber products and a higher proportion of biomass residues, the cooperation between timber and bioenergy production needs to be strengthened to enhance the economic feasibility of forest salvage utilization. Integrating timber and bioenergy production in planning may improve the performance of the entire forest supply chain network.

In recent years, an increasing number of studies adopt multi-objective optimization (MOO) technique (Deb 2001) to evaluate environmental impacts of the biomass supply chain in addition to its economic performance (Yue et al. 2013; Cambero and Sowlati 2014). The economic objective is often formulated as minimizing operation costs (You and Wang 2011; You et al. 2012) or maximizing net revenues (Santibañez-Aguilar et al. 2011; Čuček et al. 2012; Sacchelli et al. 2014). As for the environmental objective, among various criteria that can be considered (e.g., eco-indicator 99 points, impact 2002+ points, carbon footprint) (Santibañez-Aguilar et al., 2011; Pérez-Fortes et al., 2014; Čuček et al., 2012), minimizing product life cycle GHG emissions via Life Cycle Assessment (LCA) (Corporation and Curran 2006) has been used most frequently due to interests in mitigating climate change (You and Wang 2011; You et al. 2012; Kanzian et al. 2013). Cambero et al (2016a) argued that minimizing GHG emissions does not guarantee to provide the maximum environmental benefits when considering the substitution effect of wood products. Therefore, maximizing the net GHG emission savings is a more appropriate environmental objective for the optimization model. Similarly, Sacchelli et al (2014) optimized the environmental performance as maximizing the amount of avoided carbon emissions by combustion of renewable resources.

So far most studies have presumed timber and bioenergy products to be "carbon neutral" under sustainable forest management, meaning there is a net zero emission because the amount of carbon released from biomass sources (i.e., biogenic carbon) is captured by plants during regrowth (Cherubini et al. 2009). However, this assumption has been questioned increasingly because it neglects the fact that forest regrowth is a much longer process compared to the immediate emissions (e.g., burning) (Johnson 2009; Zanchi et al. 2012). A carbon debt (Mitchell et al. 2012) is created referring to a deficiency between carbon emission and sequestration that requires a "payback period" (Jonker et al. 2014) to offset. Evidence further shows that carbon benefits of timber and bioenergy products greatly depend on the accounting method of biogenic carbon (Bergman et al. 2013; Klopp and Fredeen 2014) and the "carbon neutrality" assumption may be need to be revaluated (Cherubini et al. 2011). One proposal is to use a global warming potential of biogenic carbon (GWP_{bio}) indicator, based on regional forest growth, rotation length, time horizon, etc., to assess the effects of biogenic carbon relative to fossil carbon (Cherubini et al. 2011; Guest et al. 2013). As carbon accounting is critical in evaluating trade-offs between revenues and carbon benefits, it is useful to include such considerations and explore the effects of carbon accounting method to assist the decision-making in salvaging MPB-attacked forests.

In this study, we compared the Sequential scenario and our proposed Integrated scenario in managing timber and bioenergy production from beetle-killed forests. We applied a multi-objective optimization approach to evaluate the economic and environmental objectives (*i.e.*, net revenues and net GHG emission savings) of the entire forest supply chain from stump to mill or processing facility while taking into account options in the upstream timber harvesting and residue management operations. We showed the potential improvement to achieve in both objectives when the timber and bioenergy supply chains are integrated and managed simultaneously. Biogenic carbon is accounted by a series of GWP_{bio} values to fully investigate the carbon benefits of forest salvage utilization, trade-offs between economic and environmental objectives, and influences on forest supply chain management decisions.

3.2 Problem statement

In the Colorado State Forest in northern Colorado (40°57′N, 106°00′W), lodgepole pine (*Pinus contorta*) stands (Figure 3.1) have been heavily impacted by the MPB outbreak since 2008 and the current mortality rate is 47.3%. The 3,400 ha infested forest is located on relatively flat terrain with a stand density of 865 trees ha^{-1} and a basal area of 34.6 m^2 ha^{-1}. The average diameter at breast height (dbh) of trees is 22.4 cm and the average height is 19.6 m. Ground-based clearcut operation is prescribed for salvage harvest in this area due to the high level of mortality rate. After accounting for slope and primary transportation distance, in total 627 harvest units are applicable for salvage harvest with an average size of 5.4 ha (Han et al. 2018). Depending on the small-end diameter and defects, three log products, saw logs, post and pole, and firewood, are produced and sold to a timber mill (45 km away) based on oven dry weight. As for logging residues, potential bioenergy alternatives include hog fuels (a biomass power plant 238 km away), wood pellets (a pellet plant 45 km away), and biochar (mobile pyrolysis equipment on-site).

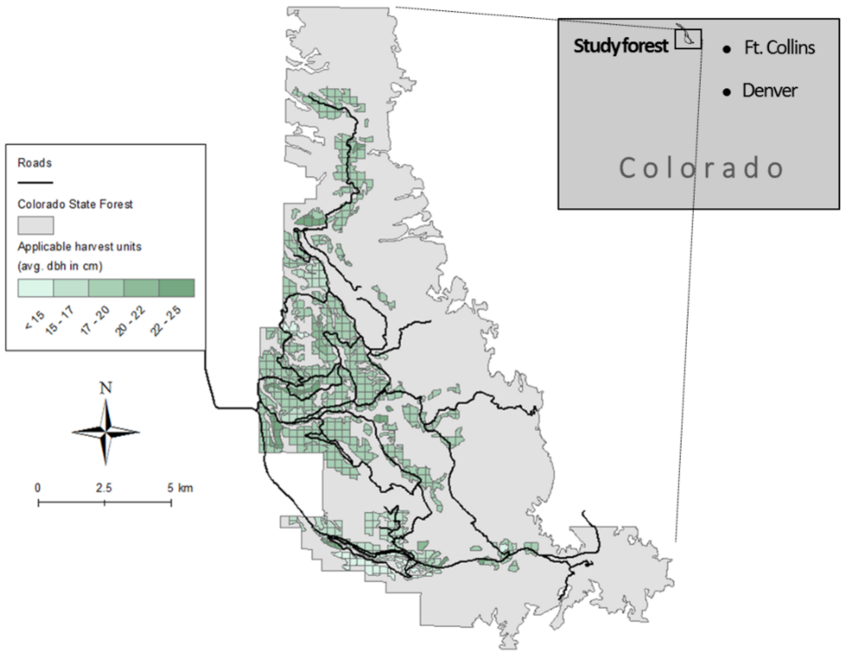

Figure 3.1 Mountain Pine Beetle infested lodgepole pine stands in Colorado State Forest.

The supply chain network of forest salvage utilization consists of a timber supply chain (TSC) and a bioenergy supply chain (BSC), where each operation is associated with a cost and GHG emission but revenues and GHG savings are achieved through end products use (Figure 3.2). At the TSC, *lop-and-scatter* (LS) and *whole-tree harvesting* (WT) are the primary harvesting systems and they employ the same set of equipment. The distinct feature of LS is that delimbers delimb and buck trees to logs at the stump. While processed logs are brought to the landing by a skidder, logging residues are dispersed over the harvest unit and left on the forest floor (i.e., not economical to collect). By comparison, whole trees are transported in WT by a skidder and processed by delimbers at the landing, where slash piles are accumulated as part of timber harvesting (Nisbet et al. 1997). In addition to the two existing systems, a *whole-tree harvesting with sorting* (WTwS) system can be deployed by including a sorting procedure in the delimbing process of the WT system (Kizha and Han, 2016). WTwS separates sorted biomass (e.g., tree tops left from saw log processing, small diameter trees delimbed) from slash piles, which facilitates the production of high-quality (i.e., less contamination from dirt, and uniform in size) feedstock and thus high-value bioenergy products but also increases the overall cost of timber harvesting compared to that of WT.

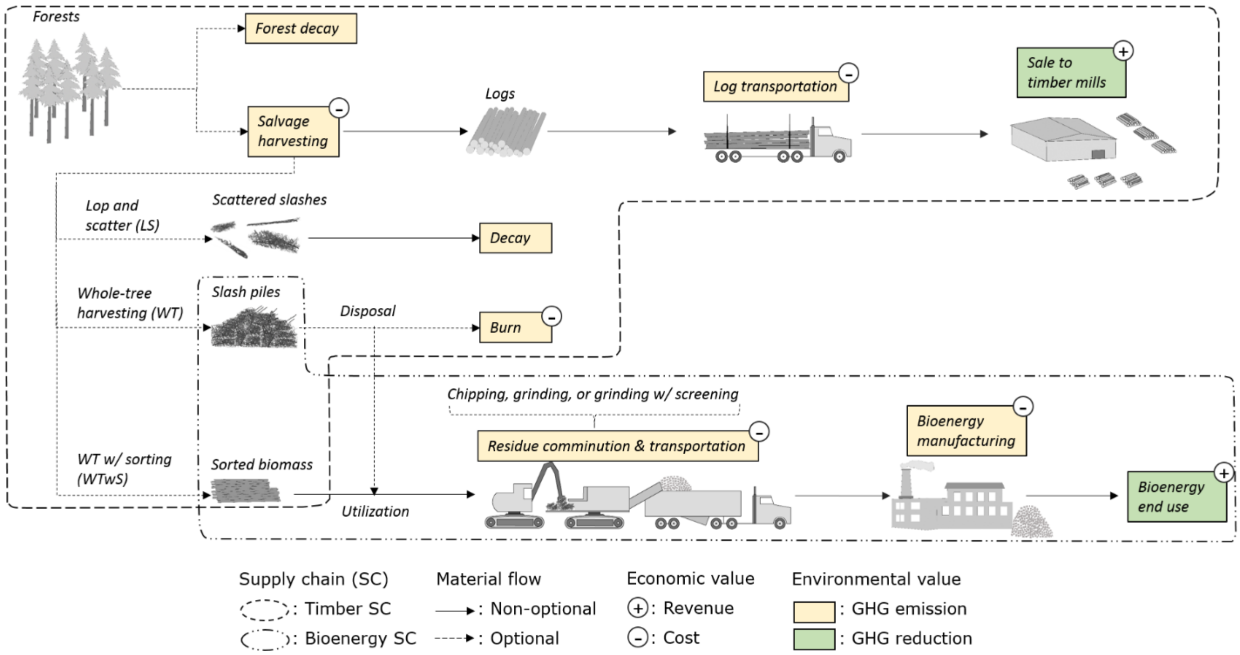

Figure 3.2 The supply chain network of salvage harvest of Mountain Pine Beetle infested forests in Colorado State Forest.

Upon completion of salvage harvest, trees at unharvested units and scattered logging residues from LS harvested units are left to decay and emit GHG as carbon sources. Forest residues and sorted biomass from WT and WTwS harvested units, respectively, can be further utilized at the BSC for bioenergy production. Pellets and biochar production normally require homogenous sized, less contaminated feedstock, which can be produced through chipping sorted biomass with a chipper. In contrast, forest residues from WT harvest units contain a wide range of woody materials (e.g., tops, limbs and chunks) and high amount of soil contaminations so that comminution is limited to grinding, which is capable of handling such materials and produces low-quality feedstock (i.e., hog fuels) (Han et al. 2015). To use them for pellet or biochar production, we assume a screening process has to be added after grinding to reduce contamination content and improve feedstock quality (Dukes et al. 2013). After comminution, produced feedstock is transported to the selected bioenergy facility to manufacture bioenergy products, whereas unutilized forest residues should be burnt as part of disposal management.

Timber harvesting and biomass utilization in the study region are conducted by different stakeholders (i.e., timber and bioenergy producers) and the landowner works with them separately to manage the TSC and BSC, where harvest decisions are made to optimize performances of the

TSC without considering influences on or from the BSC, even though salvage harvesting affects the amount and form of recoverable biomass feedstock and biomass utilization affects the residue disposal management. Post to harvest, biomass availability is assessed as outcomes from the TSC and managed for bioenergy production accordingly to optimize performances of the BSC. Disposal of unutilized biomass residues remains as a responsibility of the TSC. Such a sequential decision-making process (referred as a Sequential scenario) lacks cooperation between the TSC and BSC, neglects interactions of the two supply chains, and may lead to suboptimal outcomes when their performances are combined and evaluated afterward.

We hypothesize that an Integrated scenario where the TSC and BSC are managed jointly may utilize the beetle-killed forest resource more efficiently and benefit both timber and bioenergy production. This scenario represents a fully communicated and cooperative supply chain network where the landowner collectively work with timber and bioenergy producers optimize the performance of the overall forest supply chain (FSC) rather than individual performances of TSC and BSC separately.

3.3 Methods

3.3.1 Mathematical model

We combined multi-objective optimization (MOO) with mixed integer linear programming (MILP) to optimize the economic and environmental objectives of the forest supply chain under the Sequential and Integrate scenarios. The economic objective was measured by net revenues (NR) and the environmental objective was measured by the net GHG emission savings (NS). For the MOO outputs, instead of a single solution optimizing both objectives, a set of "Pareto optimal solutions" were obtained where in each solution, one objective could not be improved without sacrificing the other objective (Ehrgott 2006). NR and NS values calculated from the solution set constructed the Pareto front which showed the trade-offs between the two objectives (Deb 2001). In model formulation, the Sequential and Integrate strategies shared the same variables, parameters (Table 3.1), and constraints but differed in the solving procedures, simulating the distinctive decision-making processes of the two planning strategies.

Table 3.1 Nomenclature.

Sets	
I	$Set\ of\ harvesting\ units\ i$
S	$Set\ of\ harvesting\ systems\ s$
T	$Set\ of\ logging\ residue\ treatments\ t$
C	$Set\ of\ comminution\ methods\ c$
L	$Set\ of\ log\ products\ l$
K	$Set\ of\ bioenergy\ feedstocks\ k$
P	$Set\ of\ bioenergy\ products\ p$
Parameters	
1) General	
$m_{i,l}^{Log}$	$Available\ log\ product\ l\ at\ harvest\ unit\ i\ (\mathrm{odt})$
m_i^{Res}	$Available\ logging\ residues\ at\ harvest\ unit\ i\ (\mathrm{odt})$
a_i	$Area\ of\ harvest\ unit\ i\ (ha)$
d_i^{Log}	$Distance\ between\ harvest\ unit\ i\ and\ the\ timber\ mill\ (km)$
$d_{i,p}^{Feed}$	$Distance\ between\ harvest\ unit\ i\ and\ the\ bioenergy\ product\ p\ facility\ (km)$
GWP_{bio}^{decay}	$GWP\ factor\ of\ biogenic\ carbon\ emission\ from\ biomass\ decaying$
GWP_{bio}^{burn}	$GWP\ factor\ of\ biogenic\ carbon\ emission\ from\ biomass\ burning$
2) Economic	
c_i^{Admin}	$Salvage\ harvest\ administration\ cost\ (\$/ha)$
$c_{i,s}^{Log,har}$	$Cost\ of\ salvage\ harvest\ using\ system\ s\ at\ unit\ i\ (\$/odt)$
$c_l^{Log,trans}$	$Transportation\ cost\ of\ log\ type\ l\ (\$/odt * km)$
r_l^{Log}	$Revenue\ of\ delivered\ log\ product\ l\ (\$/odt)$
$c^{Res,burn}$	$Cost\ of\ burning\ logging\ residues\ on\ site\ (\$/ha)$
$c_c^{Res,com}$	$Cost\ of\ comminuting\ logging\ residues\ with\ method\ c\ (\$/odt)$
$c_k^{Feed,trans}$	$Transportation\ cost\ of\ residue\ feedstock\ k\ (\$/odt\ * km)$
$r_{k,p}^{Feed}$	$Revenue\ of\ using\ feedstock\ k\ for\ bioenergy\ product\ p\ (\$/odt)$
3) Environmental	
$e_{i,s}^{Log,har}$	$GHG\ emissions\ of\ salvage\ harvest\ using\ system\ s\ at\ unit\ i\ (kg\ CO_2\text{-}eq/odt)$
$e_l^{Log,trans}$	$Transportation\ GHG\ emissions\ of\ log\ type\ l\ (kg\ CO_2\text{-}eq/odt * km)$
s_l^{Log}	$GHG\ emission\ savings\ of\ log\ product\ l\ (kg\ CO_2\text{-}eq/odt)$
e^{decay}	$GHG\ emissions\ o\ biomass\ decay\ on\ site\ (kg\ CO_2\text{-}eq/odt)$
e^{burn}	$GHG\ emissions\ of\ burning\ logging\ residues\ on\ site\ (kg\ CO_2\text{-}eq/odt)$
$e_c^{Res,com}$	$GHG\ emissions\ of\ comminuting\ logging\ residues\ with\ method\ c\ (kg\ CO_2\text{-}eq/odt)$

$e_k^{Feed,trans}$	$Transportation\ GHG\ emissions\ of\ residue\ feedstock\ k\ (kg\ CO_2\text{-}eq/odt * km)$
$s_{k,p}^{Feed}$	$GHG\ emission\ savings\ of\ using\ feedstock\ k\ for\ bioenergy\ product\ p\ (kg\ CO_2\text{-}eq/odt)$
Decision variables	
1) Continuous variables	
$x_{i,l}^{Log}$	$Amount\ of\ log\ type\ l\ produced\ at\ harvest\ unit\ i$
x_i^{Res}	$Amount\ of\ logging\ residues\ produced\ at\ harvest\ unit\ i$
$x_{i,k}^{Feed}$	$Amount\ of\ residue\ feedstock\ k\ produced\ at\ harvest\ unit\ i$
$x_{i,k,p}^{Feed}$	$Amount\ of\ residue\ feedstock\ k\ used\ to\ produce\ bioenergy\ product\ p\ at\ harvest\ unit\ i$
2) Integer variables	
$y_{i,s}$	$Binary: 1, if\ harvest\ unit\ i\ is\ harvested\ using\ system\ s; 0, otherwise$
$z_{i,t}$	$Binary: 1, if\ logging\ residues\ at\ harvest\ unit\ i\ are\ processed\ by\ treatment\ t; 0, otherwise$
$v_{i,c}$	$Binary: 1, if\ logging\ residues\ at\ harvest\ unit\ i\ are\ comminuted\ by\ method\ c;\ 0, otherwise$
u_c	$Binary: 1, if\ comminution\ method\ c\ is\ used;\ 0, otherwise$

The net revenues and net GHG emission savings of the TSC (NR_{TSC} and NS_{TSC}) and BSC (NR_{BSC} and NS_{BSC}) are summarized (Eqs. (3.1-3.4)) and are used to construct objective functions in MOO models of the Sequential and Integrated strategies. NR_{TSC} is calculated by using log sale revenues to subtract log stumpage costs, harvesting costs, residue burning costs, and log transportation costs (Eq. (3.1)). Correspondingly, NS_{TSC} is calculated by using log product GHG emission savings to subtract harvesting emissions, log transportation emissions, unharvested forest decay emissions, residue decay emissions, and residue burning emissions (Eq. (3.2)). NR_{BSC} is calculated by using bioenergy sale revenues to subtract machine move-in costs, residue comminution costs, feedstock transportation costs, and bioenergy product manufacturing costs (Eq. (3.3)). NS_{BSC} is calculated by using bioenergy GHG emission savings to subtract GHG emissions from residue comminution, feedstock transportation, bioenergy product manufacturing (Eq. (3.4)).

$$\begin{aligned} NR_{TSC} = &\sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * r_l^{Log} - \sum_{i\in I} a_i * c_i^{Admin} - \sum_{i\in I}\sum_{s\in S}\sum_{l\in L} m_{i,l}^{Log} * y_{i,s} * c_{i,s}^{Log,har} \\ &- c^{burn} * \sum_{i\in I} a_i * z_{i,burn} - \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * d_i^{Log} * c_l^{Log,trans} \end{aligned} \tag{3.1}$$

$$NS_{TSC} = \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * s_l^{Log} - \sum_{i\in I}\sum_{s\in S}\sum_{l\in L} m_{i,l}^{Log} * y_{i,s} * e_{i,s}^{Log,har}$$

$$-GWP_{bio}^{decay} * e^{decay} * \sum_{i \in I}\left(\left(\left(\sum_{l \in L} m_{i,l}^{Log} + m_i^{Res}\right)\left(1 - \sum_{s \in S} y_{i,s}\right) + m_i^{Res} * z_{i,decay}\right)\right.$$

$$-GWP_{bio}^{burn} * e^{burn} * \sum_{i \in I} m_i^{Res} * z_{i,burn} - \sum_{i \in I}\sum_{l \in L} x_{i,l}^{Log} * d_i^{Log} * e_l^{Log,trans} \quad (3.2)$$

$$NR_{BSC} = \sum_{i \in I}\sum_{p \in P}\sum_{k \in K} x_{i,k,p}^{Feed} * r_{k,p}^{Feed} - u^{Res} * c^{Move} - \sum_{i \in I}\sum_{c \in C} m_i^{Res} * v_{i,c} * c_c^{Res,com}$$

$$-\sum_{i \in I}\sum_{k \in K} x_{i,k}^{Feed} * d_{i,p}^{Feed} * c_k^{Feed,trans} \quad (3.3)$$

$$NS_{BSC} = \sum_{i \in I}\sum_{p \in P}\sum_{k \in K} x_{i,k,p}^{Feed} * s_{k,p}^{Feed} - u^{Res} * e^{Move} - \sum_{i \in I}\sum_{c \in C} m_i^{Res} * v_{i,c} * e_c^{Res,com}$$

$$-\sum_{i \in I}\sum_{k \in K} x_{i,k}^{Feed} * d_i^{Feed} * e_k^{Feed,trans} \quad (3.4)$$

In salvage harvest, each harvest unit i can be harvested at most once by one of the available harvesting systems (Eq. (3.5)). The produced amount of each log type l equals the available amount at that unit if the unit is harvested (Eq. (3.6)).

$$\sum_{s \in S} y_{i,s} \leq 1 \qquad \forall\, i \in I \quad (3.5)$$

$$x_{i,l}^{Log} = \sum_{s \in S} y_{i,s} * m_{i,l}^{Log} \qquad \forall\, l \in L, i \in I \quad (3.6)$$

For residue treatment, if a unit is harvested by the LS system, logging residues are left on-site for decaying (Eq. (3.7)). If logging residues are burnt, the unit should be harvested by the WT system (Eq. (3.8)). If logging residues are used for bioenergy production, the unit should be either harvested by the WT or WTwS system (Eq. (3.9)).

$$z_{i,decay} = y_{i,ls} \qquad \forall\, i \in I \quad (3.7)$$

$$z_{i,burn} \leq y_{i,wt} \qquad \forall\, i \in I \quad (3.8)$$

$$z_{i,use} \leq y_{i,wt} + y_{i,wtws} \qquad \forall\, i \in I \quad (3.9)$$

At each unit, if no logging residues are utilized, none comminution methods should be chosen. Otherwise, one comminution method should be chosen to process logging residues (Eq.

(3.10)). Specifically, the chipping method can only be used at units harvested by the WTwS system while grinding only or grinding with screening can be used at units harvested by the WT system (Eqs. (3.11-3.12)). For the entire forest site, if logging residues from any unit are processed by a comminution equipment, this equipment need to be deployed to the site (Eq. (3.13)).

$$\sum_{c \in C} v_{i,c} = z_{i,use} \qquad \forall\, i \in I \tag{3.10}$$

$$v_{i,chip} = y_{i,wtws} \qquad \forall\, i \in I \tag{3.11}$$

$$v_{i,grind} + v_{i,gws} \leq y_{i,wt} \qquad \forall\, i \in I \tag{3.12}$$

$$|I| * u_c \geq \sum_{i \in I} v_{i,c} \qquad \forall\, c \in C \tag{3.13}$$

At each unit, as outputs from the comminution process, low-quality feedstock is produced from the grinding operation and high-quality feedstock is produced from chipping or grinding with screening operations (Eqs. (3.14-3.15)). The total amount of feedstock used for all bioenergy products equals the available feedstock in each type (Eq. (3.16)).

$$x_{i,low}^{Feed} = m_i^{Res} * v_{i,grind} \qquad \forall\, i \in I \tag{3.14}$$

$$x_{i,high}^{Feed} = m_i^{Res} * (v_{i,gws} + v_{i,chip}) \qquad \forall\, i \in I \tag{3.15}$$

$$x_{i,k}^{Feed} = \sum_{p \in P} x_{i,k,p}^{Feed} \qquad \forall\, k \in K, i \in I \tag{3.16}$$

Lastly, Eqs. (3.17-3.18) show variable type constraints for continuous and binary variables for the MOO model.

$$x_{i,l}^{Log}, x_i^{Res}, x_{i,k,p}^{Feed}, x_{i,k}^{Feed} \in R_+ \qquad \forall\, l \in L, k \in K, i \in I, p \in P \tag{3.17}$$

$$y_{i,s}, z_{i,t}, u_c, v_{i,c} \in \{0,1\} \qquad \forall\, t \in T, c \in C, i \in I \tag{3.18}$$

We compared the Sequential and Integrate scenarios in managing the supply chain of salvaging beetle-killed stands in the Colorado State Forest. The Sequential scenario was simulated by sequentially optimizing the TSC and BSC in two steps with regards to their individual performances and then combining the performance of the two solutions for overall solution quality (Figure 3.3), whereas the Integrated scenario was simulated by simultaneously optimizing the overall performance of the two supply chains (Figure 3.4). The detailed procedures are as following.

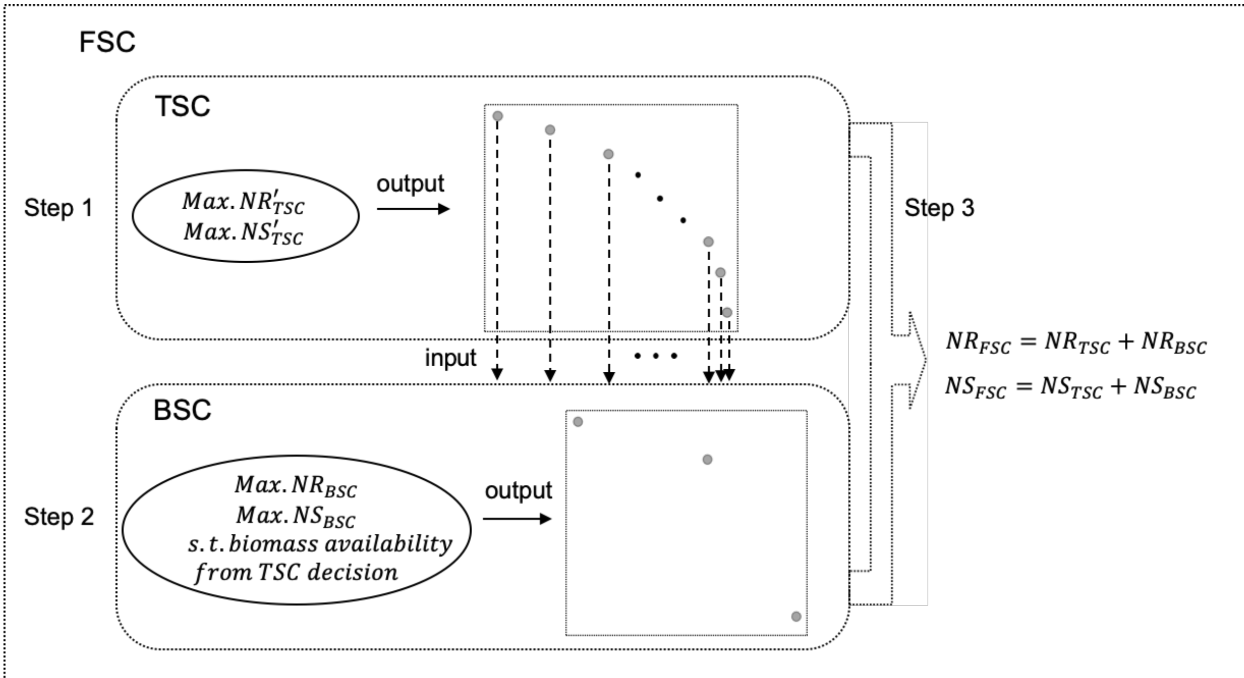

Figure 3.3 Modeling steps in the Sequential scenario.

Sequential scenario:

Step 1: Solve the TSC MOO model with objective functions to maximize NR'_{TSC} and NS'_{TSC} (Eq. (3.19-3.20)), subject to constraints Eq. (3.5-3.7, 3.17-3.18, 3.21-3.24). NR'_{TSC} and NS'_{TSC} are not the final TSC net revenues and net GHG emission savings but are estimated values where logging residues from all WT harvested units are burnt. Due to lack of cooperation between the TSC and BSC, when the infested forest is managed for salvage harvest, it is unknown whether logging residues from WT harvested units are to be used for bioenergy production or not. NR'_{TSC}, NS'_{TSC}, and $z'_{i,burn}$ are used to conservatively estimate TSC performances where piled logging residues are treated as wastes (Eq. (3.23)) and account for costs and GHG emissions associated with burning. Without cooperation with bioenergy production, timber production would not use WTwS system for salvage harvest (Eq. (3.24)) because it is always more expensive than the WT system. This step mimics the process where harvesting operations at the TSC are conducted without consideration for residue utilization at the BSC. The outputs of TSC MOO model are solutions for timber production showing trade-offs between NR'_{TSC} and NS'_{TSC}. For each solution, harvesting decisions are used as inputs to the BSC MOO model, indicating availabilities of logging residues at harvest units.

$$Economic\ objective: Maximize\ NR'_{TSC} \tag{3.19}$$

$$Environmental\ objective: Maximize\ NS'_{TSC} \tag{3.20}$$

where

$$NR'_{TSC} = \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * r_l^{Log} - \sum_{i\in I} a_i * c_i^{Admin} - \sum_{i\in I}\sum_{s\in S}\sum_{l\in L} m_{i,l}^{Log} * y_{i,s} * c_{i,s}^{Log,har}$$
$$-c^{burn} * \sum_{i\in I} a_i * z'_{i,burn} - \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * d_i^{Log} * c_l^{Log,trans} \tag{3.21}$$

$$NS'_{TSC} = \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * s_l^{Log} - \sum_{i\in I}\sum_{s\in S}\sum_{l\in L} m_{i,l}^{Log} * y_{i,s} * e_{i,s}^{Log,har}$$
$$-GWP_{bio}^{decay} * e^{decay} * \sum_{i\in I}\left(\left(\sum_{l\in L} m_{i,l}^{Log} + m_i^{Res}\right)\left(1 - \sum_{s\in S} y_{i,s}\right) + m_i^{Res} * z_{i,decay}\right)$$
$$-GWP_{bio}^{burn} * e^{burn} * \sum_{i\in I} m_i^{Res} * z'_{i,burn} - \sum_{i\in I}\sum_{l\in L} x_{i,l}^{Log} * d_i^{Log} * e_l^{Log,trans} \tag{3.22}$$

$$z'_{i,burn} = y_{i,wt} \qquad \forall\, i \in I \tag{3.23}$$

$$y_{i,wtws} = 0 \qquad \forall\, i \in I \tag{3.24}$$

Step 2: Corresponding to each solution from the TSC MOO model, solve the BSC MOO model with objective functions to maximize NR_{BSC} and NS_{BSC} (Eq. (3.25-3.26)), subject to constraints Eq. (3.3-3.4, 3.8-3.18). In the BSC MOO model, $y_{i,wt}$ and $y_{i,wtws}$ in Eq. (3.8-3.9) are not variables but input values read from the TSC solution. This step mimics the process that availabilities of logging residues are assessed post-harvest and the landowner determines whether to process residues for bioenergy production, what bioenergy pathway to choose, and how much amount of feedstock to produce. The outputs of the BSC MOO model are solutions for bioenergy production showing trade-offs between NR_{BSC} and NS_{BSC} based on the residue availability from the input TSC solution. Because each TSC solution represents a new situation for the residue availability, a new Pareto front is generated in the BSC MOO model.

$$Economic\ objective: Maximize\ NR_{BSC} \tag{3.25}$$

$$Environmental\ objective: Maximize\ NS_{BSC} \tag{3.26}$$

Step 3: Based on timber production and biomass utilization decisions made from Steps 1 and 2, calculate NR_{TSC} and NS_{TSC} (Eq. (3.1-3.2)) and combine with NR_{BSC} and NS_{BSC} to obtain NR_{FSC} and NS_{FSC} (Eq. (3.27-3.28)). In this step, every Step 1 TSC solution corresponds to a Step 2 BSC Pareto solution set.

$$NR_{FSC} = NR_{TSC} + NR_{BSC} \tag{3.27}$$

$$NS_{FSC} = NS_{TSC} + NS_{BSC} \tag{3.28}$$

Integrated scenario:

Step 1: Solve the integrated FSC MOO model with objective functions to maximize NR_{FSC} and NS_{FSC} (Eq. (3.29-3.30)), subject to constraints Eq. (3.1-3.18, 3.27-3.28). This step mimics the process that timber and bioenergy production is jointly managed during the decision-making process to optimize the overall economic and environmental performances of the forest supply chain. The outputs of the FSC MOO model are solutions for timber and bioenergy production showing trade-offs between NR_{FSC} and NS_{FSC}.

$$Economic\ objective: Maximize\ NR_{FSC} \tag{3.29}$$

$$Environmental\ objective: Maximize\ NS_{FSC} \tag{3.30}$$

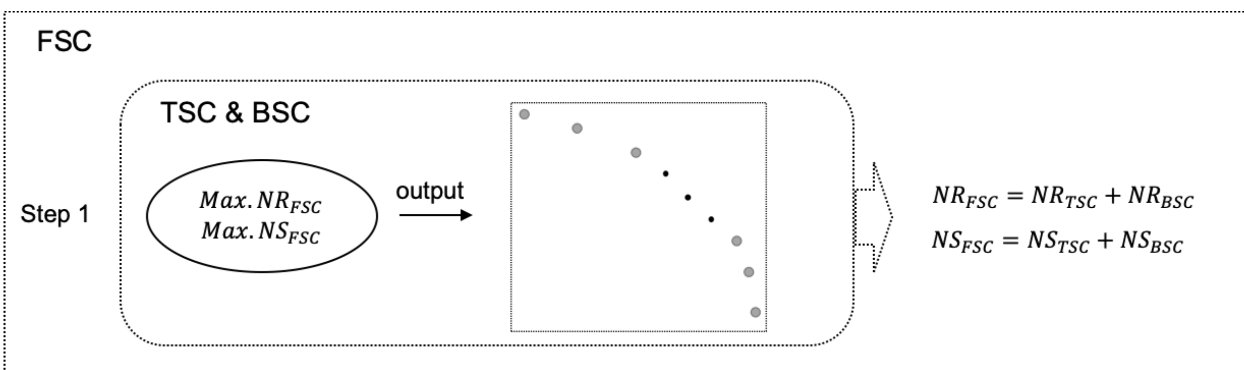

Figure 3.4 Modeling steps in the Integrated scenario.

3.3.2 Model solving

In order to solve MOO models, we applied the augmented ε-constraint (AUGMECON) method (Mavrotas 2009) which was developed based on the widely used ε-constraint method (Ehrgott 2006). During the solving process, an MOO model is first reformulated as single objective problems and solved to obtain bounds of each objective. Then one objective is selected and the others are transformed to additional constraints. The new single objective optimization problem is solved iteratively where in each iteration, the right-hand side of an objective converted constraint is changed with a user-specified step-size of ε value. The AUGMECON method improves the ε-constraint method in the sense that it uses lexicographic optimization to identify objective bounds. Slack variables are added to objective converted constraints and the final objective function to avoid the production of weakly Pareto optimal solutions (Mavrotas 2009).

In our bi-objective MOO models, after identifying bounds of each objective through single objective optimization, the environmental objective was converted to the additional ε-constraint and the economic objective was used as the objective function during the iterative optimization process. In the Sequential scenario, the TSC MOO model in Step 1 consisted 2526 constraints, 3135 binary variables, and 1896 continuous variables and the BSC MOO model in Step 2 consisted 4413 constraints, 3766 binary variables, and 1896 continuous variables. A set of 50 Pareto-optimal points was generated from the TSC MOO model and corresponding to each TSC solution, a set of 3 Pareto-optimal points was generated in the BSC MOO model. In the Integrated scenario, the FSC MOO model consisted 6942 constraints, 5647 binary variables, and 3794 continuous variables and a set of 50 Pareto-optimal points was generated. All MOO models were formulated in Python 2.7 and solved by the MIP solver CPLEX 12.6.3 on a computer with an Intel 3.40 GHz processor and 16 GB memory. Solving time for the Sequential and Integrate scenarios was 264 and 629 seconds, respectively.

We used 0.1 and 0.32 for GWP_{bio}^{decay} and GWP_{bio}^{burn} to discount the global warming potential (Corporation and Curran 2006) of biogenic carbon relative to fossil carbon (Liu et al. 2017). Other process parameters and product data used in MOO models are provided in Tables 3.2 and 3.3. The detailed estimation process of all parameters can be found in Appendix A.

Table 3.2 Process parameters.

Unit process	Criteria	Value	Assumptions and references
Timber harvesting			
Administration	Cost	494.21 $/ha	Sale preparation, environmental analysis, and harvest monitoring costs at 200 $/acre (Abt et al. 2011).
Salvage harvest	Cost	21.51~122.66 $/odt	Harvesting costs and GHG emissions for each system at each unit are estimated based on She et al. (2018)
	Emission	9.74~55.90 kg CO_2-eq/odt	
Residue treatment			
Chipping	Cost	18.14 $/odt	A chipper processes logging residues (Spinelli et al. 2012; Jernigan et al. 2013)
	Emission	12.14 kg CO_2-eq/odt	
Grinding	Cost	22.81 $/odt	A grinder processes clearcut roundwood logging residues without screening (Dukes et al. 2013).
	Emission	16.19 kg CO_2-eq/odt	
Grinding with screening	Cost	48.45 $/odt	A grinder processes clearcut roundwood logging residues with screening (Dukes et al. 2013).
	Emission	35.81 kg CO_2-eq/odt	
Burn	Cost	200 $/ha	Burning logging residues on site (Rummer 2008; Lee et al. 2011).
	Emission	1740 kg CO_2-eq/odt	
Decay	Emission	1580 kg CO_2-eq/odt	Scattered residues decay on forest floor (Lee et al. 2011).
Transportation			
Log	Cost	0.1735 $/odt*km	Two-way transportation with log truck payload of 26.7 t. Cost is $2.52/mile and fuel economy is 5.1 mile/gallon (Mason et al. 2008).
	Emission	0.1695 kg CO_2-eq/odt*km	
Feedstock	Cost	0.2038 $/odt*km	Two-way transportation with chip van payload of 22.7 t. Cost is $0.2038/km and fuel economy is 1.98 km/L (Beck and Sessions 2013; Loeffler and Anderson 2014).
	Emission	0.2183 kg CO_2-eq/odt*km	

Table 3.3 Timber and bioenergy product details.

Product	Criteria*	Value	Assumptions and references
Timber			
Saw log	a	81.53	Lumber has a recovery ratio of 0.46 (Keegan III et al.
	b	1125.12	2010) and substitutes steel stud (Bergman et al. 2014).
Post and pole	a	58.70	Pole is used as fences and stores carbon during service
	b	705.13	life (Bergman et al. 2014).
Firewood	a	48.92	Firewood is combusted in a fireplace for domestic
	b	389.31	heating, substituting natural gas (Katers et al. 2012).
Residue utilization			
Low-quality feedstock	a	55.10	Hog fuel combusted in a boiler to generate electricity,
(hog fuels)	b	1107.23	substituting coal (Loeffler and Anderson 2014).
High-quality feedstock	a	70.00	Pellet combusted in a pellet stove for domestic heating,
(pellets)	b	203.17	substituting natural gas (Katers et al. 2012).
High-quality feedstock	a	43.43	Pyrolysis outputs contain 17.5% biochar and 82.5%
(biochar & syngas)	b	983.72	syngas (Bergman et al. 2017), which are used as soil
			amendments and to generate electricity, respectively.

* a. Product unit revenue ($/odt), b. Product unit GHG emission savings (kg CO_2-eq/odt)

3.4 Results

3.4.1 Salvage harvest and residue treatment in the Sequential scenario

In the Sequential scenario, TSC solutions are sorted (x-axis) according to the environmental objective (i.e., NS'_{TSC}) in the TSC MOO model (Figure 3.5). Only LS and WT systems are used for salvage harvesting in all TSC MOO model solutions and logging residues are either decayed, burnt, or used for hog fuels in BSC MOO model solutions. The maximum NR'_{TSC} solution leads to 919.35 ha of forest area being harvested (93% by LS and 7% by WT), resulting in a production of 84.76 thousand (M) odt of timber products (63% saw logs, 22% post and pole, and 15% firewood). As the TSC MOO model focuses more on the environmental objective, meaning a higher NS'_{TSC} needs to be satisfied as the additional ε-constraint during the optimization process, LS harvested areas increase while WT harvested areas remain relatively constant. These WT areas eventually also switch to the LS system gradually as the environmental objective further increases and the entire forest stand is harvested by LS, where the maximum NS'_{TSC} solution is obtained at 203.67 M odt of timber products (52% saw logs, 27% post and pole, and 20% firewood) produced from 3070.43 ha of harvested forest area.

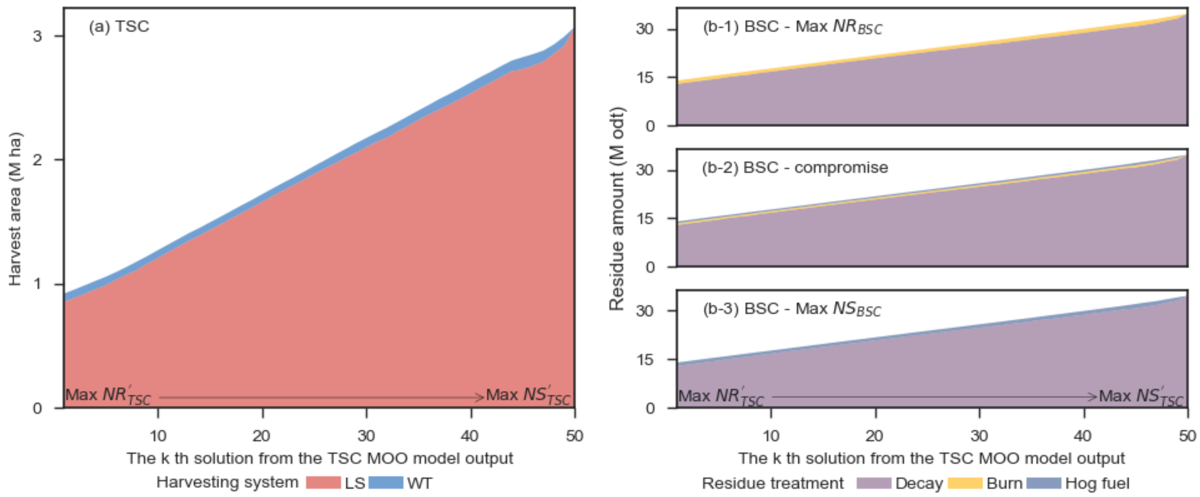

Figure 3.5 (a) Harvesting operations at timber supply chain (TSC) and (b) residue utilization at the bioenergy supply chain (BSC) in the Sequential scenario.

As for bioenergy production, the maximum NR'_{TSC} solution results in 12.89 odt of residues from LS harvested units that are left for decaying and 1.07 odt of residues from WT harvested units that are available for further utilization. The residues from WT units then become inputs to the BSC MOO model. The maximum NR_{BSC} solution results in all residues being burnt on site because no bioenergy pathway is economically feasible given the form and amount of available logging residues. The maximum NS_{BSC} solution results in all residues being utilized for hog fuels because they are the most GHG emission saving bioenergy product. A compromise solution, achieving the average NS_{BSC} of the previous two solutions, results in 0.53 odt of residues being burnt and 0.54 odt residues being utilized. As the TSC MOO model focuses more on the environmental objective, residue decay amount increases, while residue available for bioenergy production remains relatively constant. Depending on the ε-constraint in the BSC MOO model, residues are fully burnt, fully utilized for hog fuels, and partially burn and partially utilized in the maximum NR_{BSC} , the maximum NS_{BSC} , and the compromise solutions, respectively. Corresponding to the maximum NS'_{TSC} solution, no residues are available for further utilization so all BSC solutions lead to zero burning or hog fuel production.

3.4.2 Salvage harvest and residue treatment in the Integrated scenario

In the Integrated scenario, FSC solutions are sorted (x-axis) according to the environmental objective (i.e., NS_{FSC}) in the FSC MOO model (Figure 3.6). The maximum NR_{FSC} solution leads to 1,375.45 ha harvested (24% by LS, 57% by WT, and 19% by WTwS) and 109.78 M odt of timber products produced (59% saw logs, 24% post and pole, and 17% firewood). As the optimization shifts from maximizing NR_{FSC} to maximizing NS_{FSC}, a higher NS_{FSC} needs to be satisfied as the additional ε-constraint during the optimization process. As a result, LS harvested areas increase while WTwS harvested areas remain constant at first, but both change to the WT system when the NS_{FSC} is high enough. WT harvested areas increase throughout the whole process, either from harvesting previously unharvested areas or switching the harvest system at previously LS or WTwS harvested areas, until WT takes over the entire forest area of 3070.43 ha in the maximum NS_{FSC} solution.

For residue treatment at the BSC, no residue burning operations are ever chosen. The maximum NR_{FSC} solution leads to 4.97 M odt of residues being left for decaying and 13.30 M odt being used for pellet production (for comminution, 3.96 M odt are chipped and 9.34 M odt are ground and screened). As the optimization focuses more on maximizing NS_{FSC}, residue decay amount increases first and then decreases to zero, following the trend of LS harvested areas. Residue utilization amount increases because the WT system is applied to larger areas, providing greater amounts of logging residues available for bioenergy production. There is a transition in the bioenergy production from pellets (the most profitable product) to hog fuels (the most GHG emission saving product). The maximum NS_{FSC} solution utilizes 34.68 M odt of residues for hog fuel production.

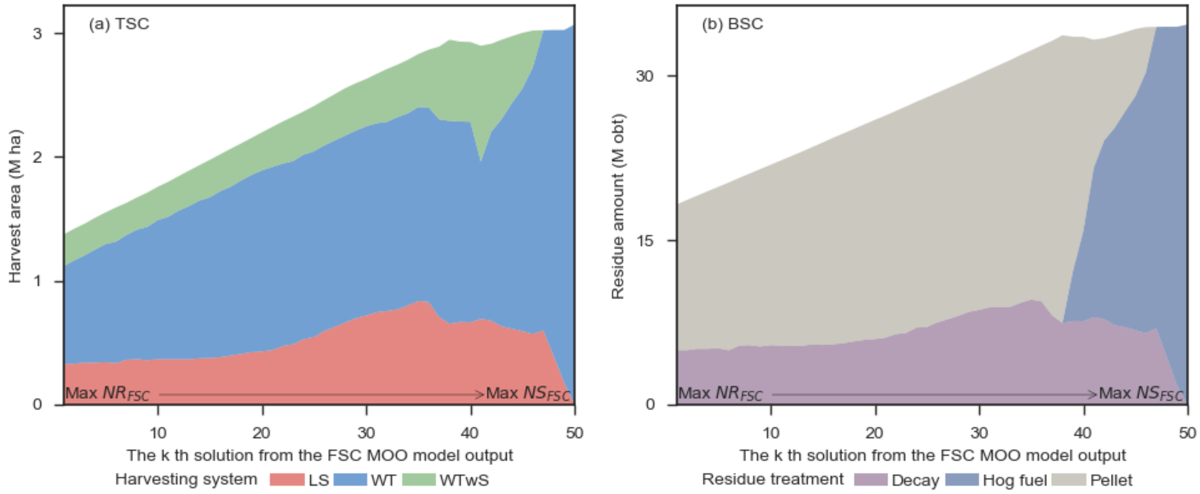

Figure 3.6 (a) Harvesting operations at timber supply chain (TSC) and (b) residue utilization at the bioenergy supply chain (BSC) in the Integrated scenario.

3.4.3 Net revenues and GHG emission savings in the Sequential and Integrated scenarios

The Sequential and Integrated scenarios produce distinctive results when either the economic or environmental objective is used for optimization (Table 3.4). In the Sequential scenario, maximizing NR'_{TSC} in the TSC MOO model and NR_{BSC} in the BSC MOO model generates 1.29 and 0 million (MM) \$ net revenues with 73.36 and 0 MM t CO_2-eq GHG emission savings from the TSC and BSC, respectively. Maximizing NR'_{TSC} from the TSC and NS_{BSC} from the BSC generates 1.31 and -0.03 million (MM) \$ net revenues with 73.96 and 1.11 MM t CO_2-eq GHG emission savings from the TSC and BSC, respectively. The increased NR_{TSC} and decreased NR_{BSC} in the second solution are shown because the TSC does not need to burn logging residues on-site and the BSC has to utilize them. When performances of TSC and BSC are combined, NR_{FSC} and NS_{FSC} of these two solutions are 1.29 MM \$ with 73.36 MM t CO_2-eq GHG emission savings and 1.28 MM \$ with 75.07 MM t CO_2-eq GHG emission savings. In the Integrated scenario, maximizing NR_{FSC} results in NR_{TSC}, NR_{BSC}, and NR_{FSC} being 1.18, 0.27, and 1.45 MM \$, respectively, and NS_{TSC}, NS_{BSC}, NS_{FSC} being 108.21, 2.21, and 110.42 MM t CO_2-eq GHG, respectively.

Table 3.4 Single objective optimization under Sequential and Integrated scenarios.

Scenario	Sequential		Integrated	Sequential		Integrated
Solution	$Max\ NR'_{TSC}$		$Max\ NR_{FSC}$	$Max\ NS'_{TSC}$		$Max\ NS_{FSC}$
	$Max\ NR_{BSC}$	$Max\ NS_{BSC}$		$Max\ NR_{BSC}$	$Max\ NS_{BSC}$	
NR_{TSC} (MM \$)	1.29	1.31	1.18	0.11	0.11	-0.32
NR_{BSC} (MM \$)	0	-0.03	0.27	0	0	-0.53
NR_{FSC} (MM \$)	1.29	1.28	1.45	0.11	0.11	-0.85
NS_{TSC} (MM t CO_2-eq)	73.36	73.96	108.21	224.76	224.76	230.42
NS_{BSC} (MM t CO_2-eq)	0	1.11	2.21	0	0	36.08
NS_{FSC} (MM t CO_2-eq)	73.36	75.07	110.42	224.76	224.76	266.50

Maximizing NS'_{TSC} in the TSC MOO model in the Sequential scenario results in 0.11 MM \$ net revenues with 224.76 MM t CO_2-eq GHG emission savings at the TSC. This corresponds to the solution where the entire forest is harvested by the LS system and no logging residues are available for the BSC to utilize. As a result, maximizing NR_{BSC} or NS_{BSC} leads to the same outputs, where 0 net revenues and 0 GHG emission savings are achieved at the BSC. In the Integrated scenario, maximizing NS_{FSC} results in NR_{TSC}, NR_{BSC}, and NR_{FSC} being -0.32, -0.53, and -0.85 MM \$, respectively, and NS_{TSC}, NS_{BSC}, and NS_{FSC} being 230.42, 36.08, and 266.50 MM t CO_2-eq GHG, respectively.

In the Sequential scenario, given the same TSC solution, the three BSC solutions only show small differences due to the small amount of residue available for bioenergy production (Figure 3.7). After combining TSC and BSC performances, the resulting three curves are not very distinct in terms of trade-offs between NR_{FSC} and NS_{FSC}. The Pareto front from the Integrated scenario lies above all curves of the Sequential scenario and provides a wider range of trade-offs between NR_{FSC} and NS_{FSC}. For both scenarios, trade-off curves have negative slopes because the two objectives, NR_{FSC} and NS_{FSC}, are conflicting and cannot be improved at the same time. When the optimization emphasizes the economic objective, a small compromise in NR_{FSC} causes significant improvements in NS_{FSC}. When the optimization is skewed toward the environmental objective, a much greater sacrifice has to be made in NR_{FSC} to obtain a small increase in NS_{FSC}.

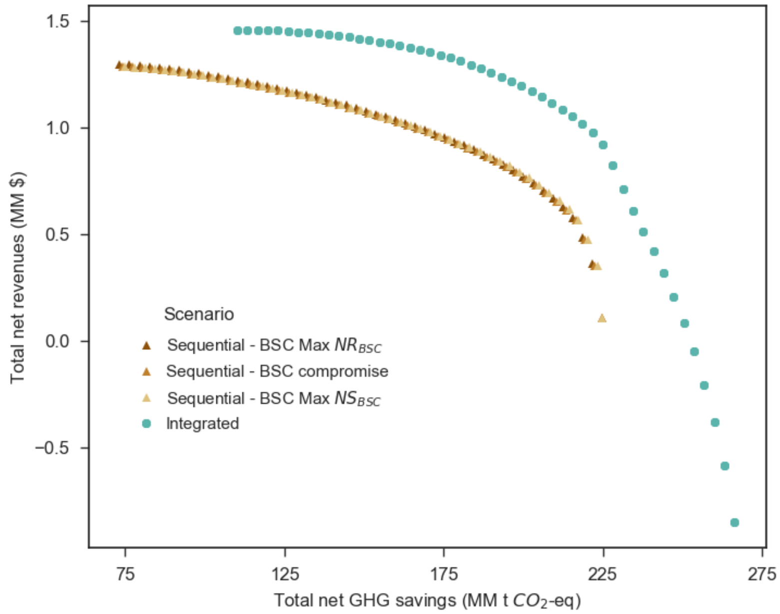

Figure 3.7 Trade-offs between NR_{FSC} *and* NS_{FSC} in the Sequential and Integrated scenarios.

3.5 Discussion

3.5.1 Fully economic-oriented or environmental-oriented solutions

When MOO models are fully economic-oriented (i.e., maximizing NR'_{TSC} and NR_{BSC} in the Sequential scenario and maximizing NR_{FSC} in the Integrated scenario), 49.6% more forest areas are harvested in the Integrated scenario (Figure 3.5 and 3.6), generating 12.3% more NR_{FSC} and 50.5% more NS_{FSC} than those in the Sequential scenario (Table 3.4). The distribution of the produced log products shows that the additional harvested areas are composed of the harvest units with lower saw log proportion, which indicates cooperation between the TSC and BSC results in the salvage harvest being economically feasible in larger harvest units. When MOO models are fully environmental-oriented (i.e., maximizing NS'_{TSC} and NS_{BSC} in the Sequential scenario and maximizing NS_{FSC} in the Integrated scenario), the entire beetle-infested forest is harvested under both scenarios. The Integrated scenario utilizes all logging residues for hog fuel production and achieves 18.6% greater NS_{FSC}, but results in loss of 0.96 MM \$ in NR_{FSC} compared to the Sequential scenario solution.

While the fully environmental-oriented solutions may be economically prohibitive for practical implementations, operations following fully economic-oriented solutions are commonly practiced. In the current salvage harvest in Colorado State Forest, timber salvage and residue utilization are managed by the landowner as two separate operations with economic feasibility being the main consideration for either operation, similar to the fully economic-oriented solution in the Sequential scenario. During the salvage harvest, although the WT system can be less expensive than the LS system when the skidding distance is short, the extra burning cost disfavors its application (Han et al. 2018). Without knowing whether residues are to be utilized, the landowner has preferred the LS system for salvage harvest up to date because it is easy to implement and more economical for slash management (Berryman et al. 2015). This suboptimal decision may lead to higher harvesting cost at the TSC and a small amount of residues in undesirable form for bioenergy production at the BSC. Consequently, only a small portion of infested forests are harvested and no bioenergy products are produced from logging residues.

In this study, the fully economic-oriented solutions clearly demonstrate that the Integrated scenario outperforms the Sequential scenario in both NR_{FSC} and NS_{FSC}. Our analysis confirms that the BSC generates net revenues and GHG emission savings at a much smaller scale than the TSC. However, timber production should still be managed together with bioenergy production to prepare residues in a desirable form for bioenergy production and avoid on-site pile burning. The joint management in the TSC and BSC, through an integrated decision-making process, results in quite distinct decisions in salvage harvest and residue utilization (Figure 3.6) compared to those in the Sequential scenario (Figure 3.5). The integrated solution promotes more efficient use of logging residues and thus can benefit the landowner both economically and environmentally.

3.5.2 Trade-offs between NR_{FSC} and NS_{FSC}

As the ε-constraint sets a higher environmental objective, harvest areas increase in both scenarios, but the difference in harvest system selection is apparent. The Sequential scenario favors the LS system to avoid residue burning (Figure 3.5) while the Integrated scenario favors WT and WTwS systems to facilitate bioenergy production (Figure 3.6). As a result, logging residue availability and utilization is limited in the Sequential scenario (Figure 3.5), whereas utilized residue amount increases and bioenergy production switches from the most profitable product (*i.e.*, pellets) to the most GHG saving product (*i.e.*, hog fuels) in the Integrated scenario.

In terms of trade-offs between NR_{FSC} and NS_{FSC} (Figure 3.7), all three curves of the Sequential scenario are completely dominated (Zitzler and Thiele 1998) by the Pareto front of the

Integrated scenario, meaning for any solution from the Sequential scenario, there always exists at least one solution from the Integrated scenario that outperforms in both NR_{FSC} and NS_{FSC}. Therefore, the Integrated scenario is proved strictly better than the Sequential scenario.

3.5.3 Impact of carbon accounting on trade-offs between NR_{FSC} and NS_{FSC}

Carbon accounting has a strong influence on evaluating the GHG emission savings of timber and bioenergy products. Because the estimation of carbon sequestration (e.g., biomass growth, soil carbon pool, land use changes) is site-specific, the exact values of GHG emission savings provided by woody products are often uncertain (Cherubini et al. 2009). The assumption of carbon neutrality of all biogenic sources appears to be inappropriate and has raised debate especially on how to account for carbon emissions from burning woody materials (Katers et al. 2012; Zanchi et al. 2012; Guest et al. 2013). We explored different GWP_{bio}^{burn} values when solving the MOO models to assess the influence of carbon accounting on trade-offs between NR_{FSC} and NS_{FSC} (Figure 3.8). GHG emissions from biomass burning are treated equivalently to biomass decay emissions when GWP_{bio}^{burn} equals 0.1 and equivalently to fossil carbon when GWP_{bio}^{burn} equals 1.0. The results show a significant difference in the Pareto fronts when different GWP_{bio}^{burn} values are used for GHG accounting. As GWP_{bio}^{burn} increases from 0.1 to 1, the maximum NR_{FSC} in the Sequential and Integrated scenarios do not change because economic features of timber and bioenergy products remain the same. However, the maximum NS_{FSC} of the two scenarios decrease drastically because carbon benefits of timber and bioenergy products are considered much smaller. Trade-offs between NR_{FSC} and NS_{FSC} become more apparent with low GWP_{bio}^{burn} cases than high GWP_{bio}^{burn} cases because with high GWP_{bio}^{burn},greater economic compromises should be made to obtain the same environmental improvement. In addition, the GWP_{bio}^{burn} also affects the bioenergy product produced. If GWP_{bio}^{burn} equals 0.1 or 0.32, meaning burning woody biomass has small global warming potential relative to emitting fossil carbon, substituting coal with hog fuels is the most GHG emission saving pathway and is selected to achieve high NS_{FSC}. In contrast, if GWP_{bio}^{burn} equals 1, meaning there is no difference between burning woody biomass and emitting fossil carbon, producing biochar to preserve carbon is the most GHG emission saving pathway and is selected to achieve high NS_{FSC}.

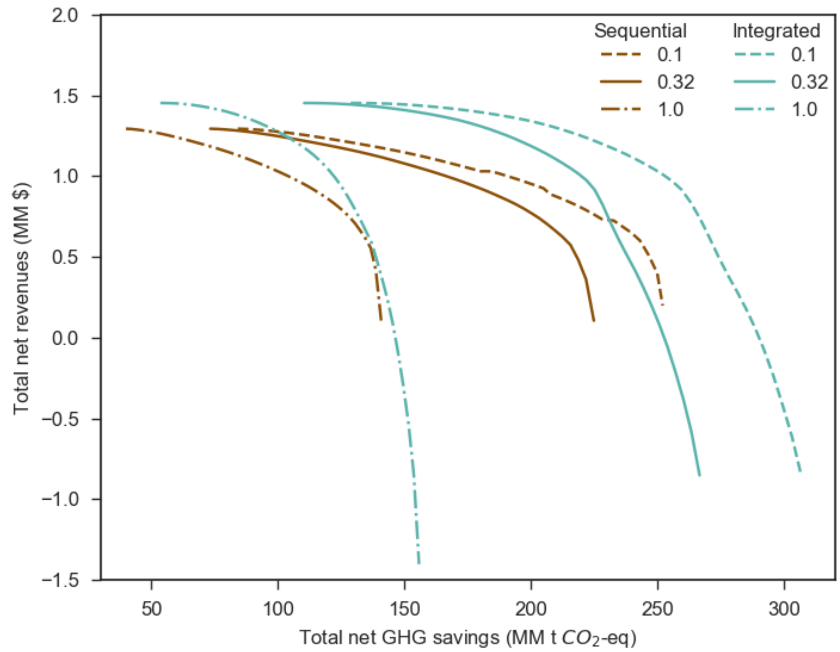

Figure 3.8 Trade-offs between NR_{FSC} and NS_{FSC} in the Sequential and Integrated scenarios with various GWP_{bio}^{burn}.

Given the same GWP_{bio}^{burn} value, the Integrated scenario always outcompetes the Sequential scenario, shown by the dominating relationship of the two trade-off curves (Zitzler and Thiele 1998). This is because cooperation between the TSC and BSC in the Integrated scenario avoids residue burning and facilitates bioenergy production no matter what the GWP_{bio}^{burn} value is. However, as GWP_{bio}^{burn} increases from 0.1 to 1, the gap between trade-off curves shrinks, indicating a decreasing difference in trade-offs between NR_{FSC} and NS_{FSC} of the two scenarios. This is because higher GWP_{bio}^{burn} decreases the amount of carbon benefits of timber and bioenergy products, and therefore the gain in NS_{FSC} is not as significant as in the low GWP_{bio}^{burn} case.

3.6 Conclusion

Salvage harvesting of beetle-kill trees in northern Colorado provides an opportunity to mitigate economic losses and produce carbon benefits. Our multi-objective optimization analysis shows that the Integrated scenario representing joint management for timber and bioenergy production can enhance the economic feasibility of forest salvage utilization and simultaneously increases GHG emission savings. When the optimization is fully economic-oriented, the Integrated scenario tends to harvest more forest areas and produce more bioenergy products than the

Sequential scenario, generating greater total net revenues and GHG emission savings from timber and bioenergy production. Comparison of Pareto fronts indicates the Integrated scenario offers more efficient trade-offs between NR_{FSC} and NS_{FSC} and always outperforms the Sequential scenario in both objectives even under different carbon accounting scheme. From landowner's perspective, the Integrated scenario generates more profits and requires less monetary sacrifice than the Sequential scenario for the same GHG emission savings.

Chapter 4

Using Multi-objective Record-to-Record Travel metaheuristic to solve forest supply chain management problems with economic and environmental objectives

Abstract

Multi-objective optimization has been increasingly used to assist decision-making in forest management with consideration in multiple aspects that are sometimes conflicting with each other. Exact methods have been used to solve such problems and produce the Pareto front as the output, where one objective of any solution cannot be improved without sacrificing other objectives. However, some forest management practice, such as forest supply chain problems, may deal with combinatorial optimization that involves many units, products, processes and many planning periods, with multiple objectives and large sets of constraints. The computation complexity increases exponentially and becomes overwhelming for exact methods. We propose a multiple-objective metaheuristic method, referred to as Multi-objective Record-to-Record Travel (MRRT), to solve such challenging problems. We examined the performance of MRRT on a forest supply chain multi-objective optimization problem where net revenues and greenhouse gas emission savings from the salvage harvest and utilization of beetle killed forest stands are simultaneously considered. Solutions from the MRRT algorithm were compared against those obtained from a Mixed Integer Programming (MIP) optimizer. Through testing on four cases of different sizes, we showed that MRRT performed satisfactorily in approximating the actual Pareto fronts (in terms of both convergence and coverage) and distribution of solutions was approximately uniform. MRRT

produced such solutions within reasonable computation time and the computational advantage over MIP was more apparent for large-scale test cases.

Key words: Multi-objective optimization, metaheuristics, forest supply chain

4.1 Introduction

Linear Programming (LP), Integer Programming (IP), and Mixed Integer Programming (MIP) have long been used as optimization tools in forestry such as selection of silvicultural regime and regeneration strategies, harvesting and transportation management, and cutting pattern selection (Rönnqvist et al. 2015). Traditionally, these mathematical programming models are formulated given an objective function to optimize (e.g., maximizing net present value, minimizing deviations in wood flow) and a series of constraints to satisfy (e.g., capacity limitation, harvest area restriction) which represent the management goal and limitations in practice, respectively (Kaya et al. 2016). The obtained optimal solution assists forest managers and public forestry organizations in their decision-making (D'Amours et al. 2008).

With an increasing interest in addressing sustainability considerations in forest management, multi-objective optimization, as one of the most popular multi-criteria decision-making methods, has been widely applied to account for multiple, non-comparable, and sometimes conflicting objectives simultaneously (Ananda and Herath 2009). The output of multi-objective optimization is a set of "Pareto optimal" nondominated solutions, of which there is no other solution that is equal or better in all objectives (i.e., dominate this solution) (Ehrgott 2005). In these solutions, one objective cannot be improved without sacrificing other objectives and the solutions form the Pareto front which shows trade-offs among objectives (Deb 2001). Decision makers can then select solutions that balance among objectives such as economic gains (e.g., property values), ecosystem services (e.g., water quality, wildlife habitat), and social influences (e.g., job generation, public acceptance) (Yue et al. 2013; Schroder et al. 2016). In recent years, the application of multi-objective optimization has grown substantially in forest biomass supply chain management as the bioenergy/biofuel industry expands (Cambero and Sowlati 2014). In addition to an economic objective (e.g., minimizing logistics costs, maximizing net revenues), many studies incorporate an environmental objective that minimizes greenhouse gas emissions (You and Wang 2011; You et al. 2012; Kanzian et al. 2013) or maximizes carbon benefits

(Sacchelli et al. 2014; Cambero et al. 2016b) of the supply chain network. The goal is to design the supply chain to efficiently utilize the biomass resource and perform satisfactorily in both economic and environmental aspects.

In order to solve multi-objective optimization problems (MOPs), many exact methods have been proposed including the weighted sum method, the two-phase method, the ε-constraint method, modified branch and bound methods (Ehrgott 2005). Although any solution identified is Pareto optimal, there is no guarantee that all Pareto optimal solutions can be found and the solution time varies substantially (Tóth et al. 2006). In addition, many forest management problems deal with combinatorial optimization so that as the problem scale increases, the computation complexity increases exponentially and becomes overwhelming (Bettinger et al. 2016). For these problems, even solving single-objective optimization (i.e., one optimal solution) with exact methods is prohibitive, not to mention the difficulty of finding the Pareto front in multi-objective optimization. Since forest supply chain planning typically involves many units, products, processes and many planning periods, with multiple objectives and large sets of constraints, it easily becomes a large scale MOP that is difficult to be solved (Rönnqvist et al. 2015).

A number of metaheuristic methods, referred as multi-objective metaheuristics (MOMHs), have been developed as alternatives to exact methods to tackle challenging MOPs (Gandibleux et al. 2004). Instead of trying to find all efficient solutions, MOMHs intend to obtain satisfactory nondominated solutions that approximate the Pareto front as much as possible within reasonable computation time (Durillo and Nebro 2011). Through testing on various benchmark problems (Zitzler and Thiele 1999; Zitzler et al. 2000; Huband et al. 2006), many MOMHs have demonstrated strong performances (Zhang and Li 2007; Zouache et al. 2018). However, while newly emerged MOMHs continue to strengthen performances, their algorithm structure also becomes increasingly complex which involves a number of sub-processes and contains many parameters that require user-inputs and fine tuning. Not only does it contribute to the algorithm computation complexity, it also complicates the parameterization process because determining parameter values itself becomes a combinatorial optimization problem. Since parameters in metaheuristics are highly instance sensitive, meaning that no common values are suitable for solving all problems, a complicated parameterization process is effort-demanding and significantly restricts the algorithm adaptability and application. Nevertheless, this is often neglected in MOMH development and few efforts have been seen in exploring simple algorithms.

Record-to-Record Travel (RRT) algorithm (Algorithm 1) was proposed for single-objective optimization with the intention of identifying a high performance Monte Carlo method with a simpler algorithm structure than Simulated Annealing (Dueck and Scheuer 1990; Dueck 1993). The simplification aims at accelerating algorithm run time and easing parametrization process. In RRT, only two parameters are required: an allowed disimprovement *deviation* and a terminating condition (e.g., number of iterations). During the RRT optimization process, these two parameters control the extent of exploitation and exploration, respectively. The random search at each iteration is generated from the local record and is constrained within the deviating range of the global record. The search process is terminated and the global record is reported when the terminating condition is fulfilled.

Algorithm 1 Record-to-Record Travel (RRT)*

Generate a random initial solution $\boldsymbol{x}$, local record $\boldsymbol{l} \leftarrow \boldsymbol{x}$, global record $\boldsymbol{g} \leftarrow \boldsymbol{x}$
Determine an allowed deviation $\boldsymbol{dev} > \boldsymbol{0}$
while terminating condition not met **do**
    Generate a candidate solution $\boldsymbol{x}$ randomly from the neighborhood of $\boldsymbol{l}$
    if $\boldsymbol{x} > \boldsymbol{g} * (\boldsymbol{1} - \boldsymbol{dev})$ **then**
        $\boldsymbol{l} \leftarrow \boldsymbol{x}$
        if $\boldsymbol{x} > \boldsymbol{g}$ **then**
            $\boldsymbol{g} \leftarrow \boldsymbol{x}$
        end if
    end if
end while
Output $\boldsymbol{g}$

* The algorithm is used for a maximization problem.

Although high quality outputs have been reported in most applications (Li et al. 2007; Mafarja and Abdullah 2015), the RRT algorithm has not received much attention since developed relative to other metaheuristic algorithms, such as Simulated Annealing and Tabu Search (Glover 1989). To the best of our knowledge, the RRT algorithm has never been modified or adapted for multi-objective optimization. However, simpler solution processes and fewer parameters in RRT could be an advantage when tackling complex MOPs that require intensive computation for repeated solution comparisons.

In this study, we develop a new MOMH, referred to as Multi-objective Record-to-Record Travel (MRRT), based on RRT for multi-objective optimization. We incorporate a population strategy that facilitates parallel searching to increase the algorithm efficiency. We apply MRRT to a combinatorial optimization problem in forest management where two objectives are of interests. The problem focuses on salvaging forests infested by the mountain pine beetle (*Dendroctonus ponderosae*) for timber and bioenergy production, in which sound supply chain planning is needed to make timely and efficient use of these resources from both economic and environmental perspectives. Four test cases are created with different numbers of units and time periods involved in management to examine MRRT in solving multi-objective optimization at various problem scales. The mathematical programming formulation is also developed and solved via the mixed-integer programming (MIP) approach to build the actual Pareto front in each test case. Performances of the MRRT and MIP approaches are compared in terms of solution quality and computation time.

4.2 Problem statement

The recent mountain pine beetle epidemic has affected a massive area of forests in North America, caused high rates of tree mortality, and created a vast amount of dead forest resource (US Department of Agriculture Forest Service 2017). Salvage harvesting dead trees for timber and forest biomass, such as logging residues (e.g., degraded wood, tree tops, branches and non-merchantable parts) for bioenergy production provides an opportunity to utilize forest resources that are otherwise wasted, and to contribute to the economies of rural areas and local wood product industries. Environmentally, utilization of infested forests creates carbon benefits by reducing dead wood decay emissions (Campbell et al. 2016), replacing non-wood alternatives that require more energy intensive manufacturing than timber products (Werner et al. 2005; Gustavsson et al. 2006), and reducing greenhouse gas (GHG) emissions by using bioenergy to replace fossil fuel burning (Lamers et al. 2014).

Managing the supply chain of beetle-killed timber and biomass considering both the net revenues and GHG emission savings presents a multi-objective optimization problem. In Colorado State Forest (40°57′N, 106°00′W), lodgepole pine (*Pinus contorta*) forests (Figure 4.1) have been heavily impacted by the MPB outbreak since 2008 and the current mortality rate is 47.3% (Han et al. 2018). We selected a portion of the Colorado State Forest as our study area (size: 3,400 ha, stand density: 865 trees ha^{-1}, basal area: 34.6 m^2 ha^{-1}) that is located in relatively flat terrain (i.e., slope < 35%) and close to existing roads (i.e., average skidding distance < 610 m, or 2,000 ft) so that ground-based clearcut operations are applicable. Forest salvage harvest in the study area typically produces three log products (i.e., saw logs, post and pole, and firewood depending on small-end diameter) and one potential bioenergy product (i.e., pellet). Timber and biomass harvesting, collection and transport operations incur associated costs and produce GHG emissions throughout the supply chain, whereas revenues and GHG emission savings are usually realized when end products are used (Figure 4.1). The two objectives in the beetle kill salvage harvest and utilization are set to maximize net revenues and net GHG emission savings of the supply chain network.

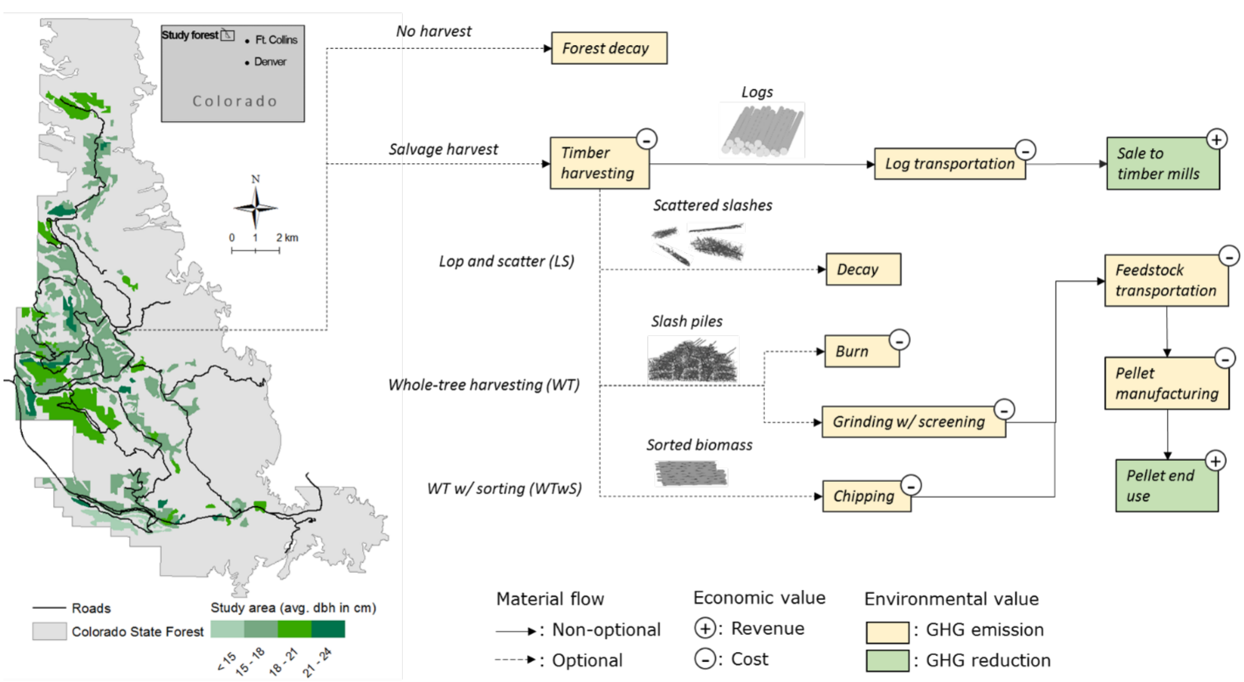

Figure 4.1 Forest supply chain for beetle kill timber and pellet production in Colorado State Forest.

Three harvesting systems, *lop-and-scatter* (LS), *whole-tree harvesting* (WT), and *whole-tree harvesting with sorting* (WTwS), can be configured with the same set of equipment for timber harvest and are considered in this study. The LS system delimbs and bucks trees to logs at the stump, resulting in logging residues dispersed over the harvest unit and left on the forest floor for decaying (i.e., not economical to collect). In contrast, whole trees are transported in WT and WTwS systems by a skidder and processed at the landing by delimbers. WTwS includes a sorting procedure in the delimbing process to separate woody biomass (e.g., tree tops left log processing, small diameter trees delimbed) from slashes to facilitate biomass feedstock production for pellets (Kizha and Han, 2016). As a result, slash piles and sorted biomass (with small amount of slashes) are accumulated at the landing as part of timber harvesting in WT and WTwS, respectively. The additional sorting procedure raises WTwS harvesting costs compared to WT but sorted biomass represents a better quality bioenergy feedstock with higher woody content and less contamination from dirt.

Post to harvest, trees in unharvested units and scattered slashes from LS harvested units decay and emit GHG as carbon sources. Slash piles from WT harvested units are either burnt or further utilized together with sorted biomass from WTwS harvested units for pellet production. Pellet production requests homogenous sized, less contaminated feedstock, which can be produced by sorted biomass through chipping or by slash piles through grinding with screening (Dukes et al. 2013). After comminution, feedstock is transported to a pellet plant for manufacturing and produced pellets are delivered to end users.

It is of critical importance to account for the changes at beetle-killed forests along time when managing the supply chain to enhance economic and environmental benefits obtained through forest salvage utilization. As time passes since the beetle infestation, dead trees deteriorate and wood quality degrades (Lewis and Thompson 2011). The proportion of high value log products also decreases (Loeffler and Anderson 2018), resulting in low market values of final products (Barrette et al. 2015). Meanwhile, unused dead trees decay and become a net source of carbon (i.e., dead trees stop absorbing CO_2 and emit CO_2 during decomposition) that may contribute to climate change (Kurz et al. 2008). On the other hand, the proportion of downed trees generally increases over time especially between 10 to 18 years post-mortality when most fall-down occurred (Lewis and Hartley 2005). Compared to standing trees, handling downed trees is more time-consuming during harvesting operations resulting in reduced system productivity and increased harvest costs (Kim et al. 2017; Han et al. 2018). Assuming 5% annual product degrade rate and 5% annual tree fall rate, we estimated the available timber and residue amounts as well as unit production costs of the three harvesting systems (Chung et al. 2017; She et al. 2018) at the beetle-killed forest of the study area in Colorado State Forest in the following 10 years (Figure 4.2).

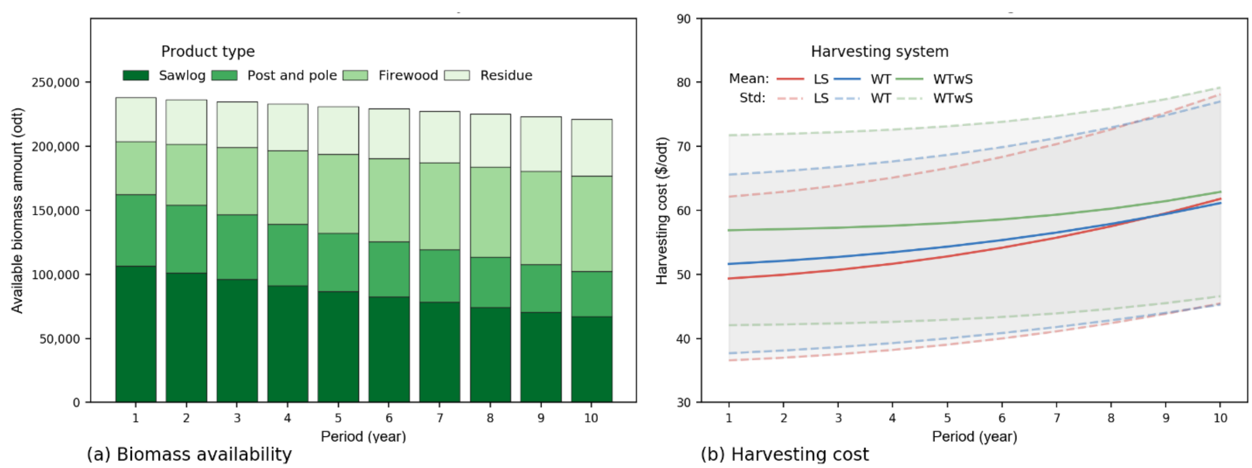

Figure 4.2 Changes in (a) available timber product and residue amount (b) mean and standard deviation (std) of lop-and-scatter (LS), whole-tree harvesting (WT), and whole-tree harvesting with sorting (WTwS) harvesting costs over time.

4.3 Methods

4.3.1 Multi-objective Record-to-Record Travel Algorithm

We developed a multi-objective metaheuristic referred to as Multi-objective Record-to-Record Travel (MRRT) to solve the multi-objective supply chain management problem. The MRRT algorithm incorporates the record travel search process of the RRT algorithm, but five modifications were made as follows to adapt the algorithm to optimize the economic and environmental objectives simultaneously.

- Deviation set. MRRT uses a deviation set where an individual deviation rate is selected for each objective. This serves to resolve the problem that value changes associated with one random move may be different in each objective, which is highly likely because of the two objective functions are in different units and magnitudes.
- Deviation rates are not constant. Objective function values may change significantly over the course of optimization, so does the ratio of the effects caused by a random move to the objective values. We modified the RRT algorithm so that it can track these changes and vary deviations according to recent disimproving moves during the optimization. Also, we set deviations as the actual values instead of ratios because objective values (as denominators in

the ratios) are always changing. Therefore, deviations are no longer input by users but determined from recent random moves. The user instead defines the allowed proportion of disimprovement of random moves as an input parameter.

- MRRT maintains a set of global and local records. The former results from the nature of multi-objective optimization outputs (i.e., generating a number of nondominated solutions) and the latter intends to increase the search efficiency by parallel searching (i.e., exploring different regions in the search space) during the optimization process. Global records do not dominate each other and are in sorted order based on the first objective.
- The record accepting scheme is different. Because there is no single global optimum, we compare a new solution against the local record that it derives from when assessing its acceptance as a local record. If both objectives are improved or one objective is improved and the other is disimproved within the allowed deviation, the new solution is accepted to replace the corresponding old local record. If there is not a global record dominating the new solution, it is added to the global record set.
- Solution pruning and thinning. Pruning and thinning ensure the global record set only contain nondominated solutions and is within the set size limit, respectively. After a solution is added the global record set, MRRT checks if any existing global records become dominated and removes them from the global record set (pruning). In addition, each global record has a crowding distance (Deb et al. 2002), a measure of how close a solution is to its neighbors (solutions on the boundary have crowding distance of infinity), to indicate its “uniqueness”. MRRT removes the solution with the lowest crowding distance (i.e., most crowded) when number of global records exceeds the record size limit (thinning).

The MRRT algorithm requires three user defined parameters: allowed disimprovement proportion δ, record size n, and terminating iteration $ITER$. The solving process of MRRT begins with performing RRT for each objective to find initial objective bounds (i.e., lower bound for a maximizing objective and upper bound for a minimizing objective). Then $n/k-1$ random solutions are generated from each bound, where k is the number of objectives (for the application in this study, $k=2$). This process generates a total of n initial local records including n/k solutions generated for initial objective bounds. Nondominated solutions among the local records are identified as the initial global records. In the record travel process, n also becomes the maximum size of the global record set. The exact number of global records may vary at each iteration.

During the solving process, the changes in objective function values of recent 100,000 deteriorating moves (i.e., objective function values disimprove in all objectives) are recorded and the lower $100 \times \delta$ percent moves are considered as allowed disimproving moves. The cutoff values are used as the allowed deviation quantity from local records until the next 100,000 deteriorating moves are recorded. To be noted, 100,000 is an arbitrarily selected large number to concrete the consideration of recent moves and it does not significantly affect the performance of MRRT as long as the number is within a reasonable range. The purpose is to find a relative long-term average to determine the allowed deviation so that the influence of any erratic move is minimal. Algorithm 2 details the operating steps of the MRRT algorithm.

Algorithm 2 Multi-objective Record-to-Record Travel

Input allowed disimprovement proportion $\boldsymbol{\delta}$, record size $\boldsymbol{n}$, and terminating iteration $\boldsymbol{ITER}$
Run RRT for all $\boldsymbol{k}$ objectives to get the initial objective bounds
Generate $\boldsymbol{n/k-1}$ solutions from each objective, local record set $\boldsymbol{L} \leftarrow$ all initial solutions
Identify nondominated solutions in $\boldsymbol{L}$, global record set $\boldsymbol{G} \leftarrow$ nondominated initial solutions
Sort $\boldsymbol{G}$, create crowding distance dictionary
Initiate deviation set $\boldsymbol{dev = 0}$
while terminating iteration $\boldsymbol{ITER}$ not reached **do**
    for all $\boldsymbol{l \in L}$
        Generate a candidate solution $\boldsymbol{x}$ randomly from the neighborhood of $\boldsymbol{l}$
        if $\boldsymbol{x \prec l}$ **then**
            track disimprovement and update $\boldsymbol{dev}$ set based on $\boldsymbol{\delta}$ if necessary
        end if
        if not $\boldsymbol{x \prec l - dev}$ **then**
            $\boldsymbol{l \leftarrow x}$
            if $\boldsymbol{g \prec x, \nexists g \in G}$ **then**
                Insert $\boldsymbol{x}$ to $\boldsymbol{G}$, prune $\boldsymbol{g \prec x, \forall g \in G}$, update crowding distance dictionary
            end if

end if

end for

while $|\boldsymbol{G}| > \boldsymbol{n}$ **do**

thin $\boldsymbol{G}$ based on crowding distance, update crowding distance distionary

end while

end while

Output $\boldsymbol{G}$

The computation complexity of MRRT is explained using the Big O notation (Cormen et al. 2009), where $O(1)$, $O(1)$, $O(1)$, $O(1)$ indicate constant, linear, logarithmic, and quadratic time complexities, respectively. At each iteration, the MRRT performs only one main loop on local record neighborhood search with $O(n)$ computation complexity. The deviation updating process is $O(D)$ where D is the number of disimprovement threshold for updating dev. For each newly generated solution, the local record comparison is $O(k)$ and replacement is $O(1)$. The global record identification is $O(lg(n))$ (i.e., to determine from which global record to start comparing with the new solution), comparison is $O(kn)$, insertion is $O(klg(n))$, and the crowding distance updating is $O(k)$. The pruning process is $O(kn)$ on average and $O(kn^2)$ as the worst case, which corresponds to the situation that a newly generated solution prunes one solution and all previous solutions (very unlikely to happen due to the existence of bounds), respectively. The thinning process is $O(kn)$ and the crowding distance updating is again $O(k)$. It is noteworthy that the thinning process is triggered only when the global record size exceeds n, so it does not happen together with the pruning process. In terms of record update in one iteration, three scenarios may happen:

- No local record is replaced. Then computation only includes local record comparisons and the running time is $O(kn)$.
- All local records and global records are updated for each new solution. In this extreme case, the runtime complexity of local record comparison with replacement is still $O(kn)$ and the global record update is $O(kn^2)$.
- Some local records are replaced, and the global records are changed a few times. This is the most likely scenario and the time complexity is between $O(kn)$ and $O(kn^2)$.

Over the course of optimization, the running time at each iteration shifts towards $O(kn)$ because it is decreasingly probable to identify new global records. Because there are in total $ITER$ iterations, the maximum computation complexity of MRRT is bounded by $O(ITER * kn^2)$, but must be sufficiently less than that.

4.3.2 Mixed integer programming model of the test problem

A deterministic multi-objective mixed integer linear programming model is formulated to mathematically represent the supply chain network of the beetle kill salvage harvest and utilization with an economic objective and an environmental objective. The two objectives aim at maximizing the net present value and the net GHG emission savings of the forest salvage utilization in the study area. The integer variables determine harvesting system and time period (i.e., year) for each unit, as well as residue treatment and its time period. The continuous variables are calculated based on the harvest and residue treatment decisions, showing the amount of timber and pellet production, and residue burn. The complete list of indices, sets, parameters and decision variables is provided in Table 4.1.

Table 4.1 Nomenclature.

<u>Sets</u>	
I	$Set\ of\ harvesting\ units\ i$
T	$Set\ of\ time\ periods\ t$
S	$Set\ of\ harvesting\ systems\ s$
C	$Set\ of\ logging\ residue\ process\ methods\ c$
L	$Set\ of\ log\ products\ l$
<u>Parameters</u>	
1) General	
$m_{i,l,t}^{Log}$	$Available\ log\ product\ l\ at\ harvest\ unit\ i\ in\ period\ t$ (odt)
$m_{i,t}^{Res}$	$Available\ logging\ residues\ at\ harvest\ unit\ i\ in\ period\ t\ if\ unit\ is\ not\ harvested$ (odt)
λ	$Degrade\ rate\ of\ biomass\ product\ by\ weight\ due\ to\ decomposition$
a_i	$Area\ of\ harvest\ unit\ i\ (ha)$
h	$Available\ scheduled\ machine\ hour\ (SMH) for\ each\ period\ (SMH)$
$p_{i,s,t}^{Log,har}$	$Harvesting\ productivity\ using\ system\ s\ at\ unit\ i\ in\ period\ t\ (odt/SMH)$
$p_{i,c,t}^{Res,com}$	$Comminution\ productivity\ using\ method\ c\ at\ unit\ i\ in\ period\ t\ (odt/SMH)$

d_i^{Log}	$Distance\ between\ harvest\ unit\ i\ and\ the\ timber\ mill\ (km)$
d_i^{Res}	$Distance\ between\ harvest\ unit\ i\ and\ the\ pellet\ plant\ (km)$
ρ^{Pel}	$Weight\ recovery\ ratio\ from\ logging\ residues\ to\ pellets$
GWP_{bio}^{decay}	$Global\ warming\ potential\ factor\ of\ biogenic\ carbon\ from\ biomass\ decaying\ relative\ to\ fossil\ carbon$
GWP_{bio}^{burn}	$Global\ warming\ potential\ factor\ of\ biogenic\ carbon\ from\ biomass\ burning\ relative\ to\ fossil\ carbon$

2) Economic

α	$Depreciation\ rate$
$c_l^{Log,mass}$	$Unit\ stumpage\ cost\ of\ log\ type\ l\ (\$/odt)$
$c_{i,s,t}^{Log,har}$	$Unit\ harvesting\ cost\ using\ system\ s\ at\ unit\ i\ in\ period\ t\ (\$/odt)$
$c^{Log,trans}$	$Unit\ transportation\ cost\ of\ logs\ (\$/odt * km)$
r_l^{Log}	$Unit\ revenue\ of\ delivered\ log\ type\ l\ \ (\$/odt)$
c_c^{Move}	$Equipment\ move\text{-}in\ cost\ for\ comminution\ method\ c\ (\$)$
$c^{Res,burn}$	$Unit\ cost\ of\ burning\ logging\ residues\ on\ site\ (\$/ha)$
$c_c^{Res,com}$	$Unit\ cost\ of\ comminuting\ logging\ residues\ using\ method\ c\ (\$/odt)$
$c^{Res,trans}$	$Unit\ transportation\ cost\ of\ communited\ residues\ (\$/odt\ * km)$
$c^{Pel,manu}$	$Unit\ pellet\ manufacturing\ cost\ (\$/odt)$
r^{Pel}	$Unit\ revenue\ of\ produced\ pellets\ (\$/odt)$

3) Environmental

$e_{i,s,t}^{Log,har}$	$Unit\ harvesting\ GHG\ emissions\ using\ system\ s\ at\ unit\ i\ \ in\ period\ t\ (kg\ CO_2\text{-}eq/odt)$
$e^{Log,trans}$	$Unit\ transportation\ GHG\ emissions\ of\ logs\ (kg\ CO_2\text{-}eq/odt * km)$
s_l^{Log}	$Unit\ GHG\ emission\ savings\ of\ log\ product\ l\ (kg\ CO_2\text{-}eq/odt)$
e_c^{Move}	$Equipment\ move\text{-}in\ GHG\ emissions\ for\ comminution\ method\ c\ (kg\ CO_2\text{-}eq)$
e^{decay}	$Unit\ GHG\ emissions\ of\ biomass\ decay\ on\ site\ (kg\ CO_2\text{-}eq/odt)$
e^{burn}	$Unit\ GHG\ emissions\ of\ burning\ logging\ residues\ on\ site\ (kg\ CO_2\text{-}eq/odt)$
$e_c^{Res,com}$	$Unit\ GHG\ emissions\ of\ comminuting\ logging\ residues\ using\ method\ c\ (kg\ CO_2\text{-}eq/odt)$
$e^{Res,trans}$	$Unit\ transportation\ GHG\ emissions\ of\ comminuted\ residues\ (kg\ CO_2\text{-}eq/odt * km)$
$e^{Pel,manu}$	$Unit\ pellet\ manufacturing\ GHG\ emissions\ (kg\ CO_2\text{-}eq/odt)$
s^{Pel}	$Unit\ GHG\ emission\ savings\ of\ produced\ pellets\ (kg\ CO_2\text{-}eq/odt)$

<u>Decision variables</u>

1) Continuous variables

$x_{i,l,t}^{Log}$	$Amount\ of\ log\ type\ l\ produced\ at\ harvest\ unit\ i\ in\ period\ t$
$x_{i,c,t}^{Res,com}$	$Amount\ of\ logging\ residues\ comminuted\ by\ method\ c\ at\ harvest\ unit\ i\ in\ period\ t$
$x_{i,t}^{Res,burn}$	$Amount\ of\ logging\ residues\ burnt\ at\ harvest\ unit\ i\ in\ period\ t$

$x_i^{Bio,decay}$	$Amount\ of\ biomass\ decay\ at\ harvest\ unit\ i\ throughout\ all\ periods$
x_t^{Pel}	$Amount\ of\ pellet\ produced\ in\ period\ t$
2) Integer variables	
$y_{i,s,t}^{har}$	$Binary: 1, if\ harvest\ unit\ i\ is\ harvested\ by\ system\ s\ in\ period\ t; 0, otherwise$
$y_{i,t',c,t}^{com}$	$Binary: 1, if\ harvest\ unit\ i\ is\ harvested\ in\ period\ t'\ and\ logging\ residues\ are\ comminuted\ by\ methond\ c\ in\ period\ t;\ 0, otherwise$
$y_{i,t',t}^{burn}$	$Binary: 1, if\ harvest\ unit\ i\ is\ harvested\ in\ period\ t\ and\ logging\ residues\ burnt\ in\ period\ t';\ 0, otherwise$
$z_{c,t}^{com}$	$Binary: 1, if\ comminution\ method\ c\ is\ used\ in\ period\ t;\ 0, otherwise$

The economic objective is to maximize the net revenues (NR) of the forest supply chain, which consists of the sum of all discounted cash-flows associated with the revenue from all timber and bioenergy product (sales of logs and pellets to entities external to the forest industry), biomass procurement costs, harvesting cost, transportation cost, residue burning and comminution costs, and pellet manufacturing costs (Eqs. (4.1-4.3)).

$$Max\ NR = \sum_{t \in T} \frac{1}{(1+\alpha)^{t-1}} * (Revene_t - Cost_t) \tag{4.1}$$

where

$$revene_t = \sum_{i \in I} \sum_{l \in L} x_{i,l,t}^{Log} * r_l^{Log} + x_t^{Pel} * r^{Pel} \qquad \forall t \in T \tag{4.2}$$

$$\begin{aligned} cost_t = & \sum_{i \in I} \sum_{l \in L} x_{i,l,t}^{Log} * c_l^{Log,mass} + \sum_{i \in I} \sum_{s \in S} \sum_{l \in L} m_{i,l,t}^{Log} * y_{i,s,t}^{har} * c_{i,s,t}^{Log,har} \\ & + \sum_{i \in I} \sum_{l \in L} x_{i,l,t}^{Log} * d_i^{Log} * c^{Log,trans} + \sum_{i \in I} \left(a_i * c^{Res,burn} * \sum_{t' \in T} y_{i,t',t}^{burn} \right) + \sum_{c \in C} z_{c,t}^{com} * c_c^{Move} \\ & + \sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} * c_c^{Res,com} + \sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} * d_i^{Res} * c^{Res,trans} \\ & + x_t^{Pel} * c^{Pel,manu} \qquad \forall t \in T \end{aligned} \tag{4.3}$$

The environmental objective is to maximize the net GHG emission savings associated with the salvage utilization of the beetle-killed forests (Eq. (4.4)), where GHG emission savings are obtained through the end use of log products and wood pellets (Eq. (4.5)), and GHG emissions consist of emissions associated with operations include timber harvesting, log transportation, residue burning, and comminution, residue transportation, and pellet manufacturing (Eq. (4.6)) and biomass decay emissions.

$$Max\ NS = \sum_{t \in T} (Saving_t - Emission_t) - GWP_{bio}^{decay} * \sum_{i \in I} x_i^{Bio,decay} * e^{decay} \tag{4.4}$$

where

$$saving_t = \sum_{i \in I} \sum_{l \in L} x_{i,l,t}^{Log} * s_l^{Log} + x_t^{Pel} * s^{Pel} \qquad \forall t \in T \tag{4.5}$$

$$\begin{aligned} emission_t = & \sum_{i \in I} \sum_{s \in S} \sum_{l \in L} m_{i,l,t}^{Log} * y_{i,s,t}^{har} * e_{i,s,t}^{Log,har} + \sum_{i \in I} \sum_{l \in L} x_{i,l,t}^{Log} * d_i^{Log} * e^{Log,trans} \\ & + GWP_{bio}^{burn} * \sum_{i \in I} x_{i,t}^{Res,burn} * e^{burn} + \sum_{c \in C} z_{c,t}^{com} * e_c^{Move} + \sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} * e_c^{Res,com} \\ & + \sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} * d_i^{Res} * e^{Res,trans} + x_t^{Pel} * e_t^{Pel,manu} \end{aligned} \tag{4.6}$$

During the salvage harvest and utilization, a series of constraints need to be satisfied. For harvest operations, each unit i can be harvested at most once by one of the available harvesting systems throughout all periods (Eq. (4.7)). Post to harvest, logging residues from units harvested the LS system does not require any further treatment and are left on-site for decaying. However, if a unit is harvested by the WT system in one period, logging residues should be either ground with screening (gws) to produce feedstock for pellet production or burnt on-site through disposal management in the same or later periods (Eq. (4.8)). If a unit is harvested by the WTwS system in one period, logging residues must be chipped to produce feedstock in the same or later periods (Eq. (4.9)). In each period, if logging residues from any harvested unit is comminuted, corresponding machineries need to be allocated to the site (Eq. (4.10)). For either harvesting or comminution operations, the accumulated working hour cannot exceed the scheduled machine hour (Eqs. (4.11-4.12)).

$$\sum_{t \in T} \sum_{s \in S} y_{i,s,t}^{har} \leq 1 \qquad \forall\, i \in I \tag{4.7}$$

$$\sum_{t \in T} \sum_{t' \in 1..t} \left(y_{i,t',gws,t}^{com} + y_{i,t',t}^{burn} \right) = \sum_{t \in T} y_{i,wt,t}^{har} \qquad \forall\, i \in I \tag{4.8}$$

$$\sum_{t \in T} \sum_{t' \in 1..t} y_{i,t',chip,t}^{com} = \sum_{t \in T} y_{i,wtws,t}^{har} \qquad \forall\, i \in I \tag{4.9}$$

$$|I| * z_{c,t}^{com} \geq \sum_{i \in I} \sum_{t' \in 1..t} y_{i,t',c,t}^{com} \qquad \forall\, c \in C, t \in T \tag{4.10}$$

$$\sum_{i \in I} \sum_{s \in S} \sum_{l \in L} y_{i,s,t}^{har} * m_{i,l,t}^{Log} / p_{i,s,t}^{Log,har} \leq h \qquad \forall\, t \in T \tag{4.11}$$

$$\sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} / p_{i,c,t}^{Res,com} \leq h \qquad \forall\, t \in T \tag{4.12}$$

In each period, the amount of each log type l produced equals the available amount in that unit if the unit is harvested by any system (Eq. (4.13)). Logging residues comminuted or burnt at a unit equals the available residues on-site after accounting for the decay since the time of harvest (Eqs. (4.14-4.15)). The produced pellet amount is equal to residue comminution amount from all methods multiply by the recovery ratio (Eq. (4.16)). For any unit, biomass decay amount equals the total biomass amount from period 1 subtracting any utilized log amount, utilized residue amount, and burn residue amount throughout all periods (Eq. (4.17)). In other words, biomass decay amount at a unit includes unharvested trees, biomass decay prior to harvest, residue decay if LS is applied, and residue decay between the times of harvest and residue comminution or burning.

$$x_{i,l,t}^{Log} = \sum_{s \in S} y_{i,s,t}^{har} * m_{i,l,t}^{Log} \qquad \forall\, l \in L, i \in I, t \in T \tag{4.13}$$

$$x_{i,c,t}^{Res,com} = \sum_{t' \in 1..t} y_{i,t',c,t}^{com} * m_{i,t'}^{Res} * (1-\lambda)^{t-t'} \qquad \forall\, c \in C, i \in I, t \in T \tag{4.14}$$

$$x_{i,t}^{Res,burn} = \sum_{t' \in 1..t} y_{i,t',t}^{burn} * m_{i,t'}^{Res} * (1-\lambda)^{t-t'} \qquad \forall\, i \in I, t \in T \tag{4.15}$$

$$x_{t}^{Pel} = \rho^{Pel} * \sum_{i \in I} \sum_{c \in C} x_{i,c,t}^{Res,com} \qquad \forall\, t \in T \tag{4.16}$$

$$x_{i}^{Bio,decay} = \sum_{l \in L} m_{i,1}^{Log} + m_{i,1}^{Res} - \sum_{t \in T} \left(\sum_{l \in L} x_{i,l,t}^{Log} + \sum_{c \in C} x_{i,c,t}^{Res,com} + x_{i,t}^{Res,burn} \right) \qquad \forall\, i \in I \tag{4.17}$$

Finally, there are non-negativity constraints and variable type constraints for all continuous and binary variables (Eqs. (4.18-4.19)).

$$x_{i,l,t}^{Log}, x_{i,c,t}^{Res,com}, x_{i,t}^{Res,burn}, x_{i}^{Bio,decay}, x_{t}^{Pel} \in R_{+} \qquad \forall\, l \in L, c \in C, i \in I, t \in T \tag{4.18}$$

$$y_{i,s,t}^{har}, y_{i,t',c,t}^{com}, y_{i,t',t}^{burn}, z_{c,t}^{com} \in \{0,1\} \qquad \forall\, s \in S, c \in C, i \in I, t \in T, t' \in T \tag{4.19}$$

Four test cases of this forest supply chain MOP were analyzed which represent management at different spatial and temporal scales, where 60, 180, 300, and 627 harvest units were managed over 1, 3, 5, and 10 periods (Figure 4.3). The number of total periods available in each case was determined by estimating the total scheduled machine hours needed if all units were harvested by the most time-consuming harvesting system. The four cases include a total amount of 12,935, 54,251, 102,998, and 203,665 odt of timber and 2,349, 9,390, 17,606, and 34,684 odt of biomass residues in the beginning period, respectively. In each case, it was assumed that there was only one timber buyer and one pellet producer, and the potential biomass flow between the two buyers was not considered.

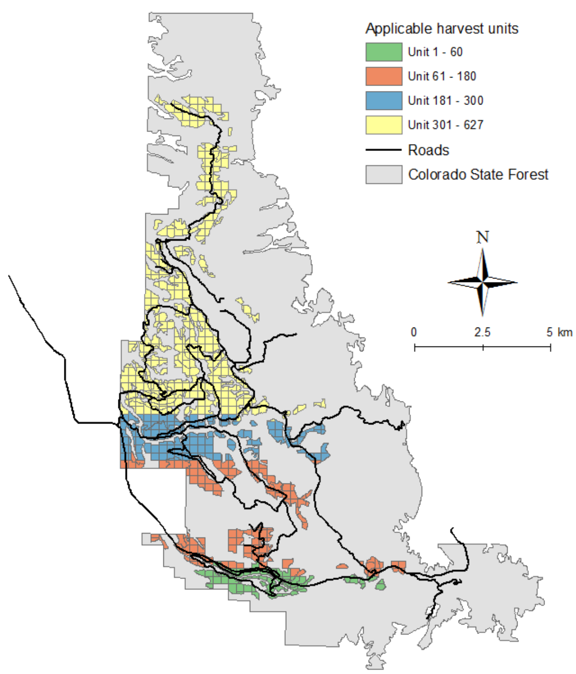

Figure 4.3 Forest supply chain multi-objective optimization problem with (a) 60 units (Unit 1-60) and 1 period (b) 180 units (Unit 1-180) and 3 periods (c) 300 units (Unit 1-300) and 5 periods (d) 627 units and 10 periods (Unit 1-627).

According to our model formulation, in general, a test case includes $(|S| + |C| + 1) \times |I| \times |T|$ binary variables, $\big((|L| + |C| + 1) \times |I| \times |T| + |I| + |T|\big)$ continuous variables, and $\big((|L| + |C| + 1) \times |I| \times |T| + |C| \times |T| + 4|I| + 3|T|\big)$ constraints, where $|S|$, $|C|$, $|L|$, $|I|$, $|T|$

are numbers of harvesting systems, comminution systems, log product types, harvesting units, and time periods, respectively. If a unit is harvested, combining harvesting systems and residue comminution/burning, there are $(|S|+1)$ operational alternatives since residues from the WT system can either be ground or burnt. Because harvesting operations can occur in any period and residue comminution or burning must be conducted in the same or later periods, the number of operational alternatives is $(|S|+1) \times \frac{(|T|+1)\times|T|}{2}$. Alternatively, a unit may not be harvested at all and there is no residue treatment for the unit. As a result, the total number of combinations in a test case is $\left((|S|+1) \times \frac{(|T|+1)\times|T|}{2} + 1\right)^{|I|}$. Given the increased numbers of units and periods, the complexity in solving test case from (a) to (d) increases exponentially due to the combinatorial optimization nature of this test problem (Table 4.2).

Table 4.2 Numbers of binary variables, continuous variables, constraints, and combinations in each test case of the forest supply chain multi-objective optimization test problems.

Test case (unit, period)	Number of binary variables	Number of continuous variables	Number of constraints	Number of combinations
(a) 60, 1	360	421	605	5^{30}
(b) 180, 3	3,240	3,423	3,975	25^{180}
(c) 300, 5	9,000	9,305	10,225	61^{300}
(d) 627, 10	37,620	38,257	40,178	221^{627}

4.3.3 Setting parameters

MRRT requires values for the allowed disimprovement proportion δ, the record size n, and the terminating iteration $ITER$. δ sets the threshold for acceptance of disimproving moves when conducting random search around a local solution. n determines the number of local and global records, which are spread across the entire search space. These two parameters control the extent of exploration locally and across the solution ranges, respectively. By comparison, $ITER$ does not affect the search or record updating procedures but determines the amount of computation allowed for MRRT when solving a problem. It thus controls the extent of exploitation of the entire search process. When setting parameter values, δ should allow enough deviation from the local optima but constrain the limit within a reasonable range so that the local search is not trapped at the local optima or wandering too far away. n should ensure the coverage of the full search space while keeping solutions well-spaced so that each local search is efficient and does not largely overlap. $ITER$ should be determined to give the algorithm enough time to find a high-quality solution set that does not improve frequently. Based on initial runs, δ and n were set to be 0.05 and 100, respectively, in all test cases while $ITER$ was set to 10^4, 5×10^4, 2×10^6, and 5×10^6 in test cases (a) through (d), respectively. The MRRT algorithm was implemented in Python 2.7 on a computer with a 3.40 GHz processor and 16 GB memory.

4.3.4 Model verification and performance evaluation

To evaluate the performance of MRRT and verify the results, we solved the MOPs via the augmented ε-constraint method (Mavrotas 2009) and obtained the actual Pareto front in each test case. During the iterative solving process, the economic objective was used as the objective function and the environmental objective was used as the additional constraint, where in each iteration, the right-hand side was changed with a user-specified step-size of ε value. The multi-objective optimization model was formulated in Python 2.7 and solved with the MIP solver CPLEX 12.6.3 on the same computer. The default MIP terminating criteria in CPLEX (relative MIP gap 10^{-4}) was used for test case (a) through (c), which means in each iteration, the MIP solver terminates the solving process and reports the best integer solution when the difference in objective functions between the best integer solution and the linear solution bound is less than or equal to 10^{-4}. However, due to overwhelming computation in case (d), the terminating relative MIP gap was increased to 10^{-2} to allow the feasibility of using the MIP solver.

We compared nondominated solutions produced by MRRT against the Pareto fronts produced by MIP in each test case. When evaluating metaheuristic solutions, convergence towards the Pareto front and preservation of the solution set diversity are two important criteria, where the former affects solution quality in terms of dominance and the latter relates to the spread of solutions (Zitzler and Thiele 1999). Therefore, we used four solution quality indicators to quantitatively evaluate the performance of MRRT regarding to convergence and diversity. Because the economic and environmental objectives in our test problem are of different units and magnitudes, their values were normalized prior to calculating indicator values.

- *End-point distance*. End-point distance (ED) shows the "coverage" of the entire Pareto optimal set by heuristic solutions. It is calculated as the Euclidean distances between the extreme points of the actual Pareto front and the boundary solutions of the obtained heuristic solutions (Deb et al. 2002).

- *Generational Distance*. Because metaheuristic solutions are approximations to the Pareto front, one of the most important evaluation criteria is the convergence to the actual Pareto optimal solutions (Veldhuizen and Lamont, 1998; Zitzler, 1999). We used generational distance (GD) (Veldhuizen and Lamont, 1998) to estimate the distance from heuristic solutions to the true Pareto front in each generation, which is defined in Eq. (4.20):

$$GD = \frac{\sqrt{\sum_{i=1}^{N} d_i^2}}{N} \tag{4.20}$$

where d_i is the minimum Euclidean distance from the solution point i to the actual Pareto front, indicating its "closeness" to convergence, and N is the number of nondominated solutions obtained. $GD = 0$ indicates that all solutions are in the actual Pareto optimal solutions.

- *Inverted Generational Distance*. We also used inverted generational distance (IGD) (Coello and Cortés, 2005) which calculates the distance from each Pareto optimal solution to the nondominated solutions generated by MRRT (Eq. (4.21)). The purpose of IGD is to reduce the potential problems with GD when very few nondominated solutions are generated by MRRT.

$$IGD = \frac{\sqrt{\sum_{j=1}^{M} d_j^2}}{M} \tag{4.21}$$

where d_j is the minimum Euclidean distance from the Pareto optimal solution j to the algorithm generated solutions and M is the number of Pareto optimal solutions. A small IGD indicates good performance of the algorithm, and $IGD = 0$ means that all Pareto optimal solutions are included in the nondominated solution set.

- *Spacing*. The spacing (SP) metric calculated with Eq. (4.22) evaluates the extent of uniform distribution of nondominated solutions (Schott 1995):

$$SP = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\bar{d} - d_i\right)^2} \tag{4.22}$$

where d_i is the Manhattan distance between solution i and its nearest neighbor, defined by Eq. (4.23):

$$d_i = min_{j \in Q \wedge j \neq i} \sum_{k=1}^{K} \left| f_k^i - f_k^j \right| \tag{4.23}$$

where K is the number of objectives, f_k^i is the value of objective k of solution i, and Q is the nondominated solution set. $\bar{d}$ denotes the average of the d_i distances and SP denotes the standard deviation of d_i in set Q. A smaller SP value represents a better distribution of the solutions in terms of uniformity and a null value indicates that all solutions are equidistant.

4.4 Results

The MRRT was able to find feasible solutions for all four test cases of the forest supply chain MOP. The MIP solver was run to optimality for all test cases, but with a greater relative MIP gap (10^{-2}) than default (10^{-4}) in the 627-unit, 10-period test case. In each test case, a set of 100 nondominated solutions were generated by either approach, where MRRT reported the global record set when terminating algorithm running while MIP solved the single-objective (economic objective) optimization problem for 100 times with stepwise-increasing ε-constraint (transformed from the environmental objective).

Table 4.3 Comparisons on end points produced by MRRT and MIP in four test cases.

Case (unit, period)	Scenario	MRRT	MIP	Difference*	ED
(a) 60, 1	$Max\ NR$	(4.62e4, 8.89e5)†	(4.62e4, 8.89e5)	0	0
	$Max\ NS$	(-2.42e5, 1.41e7)	(-2.42e5, 1.41e7)	0	0
(b) 180, 3	$Max\ NR$	(2.73e5, 2.88e7)	(2.75e5, 2.39e7)	1.0%	0.024
	$Max\ NS$	(-2.52e5, 6.22e7)	(-2.39e5, 6.23e7)	0.2%	0.024
(c) 300, 5	$Max\ NR$	(6.39e5, 5.90e7)	(6.47e5, 5.65e7)	1.2%	0.042
	$Max\ NS$	(-9.47e4, 1.17e8)	(-1.58e5, 1.18e8)	0.3%	0.079
(d) 627, 10	$Max\ NR$	(9.79e5, 6.27e7)	(1.00e6, 6.32e7)	2.0%	0.014
	$Max\ NS$	(-4.97e5, 2.17e8)	(-5.26e5, 2.19e8)	1.1%	0.022

* Difference of the maximized objective function values between MRRT and MIP.
† The values in the pair are values of NR and NS, of which measuring units are dollars and kg CO_2-eq, respectively. The expression "e n" is equivalent to "$\times 10^n$" (e.g.,4.62e4 is equivalent to 4.62×10^4).

Objective function values of end points from the two approaches are compared to show the coverage of MRRT nondominated solution set on the Pareto front produced by MIP (Table 4.3). For 60-unit, 1-period test case, MRRT and MIP report the same solutions as end points, where the maximum net revenue is \$4.6×10^4 and the maximum net GHG emission saving is 8.9×10^5 kg CO_2-eq. The difference in the target objective function value is 0 in both scenarios. EDs are also both 0 because the two end points of MRRT and MIP overlap (Figure 4.4a). For other test cases, the target objective function values from MRRT are very close to those from MIP, with the largest difference to be 2.0% from the maximum NR scenario in the 627-unit, 10-period test case. EDs are also very small in most scenarios, with the only exception being 0.079 from the maximum NS scenario in the 300-unit, 5-period test case. Although the difference in NS (i.e., the target objective function) is only 0.3%, the disparate NR (\$-9.47×10^4 vs. \$-1.58×10^5) of MRRT and MIP leads to a relatively large ED. Nevertheless, the approximation to end points appear to be satisfactory in these test cases (Figure 4.4b-4.4d)

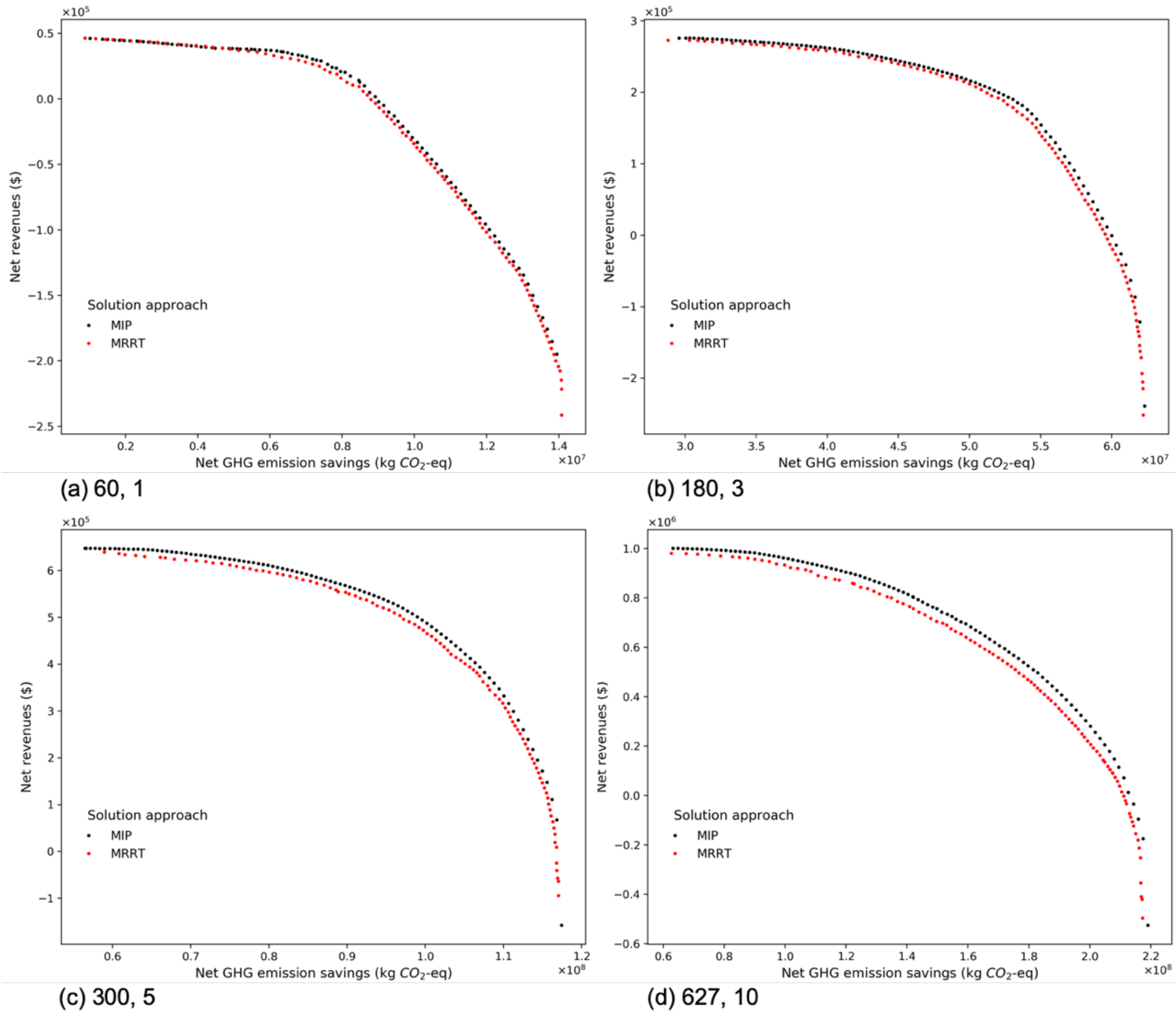

Figure 4.4 Comparisons on nondominated solutions from MRRT and Pareto fronts from MIP in test case (units, periods) (a) 60, 1 (b) 180, 3 (c) 300, 5 (d) 627, 10 for the forest supply chain MOP.

Not only are end points, the entire nondominated solution sets from MRRT generally very close to Pareto fronts from MIP in all test cases (Figure 4.4). For quantitative indicators of solution quality (Table 4.4), nondominated solution sets from MRRT have the greatest GD in the 300-unit, 5-period test case and the greatest IGD in the 627-unit, 10-period test case. This shows considering economic and environmental objectives simultaneously after normalization, the quadratic mean Euclidean distances are all within 3.2×10^{-3} when measuring MRRT solution sets to MIP Pareto fronts and are all within 2.3×10^{-3} when measuring MIP Pareto fronts to MRRT solution sets. The largest SP is 6.4×10^{-3} from the 180-unit, 3-period case and all SP values are fairly close to each other, which indicates nondominated solutions are very evenly distributed in all test cases.

Table 4.4 Performance matrix in each test case.

Test case (unit, period)	Performance matrix		
	GD	IGD	SP
(a) 60, 1	1.5e-3	9.4e-4	5.4e-3
(b) 180, 3	2.3e-3	1.2e-3	6.4e-3
(c) 300, 5	3.2e-3	2.0e-3	3.7e-3
(d) 627, 10	2.8e-3	2.3e-3	6.2e-3

Computation times taken by MRRT and MIP for test cases from (a) to (d) were 605 and 13 seconds (s), 4.5×10^3 and 1.2×10^3 s, 7.8×10^3 and 1.9×10^5 s, 4.7×10^4 and 5.5×10^5 s, respectively. As the MOP involves more units and periods, computation time of both approaches increases significantly (Figure 4.5). For MRRT, its computation time increased because the terminating iteration was increased to allow enough time for convergence. For MIP, as problem size increased, it became more difficult to implement "branch and bound" and "brand and cut" to solve the MIP problem in each iteration, resulting in higher computation time.

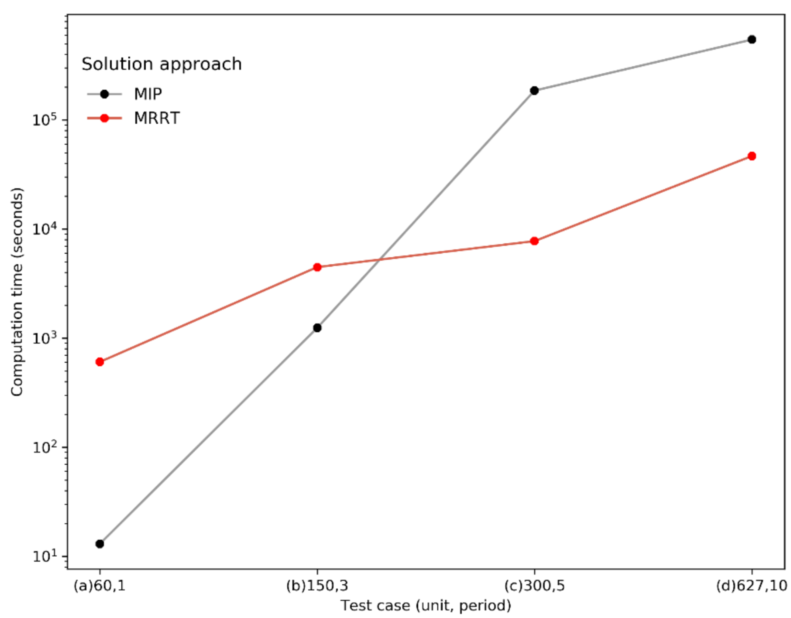

Figure 4.5 Computation time taken by MRRT and MIP to solve each test case of the forest supply chain multiple-objective optimization problem. For the MIP approach, a terminating MIP gap of 10^{-4} was used in test cases (a) through (c), whereas a gap of 10^{-2} was used in test case (d).

4.5 Discussion

In all cases, nondominated solutions from MRRT converged to Pareto fronts from MIP satisfactorily (Figure 4.4) with very small GD and IGD values (Table 4.4). As the MOP increased in size, MRRT was able to maintain solution quality at the similar level (i.e., similar GD and IGD values compared to smaller MOPs) given more iterations allowed for the algorithm to solve the problem. However, it was more difficult to cover the entire Pareto front, indicated by the increased difference in the target objective function value between MRRT and MIP (Table 4.3). MRRT nondominated solutions also become more sparse approaching to the end points as the problem size increases from test case (a) to (d) (Figure 4.4).

Solution distribution appears to be more uniform in MRRT nondominated solutions compared to MIP Pareto fronts (Figure 4.4). The augmented ε-constraint method implements a step-wise increment in the additional ε-constraint, leading to an approximately equal distance in the environmental objective between two consecutive final solutions. However, as the trade-off between the two objectives is more imbalanced while approaching to end points, the compromise made in the economic objective increases substantially when the environmental objective approaches to its maximum value. As a result, the Hamilton distance between two consecutive solutions also increases (Figure 4.4). In test cases from (a) to (d), SP of Pareto fronts from MIP are 1.8×10^{-2}, 2.5×10^{-2}, 2.9×10^{-2}, and 2.4×10^{-2}, respectively, which are significantly greater than those of MRRT solutions (Table 4.4).

In terms of computation times, the MIP approach solved the MOP faster when the problem size was small (i.e., test cases (a) and (b)) while MRRT were more efficient for large test cases (i.e., test cases (c) and (d)) (Figure 4.5). Although both approaches took longer time to solve the MOP as the problem size increased, the trend was much more dramatic for MIP. Moreover, it was time prohibitive to use the MIP solver with the default optimality MIP gap to generate the Pareto front in the 627-unit, 10-period test case because it took more than 10 h to produce one solution and the computation time kept increasing over iterations as the solving process continued. Even after relaxing the optimality MIP gap to 10^{-2}, it still took the MIP solver more than 151 h to complete the solving process.

Relaxing the terminating criteria (i.e., increasing the relative MIP gap) reduces computation time required by MIP to claim optimality when evaluating a solution, as the situation in our 627-unit, 10-period test case. However, it does not ensure computation time will be reduced to acceptable range or guarantee the quality of the final outputs. We examined the MIP approach with two new relative MIP gaps on the 300-unit, 5-period test case and contrasted outputs to previous MIP (with default relative MIP gap of 10^{-4}) and MRRT outputs. With a relative MIP gap of 10^{-2}, the MIP nondominated solutions are more converged to the Pareto fronts (i.e., MIP output solution with a relative MIP gap of 10^{-4}) than those from the MRRT approach (Figure 4.6). However, it still took 23 h for the MIP solver to produce this solution set, which was much longer than using the MRRT approach. Further increasing the gap to 5×10^{-2} dramatically reduced computation time to 13 min, but the solution quality also significantly deteriorates and becomes inferior to that of MRRT nondominated solutions in both convergence and spread (Figure 4.6). Therefore, it is thought that MRRT can serve as a useful approach considering the trade-offs between computation time and solution quality in this test case.

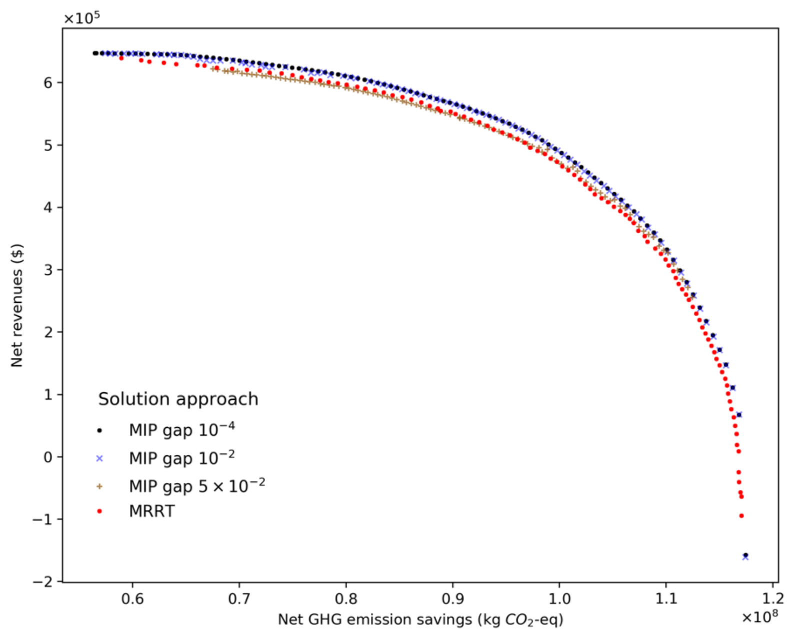

Figure 4.6 Comparisons on nondominated solutions from MIP with different terminating criteria (relative MIP gaps of 10^{-4}, 10^{-2}, and 5×10^{-2}) and MRRT in the 300-unit, 5-period forest supply chain MOP test case.

As in any metaheuristic methods, parameter values in MRRT have significant influences on the final outputs. With a population size of 100, a greater terminating criterion $ITER$ prolongs the solution process, which in turn the convergence to the Pareto front improves in all δ values (Figure 4.7a). This improvement flattens out as the solution process continues because it is increasingly difficult to find better solutions. For random search around local records, if the allowed disimprovment proportion δ is too small, the search is trapped at local optimum and cannot explore larger space for better solutions. On the other hand, if δ is too big, too many disimproving moves are accepted and the search is not focused or intensive enough to discover better solutions (Figure 4.7a). As for population size n, a greater population segments the search space into more pieces so that exploration is more exhaustive and output solution quality is higher (Figure 4.7b). However, this also means there are more local records performing local search and more comparisons on the global record set, leading to more computation in each iteration and longer computation time to complete the solution process. To complete 10,000 iterations, MRRT with population size of 50, 100, 150, and 200 took 1 h 8 min, 2 h 9 min, 3 h 20 min, and 4 h 25 min, respectively. It is critical, when setting MRRT parameter values, to balance search intensity, computation complexity and desired convergence to the Pareto front to achieve satisfactory solutions in a reasonable time.

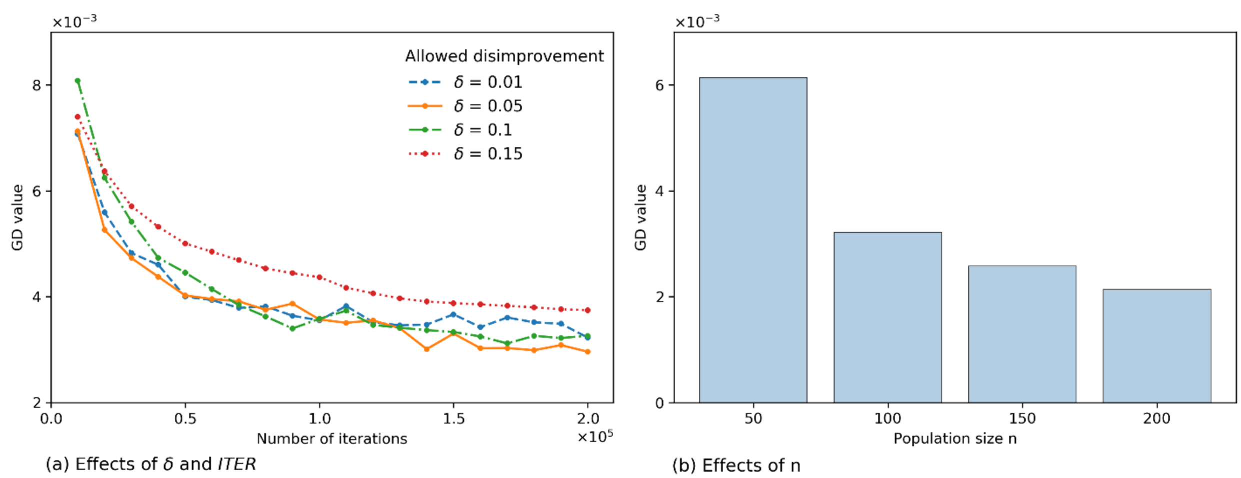

Figure 4.7 Effects of (a) allowed disimprovement proportion δ and terminating criteria $ITER$ and (b) population size n on the GD value of MRRT nondominated solutions to in the 300-unit, 5-period test case.

4.6 Conclusion

This study proposes a new multi-objective metaheuristics named Multi-objective Record-to-Record Travel (MRRT) as an optimization technique in forest supply chain management with multiple objectives. The ability to efficiently produce nondominated solutions may assist decision makers' comprehensive understanding of trade-offs among various objectives at the planning stage, especially when the problem size is large and using exact methods is prohibitive due to excessive computation burden.

Through testing on four cases of a forest supply chain multi-unit, multi-period, multi-objective optimization problem, we showed that MRRT performed satisfactorily in approximating the true Pareto fronts within a reasonable computation time. Not only the distances between MRRT nondominated solutions and MIP Pareto fronts were small, the coverage on the ranges of Pareto fronts was also complete. The distribution of solutions was more uniform in the MRRT nondominated solution sets than those from MIP with very small variance on the distance between two consecutive solutions.

MRRT has a simpler algorithm structure than most existing MOMHs that involve many sub-processes and parameters. This reduces algorithm computation complexity during the solution process and increases the speed of the algorithm. MRRT requires only three user-defined parameters: allowed disimprovement proportion δ, record size n, and terminating iteration I_{max}. This simplicity eases the parameterization process and makes MRRT adaptable for solving various MOPs.

Future work could incorporate temporal and spatial limitations of forest management problems, such as seasonal restrictions on harvesting and access, in order to improve the validity and practicality of the model solutions. Such restrictions increase problem complexity even further with additional constraints. In addition, responding to increasing demand for sustainable forest management entails consideration of multiple management objectives for management activity scheduling and decision-making. Metaheuristic approaches, such as MRRT, could provide an advantage of efficiency and simplicity over the exact methods, but potentially at the expense of solution quality.

Chapter 5
General Conclusion

Mountain pine beetle infested forests in the Rocky Mountain region represent a vast forest resource that is wasted if not utilized in a timely and efficient manner. Due to high operation costs and low product values, sound supply chain planning is of critical importance to the success of forest salvage utilization. To achieve this goal, following issues are identified and need to be solved. Knowledge gaps and operational uncertainties obscure the understanding of timber harvest in beetle attacked stands and impede forest salvage operations; lack of cooperation among stakeholders in the supply chain can constrain forest salvage utilization but the potential benefits of cooperation are unknown; the combinatorial nature of supply chain optimization makes any solution approach to multi-period, multi-unit, multi-product, multi-objective management problems analytically and computationally challenging.

In this dissertation, we applied simulation and optimization techniques of operations research to tackle the abovementioned issues in three studies. We believe our work can provide a set of useful analytical tools for the management of beetle kill forests and post-outbreak forest salvage utilization. We also hope our work offers novel approaches to solving various challenging forest management problems for future researchers and practitioners. We will conclude this dissertation by providing a summary of contributions and recommendations for future work.

5.1 Summary of contributions

Chapter 2 presents a comparison of time study and discrete-event simulation (DES) approaches in modeling a ground-based timber harvesting system. With the ability to account for variations of operations in both model inputs and outputs, DES is shown to be a more appropriate method for analyzing complex systems especially where multiple machine processes interact. We provided detailed steps in building DES models, conducting sensitivity analysis, and integrating previously collected data to evaluate alternative systems. This study demonstrates the applicability of DES in modeling forest production systems and offers a reference of model construction for future studies.

In Chapter 3, we investigated achievable net revenues and net greenhouse gas (GHG) emission savings from salvage harvesting of beetle-killed forests, and presented trade-offs between these two performances via bi-objective optimization. This study shows cooperation between the timber and bioenergy producers, through joining the management for timber and bioenergy production, can promote efficient use of logging residues and enhance the economic feasibility of forest salvage utilization, while simultaneously increasing GHG emission savings. The main contribution of this Chapter is to demonstrate and quantify the potential benefits of the integrated timber and biomass harvest operations from the economic and environmental perspectives.

Chapter 4 devoted to a new multi-objective metaheuristic, referred to as Multi-objective Record-to-Record Travel (MRRT), that was developed to solve large multi-objective combinatorial optimization problems for forest supply chain management. Requiring only three user-determined parameters, MRRT performs well in approximating actual Pareto fronts produced by the mixed integer programming method, and shows computational advantages when solving large-scale problems. The proposed method adds to the existing body of literature by offering a new, efficient metaheuristic approach for multi-objective optimization problems with promising adaptability and flexibility for various problems.

5.2 Future work

Sustainable forest management and supply chain planning is complex and involves many decisions. Operations research has provided optimization models and algorithms that lead to efficient solutions for the complex forest planning problems, and its development and applications keep evolving and expanding as forestry problems become larger and more complex with more objectives and constraints to consider. Below we present our suggestions for future development and applications of operations research methods for forest and supply chain management planning problems.

- Operations research models are usually built on well-defined problem boundaries and assumptions. However, it is a challenging task to clearly define problems in natural resources management planning due to the complex nature of the problem and its far-reaching influences on economic, environmental and social outcomes. Models can be practically useful only if they reflect reality. Strong collaboration between researchers and practitioners should be pursued in the future work in order to precisely identify and represent real world problems in mathematical terms.
- The success of simulation and optimization modeling highly depends on data availability. However, it is often the case that sufficient data are not readily available in forest operations and management. Combining modern data acquisition technology and methods (e.g., auto-video recording, GPS tracking, and sensors) with operations research models should be considered for future work.
- Even though operations research models could be useful in assisting with decision making, they often require specially trained personnel to formulate problems and process the data. Future work may include development of easy-to-use decision support tools to improve the usability of simulation and optimization models.
- In Chapter 2, discrete-event simulation modeled individual machine processes (e.g., skidder traveling speed, delimber tree-processing time) using probability distributions. Future study should collect and analyze long-term machine data to characterize machine performance specific to work conditions. This work will help develop and choose the right probability distribution for individual machines that can better represent site-specific work conditions.
- A new multi-objective metaheuristics was developed and tested against the mixed-integer programming approach on a forest supply chain bi-objective optimization problem in Chapter 4. To more rigorously evaluate the algorithm's performance, it is necessary to examine it on benchmark problems, compare it against other existing algorithms. Future work should also apply and test the algorithm for problems with more than two objectives.
- We used deterministic optimization in Chapters 3 and 4. To account for uncertainties in real-world applications, a probabilistic programming approach may be used to generate more comprehensive results and provide solutions tailored to the interest of decision-makers (e.g.,

aggressive revenue-seeking VS. risk-averse). The problem is likely to become more complicated and high performance solution algorithms would be needed.

- We presented the potential benefits of integrated decision-making on both timber and bioenergy production in Chapter 3. In practice, forest supply chains consist of many more stakeholders including landowner, logging contractor, mill, bioenergy facility, forest product and biomass market, local community, etc. It would be beneficial to understand the effects of cooperative and non-cooperative behaviors among stakeholders. Future study may use game theory to investigate and compare cooperative and non-cooperative decision-making in forest supply chain management.

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Appendix A

Table A.1 Measuring units and abbreviations.

Unit	Abbreviation
Mile	mi
Kilometer	km
Kilogram	kg
Pound	lb
US short ton	ton
Metric tonne	t
Oven dry metric tonne*	odt
Liter	L
Gallon	gal
Joule	J
Megajoule	MJ
Gigajoule	GJ
Kilowatt hour	kWh
Megawatt hour	MWh
Thousand board feet	MBF
Carbon dioxide equivalent	CO_2-eq

* Oven dry metric tonne has zero percent moisture content

Table A.2 Material moisture content (wet basis).

Material	Moisture content (%)	Assumptions and references
Timber products*	32.4	(Han et al. 2018)
Logging residues	32.4	(Han et al. 2018)
Hog fuel	32.4	(Han et al. 2018)
Pellet	11.8	(Lehtikangas 2001)
Biochar	5.0	(Denyes et al. 2014)

* Timber products includes saw logs, post and pole logs, and firewood logs

Table A.3 Recovery ratio of products from raw materials.

Raw material	Product	Recovery ratio	Assumptions and references
Saw logs	Lumber	0.46	(Keegan III et al. 2010)
	Wood chips for pellets	0.3	
	Wood used for energy	0.24	
Post and pole logs	Pole	0.877	(Morgan et al. 2005)
	Hog fuel	0.123	
Firewood logs	Firewood	1.0	Oregon Department of Forestry*
Low-quality feedstock	Hog fuel	1.0	Assumed
High-quality feedstock	Pellet	0.845	(Katers et al. 2012)
	Wood used for energy	0.155	
High-quality feedstock	Biochar	0.155	(Bergman et al. 2017)
	Syngas	0.732	

* Oregon Department of Forestry: Eastern Oregon Small Diameter Wood Study

Table A.4 Fuel higher heating values (HHV) during combustion.

Material	HHV	Assumptions and references
Coal	24.6 GJ/t	(Loeffler and Anderson 2014)
Natural gas	47.1 GJ/t	The Hydrogen Analysis Resource Center (HyARC)*
Firewood	16 GJ/odt	World Nuclear Association†
Hog fuel	16.47 GJ/odt	HyARC
Pellet	20.78 GJ/odt	(Lehtikangas 2001)
Syngas	18.06 GJ/t	(Bergman et al. 2017)

* HyARC Calculator Tools. Lower and Higher Heating Values of Fuels: http://hydrogen.pnl.gov/tools/lower-and-higher-heating-values-fuels, accessed on 4/11/2019.
† World Nuclear Association: Heat Values of Various Fuels: http://www.world-nuclear.org/information-library/facts-and-figures/heat-values-of-various-fuels.aspx, accessed on 4/11/2019.

Table A.5 Cost generated per unit processes.

Unit process	Cost	Assumptions and references
Timber harvesting		
Administration	494.21 $/ha	Sale preparation, environmental analysis, and harvest monitoring costs at 200 $/acre (Abt et al. 2011)
Salvage harvest	21.51~122.66 $/odt	Harvesting costs for each system at each harvest unit are estimated based on She et al. (2018).
Residue treatment		
Chipping	18.14 $/odt	A mobile chipper chips logging residues with a cost at 12.26 $/t (Jernigan et al. 2013).
Grinding	22.81 $/odt	A grinder grinds logging residues with a cost at 15.42 $/t (Dukes et al. 2013).
Grinding w/ screening	48.45 $/odt	A grinder grind logging residues followed by a screening process with a cost at 32.24 $/t (Dukes et al. 2013).
Burn	200 $/ha	On-site pile-burning logging residues (Rummer et al. 2005)
Transportation		
Timber products*	0.173 $/odt*km	For log trucks with a net payload of 58,835 lbs, (one-way) transportation cost is $2.52/mi (Mason et al. 2008).
Residue	0.204 $/odt*km	For chip van with a net payload of 22.7 t, (two-way) transportation cost is $0.204/km (Beck and Sessions 2013).
Biochar	0.098 $/odt*km	For biochar two-way transportation, cost is $0.15/t*mi (Qian and McDow 2013).
Manufacturing		
Biochar & Syngas	2,991.70 $/odt	Cost based on biochar output weight. Biochar production cost of 390.54 $/t (feedstock weight) with feedstock moisture content at 15.78% (Kim et al. 2014).

* Timber products includes saw logs, post and pole logs, and firewood logs

Table A.6 Greenhouse gas (GHG) emissions generated per unit process.

Unit process	**GHG emissions**	**Assumptions and references**
Supporting unit processes		
Diesel consumption	3.32 kg CO_2-eq/L	Diesel production, transport, and refining: 0.73 kg CO_2-eq/kg, or 0.62 kg CO_2-eq/L. Diesel internal combustion in engine: 10.21 kg CO_2-eq/gal, or 2.70 kg CO_2-eq/L (National Energy Technology Laboratory (NETL))[*].
Coal combustion	306.39 kg CO_2-eq/GJ	GHG emission of 1,103 g CO_2-eq/kWh is produced when generating electricity from coal fired power plants (U.S. Energy Information Administration (EIA))[†].
Natural gas heating	78 kg CO_2-eq/GJ	GHG emission of 0.078 kg CO_2-eq/MJ is produced when using natural gas for residential heating (Katers et al. 2012).
Colorado grid mix	0.71 kg CO_2-eq/kWh	GHG emission of 1,571 lbs CO_2-eq/MWh is produced on average for electricity generation in Colorado (EIA)[‡].
Timber harvesting		
Salvage harvest	9.74~55.90 CO_2-eq/odt	Harvesting GHG emissions for each system at each harvest unit are estimated based on She et al. (2018).
Residue treatment		
Chipping	12.14 kg CO_2-eq/odt	A chipper chips logging residues with diesel consumption at 3.66 L/odt (Spinelli et al. 2011).
Grinding	16.19 kg CO_2-eq/odt	A grinder grinds logging residues with diesel consumption at 3.3 L/t (Dukes et al. 2013).
Grinding w/ screening	35.81 kg CO_2-eq/odt	A grinder grinds logging residues followed by a screening process with diesel consumption at 7.3 L/t (Dukes et al. 2013).
Burn	1740 kg CO_2-eq/odt	On-site pile-burning logging residues (Lee et al. 2011).
Decay	1580 kg CO_2-eq/odt	Scattered residue decay on forest floor (Lee et al. 2011).
Transportation		
Timber products	0.170 kg CO_2-eq/odt*km	For log trucks with a net payload of 58,835 lbs, (one-way) transportation fuel economy is 5.1 mi/gal (Mason et al. 2008).
Residue	0.219 kg CO_2-eq/odt*km	For chip van with a net payload of 22.7 t, (two-way) transportation fuel economy is 1.98 km/L (Loeffler and Anderson 2014).
Pellet	0.115 kg CO_2-eq/odt*km	For pellet two-way transportation, fuel consumption is 0.013 gal/t*mi (Qian and McDow 2013).
Biochar	0.107 kg CO_2-eq/odt*km	For biochar two-way transportation, fuel consumption is 0.013 gal/t*mi (Qian and McDow 2013).
Manufacturing		

Lumber	1610.46 kg CO_2-eq/odt	12.32 lb CO_2-eq emission when producing one piece 2×4 lumber stud (7.65 od lb) (Bergman et al. 2014)
Pole	76.1 kg CO_2-eq/odt	101 lb CO_2-eq emission when producing 1,315 ob lb pole (Bergman et al. 2014)
Pellet	397.44 kg CO_2-eq/odt	Gate-to-gate pellet manufacturing process (Katers et al. 2012).
Biochar & Syngas	2974.18 kg CO_2-eq/odt	Emission based on biochar output weight. Gate-to-gate biochar manufacturing process through mobile pyrolysis.
<u>End use</u>		
Firewood	1786.40 kg CO_2-eq/odt	Firewood burnt in a fireplace (77% energy efficiency to produce heat) emits 0.145 kg CO_2-eq/MJ (Katers et al. 2012)
Hog fuel combustion	1700.67 kg CO_2-eq/odt	Hog fuel combusted in boiler emits 1149.65 kg CO_2-eq/t (Loeffler and Anderson 2014)
Pellet combustion	1869.11 kg CO_2-eq/odt	Pellet burnt in a pellet stove (83% energy efficiency to produce heat) emits 0.116 kg CO_2-eq/MJ (Katers et al. 2012)
Syngas combustion	1326.14 kg CO_2-eq/odt	Syngas burning emission (Gu and Bergman 2015)
<u>End use avoided emission</u>		
Lumber	4091.50 kg CO_2-eq/odt	Substitute steel stud and store carbon, avoiding 31.3 lb CO_2-eq per lumber stud (7.65 od lb) (Bergman et al. 2014)
Pole	1946.01 kg CO_2-eq/odt	Store carbon, avoiding 2,559 lb CO_2-eq per 1,315 ob lb pole (Bergman et al. 2014)
Firewood	960.96 kg CO_2-eq/odt	Substitute natural gas for residential heating (77% energy efficiency to produce heat) (Katers et al. 2012)
Hog fuel	1651.44 kg CO_2-eq/odt	Substitute coal for power generation (32.5% energy efficiency to produce electricity) (Loeffler and Anderson 2014)
Pellet	1257.90 kg CO_2-eq/odt	Substitute natural gas for residential heating (83% energy efficiency to produce heat) (Katers et al. 2012)
Syngas	1226.62 kg CO_2-eq/odt	Substitute state average electricity generation GHG emission (0.732 kg syngas generates 1.26 kWh) (Gu and Bergman 2015; Bergman et al. 2017)
Biochar	2937.54 kg CO_2-eq/odt	0.456 kg CO_2-eq is sequestered by 0.155 kg biochar (Gu and Bergman 2015)

* NETL unit process library https://www.netl.doe.gov/node/2573, accessed on 4/11/2019
† EIA report https://www.eia.gov/conference/2015/pdf/presentations/skone.pdf
ǂ EIA state electricity profile https://www.eia.gov/electricity/state/colorado/, accessed on 4/11/2019

Table A.7 Timber and bioenergy product unit revenue (based on input material weight).

Product	Revenue ($/odt)	Assumptions and references
Saw log	81.53	300 $/MBF* (Northwest Management, Inc†)
Post and pole	58.70	36 $/ton (Oregon Department of Forestry‡)
Firewood	25.34	Lodgepole pine firewood worth $30/cord (Southern Maine Forestry Services, Inc§) and 1 cord weighs 2,610 od lb (Utah State University Forestry Extension£)
Hog fuel	55.10	50 $/od ton (Kizha. et al. 2015)
Pellet feedstock	70 .00	70 $/odt (Qian and McDow 2013)
Biochar & Syngas	15.29	Pyrolysis output weight ratio of syngas to biochar is 82.5/17.5 (Gu and Bergman 2015). Cost saving of avoided natural gas usage (0.094 $/kWh) and biochar sale (2,512 $/t) (Campbell et al. 2018).

* 1 MBF saw logs weigh 6 green ton. Mississippi State University Extension. Pine Timber Volume-to-Weight Conversions. https://extension.msstate.edu/sites/default/files/publications/publications/p2244_0.pdf
† Northwest Management market report: http://northwestmanagement.com/log-market-report/, accessed on 4/11/2019
‡ Oregon Department of Forestry: Eastern Oregon Small Diameter Wood Study
§ Southern Maine Forestry Services, Inc: https://www.someforest.com/timber-market, accessed on 4/11/2019
£ Utah State University Forestry Extension: http://forestry.usu.edu/forest-products/wood-heating, accessed on 4/11/2019

Table A.8 Timber and bioenergy product unit GHG savings (based on input material weight).

Product	GHG savings (kg CO_2-eq/odt)*	Assumptions and reference
Saw log	1203.67	46% lumber, 30% pellet feedstock, 24% burn
Post and pole	1640.64	87.7% pole, 12.3% burn
Firewood	389.31	100% burn
Hog fuel	1107.23	100% burn
Pellet	203.17	84.5% pellet, 15.5% burn
Biochar & syngas	956.29	15.5% biochar, 73.2% syngas

* 1 kg biogenic carbon from burning has GHG potential equivalent to 0.32 kg fossil carbon (Liu et al. 2017)