Globally the forest harvesting industry is becoming increasingly mechanized. Driving this trend is the desire to increase productivity and reduce cost, as well as to improve labor-related issues. With mechanization comes an in-forest platform for the introduction of state-of-the-art communication and measurement technologies, and powerful on-board computers. These systems have the potential to increase efficiency and value gain from the whole forestry supply chain. However the performance to-date of mechanical harvesting systems has not lived up to their full potential, particularly with respect to value recovery.

One of the potential reasons for poor value recovery performance is the level of accuracy of stem diameter and length measurements on harvesters. Numerous studies have looked at the level of error in both the diameter and length measurements made by mechanical harvester/processors; however, few have looked at the economic impacts of these errors. The modeling work done in this dissertation showed that for the operations...
studied the value loss was between 3% and 23% due to measurement errors. Further analysis showed that increasing the precision of the length and diameter measurements would provide gains from reducing the measurement error rates.

One potential way of reducing the error rates is to introduce new scanning and forecasting procedures that would maintain or improve net value recovery. Five procedures were evaluated. It was shown that there was no economic advantage in partially scanning the stem. Breakeven capital investment costs were calculated for new scanning, forecasting, and optimization equipment. They ranged between zero and US$2,120,000 depending on tree species, markets, scanning speed, volume scaling rules, and scanning procedure.

Even with perfect information about the stem, the computer that controls the bucking solution still requires correct cutting instructions. These instructions are needed to obtain the optimal output log distribution that will maximize the return to the log suppliers while still meeting market and operational constraints. New algorithms were developed for efficiently planning and implementing these cutting instructions.

This dissertation demonstrated that the optimal output log distribution can be affected by measurement errors, work methods and bucking procedures.
An Investigation of Factors Affecting the Optimal Output Log Distribution from Mechanical Harvesting and Processing Systems

by

Hamish Douglas Marshall

A DISSERTATION

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Doctor of Philosophy

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APPROVED:

Major Professor, representing Forest Engineering

Head of the Department of Forest Engineering

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Hamish Douglas Marshall, Author
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An Investigation of Factors Affecting the Optimal Output Log Distribution from Mechanical Harvesting and Processing Systems

INTRODUCTION TO DISSERTATION TOPIC

Globally the forest harvesting industry is becoming increasingly mechanized. Driving this trend are the potential for increased productivity and reduced cost, as well as labor-related issues; e.g. enhancing worker safety or overcoming labor shortages and rising wage costs. With mechanization comes a platform for the introduction of state-of-the-art communication and measurement technologies, and powerful on-board computers into the forest.

Another trend facing the timber producing industry is increased global competition. Murphy (2003 pg 23-24) gave the following examples:

- The southern United States or Canada could easily fill any volume or price gap opened up by the US Pacific Northwest.
- Brazil produces wood at 1/4th to 1/3rd of the rotations of the US South and 1/10th of the US North.
- Chile exported forest products to 74 countries in 2001.
- Within five years, New Zealand will have 25 million m³ of timber available for export.
- USA is South Africa’s fourth largest importer of wood.
Competition, however, comes not only from within the forest industry but also from other industries such as steel, aluminum, plastics and composites.

Mechanization has the potential to reduce the costs and increase the productivity, safety and profitability of the forestry industry. Modern forest machines place their operators in completely enclosed cabs. These cabs not only provide a safe environment for the operator but they also allow powerful computers and communication systems to operate protected from the harsh harvesting environment. These systems have the potential to increase efficiently and value gain from the whole forestry supply chain. However the performance to-date of the mechanical harvesting systems has not been able to live up to their full potential. A survey carried out as part of this thesis showed that on average mechanical log merchandizing systems are recovering approximately 8 % less value than manual log making systems.

This dissertation is a study of potential methods that could be employed on mechanical harvesting/processing machines to increase not just their value recovery, but also their ability to successfully fulfill customers’ orders. It has been written in manuscript format and is made up of four distinct manuscripts. While each manuscript may stand alone, together they present a number of solutions for improving the ability of mechanical harvesters/processors to obtain the optimal distribution of logs. The following is a summary of this dissertation:
Chapter 1 is a summary of the histories of both mechanical harvesting and processing and optimal bucking. The chapter then investigates the potential, performance and challenges of optimal log merchandizing on mechanical harvesters and processors.

Obtaining the optimal output distribution of logs can be looked at as a complex manufacturing problem; each box in the figure above has several questions that require research. Due to the size of the problem, only the topics in the highlighted boxes will be covered in this dissertation. All three of these topics relate to assessing the importance of the different inputs that go into the bucking algorithm in obtaining the optimal log distribution.
Chapter 2 is an investigation of (1) the measurement errors in processing three different species of pines and, (2) the effects of these measurement errors on value recovery. A dynamic programming optimal bucking algorithm embedded in a simulation model was developed to simulate the economic effects of length and diameter error distributions from six mechanical processing operations.

Chapter 3 is a study of the effect of different stem scanning procedures on productivity and value recovery of mechanical processing systems. In the different stem scanning procedures only a proportion of the stem is scanned for changes in dimensions and qualities while the remainder is predicted using information from the measured portion. Breakeven capital costs for stem scanning systems are presented for different species, markets, scanning procedures and speeds.

Chapter 4 describes the development of new methodologies for buck-to-order optimal log merchandising. In buck-to-order the goal of processing a stand of trees is to find the optimal distribution of logs that both maximize the value of the stand and fulfill customer orders. A new mixed integer formulation is developed to determine the optimal volume of each product to be cut from a stand. Three different approaches are then tested for developing cutting instructions to implement the plan created by the mixed integer model.
The relationships and linkages between the results of the four chapters are presented in a short discussion at the end of this dissertation. It provides a summary of the dissertation and a view of where future research in this area should proceed.

The literature reviews and results reported in this dissertation will help to answer some of the questions related to improving the performance of mechanical harvesters/processors with respect to obtaining the optimal distribution of logs from a stand. Many more points of clarification and questions still need to be answered.
Chapter 1

OPTIMAL LOG MERCHANDIZING ON MECHANICAL PROCESSOR/HARVESTERS: OPPORTUNITIES AND CHALLENGES

By Hamish Marshall

Glen Murphy
ABSTRACT

Harvesting is a key component of the industrial forestry supply chain. Increasingly around the world, harvesting of timber is becoming mechanized. The general drivers for this trend are productivity goals or labor-related issues and in some cases reducing environmental impacts. This mechanization provides a platform for the use of state-of-the-art measurement and monitoring technologies, and the application of increasingly powerful on-board computers.

Despite all the new technology available on mechanical systems, their performance in terms of value recovery has been substantially lower than motor manual systems. On average mechanical harvesting/processing systems are losing 18% of the value of the trees. Motor-manual systems in comparison on average lose 11% of the stand’s value through incorrect log merchandizing decisions.

This paper describes the history, development and current use of mechanical and optimal log merchandizing systems. The main goal of the paper is to provide a review of the literature and to identify why value recovery performance of mechanical merchandizing is so low. The paper identifies six areas for research: measurement error, market demand and log value, stem shape and quality forecasting, bucking algorithms, harvester operator effect and stand composition.
INTRODUCTION

The harvesting process is a key component in the forestry supply chain. It is the time when a forest owner realizes a return from decades of investment. During the harvesting process many key decisions need to be made. As the entire volume of a tree is seldom merchantable (Brown 1950), one of the key decisions is cutting the log into sections, or segments, commonly referred to as logs. This process is often referred to as log making, log bucking or log merchandizing. In Brown’s textbook on logging (1950, pg. 119) he describes the reasons for reducing the tree into sections as:

* reduction of weight, elimination of defects and unmerchantable portions of the bole, adaptation to method of transportation and manufacture, and adaptation to market requirements.*

Log making if done correctly involves

* cutting trees into log lengths acceptable for a specific end use. In addition to knowing how to cut the logs the bucker must know log descriptions by grade or log type, the range of acceptable lengths, and the correct trim allowance required. In essence, the bucker’s job is manufacturing products that will result in the greatest value being recovered from the trees. Conway (1979 pg. 116)*

As Conway (1979) states, different wood markets require log characteristics different from the logs supplied to them and are willing to pay significantly different amounts. Such price differentials for different log types, means that considerable value can be lost through incorrect log making. In New Zealand, initial value recovery studies in the
early 1980’s indicated that 40% of the total stem’s value could be lost during harvesting operations (Murphy and Twaddle 1986). The largest single source of loss was from log making where up to 26% of the potential value could be lost. Results such as these validate comments made by Conway (1979) who noted that, by focusing on end-use and value recovery, millions of additional dollars per year could be gained for the forest industry. It also started an increase in focus on value recovery during the log making process which continues today particularly in New Zealand and Scandinavia where much research is being done on the subject. Focusing on value recovery is not a new concept. Almost a century ago, B.C. Bryant, in his 1913 textbook on American logging practices, commented that insufficient attention was being paid by log makers to securing quality as well as quantity (Bryant 1913).

When Brown (1950) wrote his book in the 1940’s he noted that at the time there was a shift in the location where log making occurred from being done mostly out in the forest, as part of the felling operation, to occurring on the landing. In some areas of the world, particularly Scandinavia, there has been a shift back to doing the processing at the stump with the advent of the mechanical cut-to-length harvesting systems. Almost 100% of the harvesting in Scandinavia is now performed using this type of system (Nordlund 1996).

Mechanization of forest harvesting operations is increasing worldwide, particularly as tree size decreases. The drivers for this trend generally are productivity goals or labor-
related issues e.g. enhancing worker safety or overcoming labor shortages and in some cases reducing environmental impacts. With mechanization comes the use of state-of-the-art measurement and monitoring technologies, and the application of increasingly powerful on-board computers (Sondell et al. 2002).

In the forest industry, minimizing costs still seems to be the prime goal of logging economics even though as Murphy et al. (1991) states:

*It is much easier to add $1 to unit product value by improving bucking than it is to reduce $1 from unit costs.*

The objectives of this paper are (1) to provide an overview of the evolution of optimal log making and mechanical log processing, and (2) to review the value recovery performances of in-the-forest mechanical log making systems, and (3) to investigate the opportunities and challenges for improving value recovery of mechanical log making.

This paper focuses on processors which are designed for delimming and slashing/cutting the stem to length and on harvesters which perform the same functions plus felling.
EVOLUTION OF OPTIMAL LOG MERCHANDIZING

Although optimizing the value produced when trees are cut into logs was thought about as early as 1913 (Bryant 1913), the mathematical techniques to solve the problem were not researched until the early 1960’s.

Over the last 45 years a number of mathematical optimization techniques have been developed and used to solve the two main optimal log bucking problems; the individual tree optimization problem (buck-to-value) and the multiple trees with demand constraints problem (bucking-to-order). Short histories of the algorithms that have been developed to solve these two problems will be given separately.

**Buck-to-Value (BV)**

The objective of buck-to-value optimal bucking is to obtain the maximum monetary value from an individual stem. A stem can be cut into logs in numerous ways; with each set of logs yielding a different financial return. However, there is, in many cases one unique bucking pattern that yields the maximum value. The value and logs cut using the optimal bucking pattern depends on the species, diameter, taper rate and quality of the stem plus the properties and relative market values of log grades being cut.

When strictly bucking-to-value, value loss from log-making occurs either when logs do not meet specification (e.g., inaccurate lengths, diameters too small or large, too much...
sweep, unallowable quality features) or when the combination of logs cut from a stem is sub-optimal. Figure 1.1 shows different ways that value can be lost from incorrect bucking of an individual log.

The most common optimization techniques that have been used to solve the individual tree bucking problems are dynamic programming (DP), network programming, simulation and, to a lesser extent, branch and bound integer programming and linear programming. Clemmons (1966) was the first to propose the use of dynamic
programming techniques to solve the BV problem. According to Nasberg (1985), Strand in 1967 also used DP for developing optimal cutting pattern tables for spruce. However, Pnevmaticos and Mann’s 1971 paper is credited as the first detailed, published description of using DP to solve the BV problem. Pnevmaticos and Mann's approach is now considered simplistic as they defined their stage length as the minimum log length. They also calculated the stem volume using a truncated cone which, for many tree species, is an oversimplification. Log quality was dealt with in a probabilistic way.

Briggs (1980) redeveloped the Pnevmaticos and Mann formulation removing the restriction that a stage length must be integer multiples of the minimum log length. In Briggs' formulation every log length must be an integer multiple of the stage length. He also introduced the concept of a "dummy" log which has no value; however, he did not consider any quality information.

Geerts and Twaddle (1984) developed a dynamic programming algorithm which was implemented in a software product called AVIS; ‘Assessment of Value by Individual Stems’. This formulation used the Briggs definition of a stage. The Geerts and Twaddle formulation considered stem quality in a deterministic way. Each potential log was checked to make sure that the stem qualities at that state did not violate the required log type quality. Stem shape such as sweep was dealt with by including cut zones within which a cut must be made.
The close relationship between dynamic programming and network theory makes it possible to solve the optimal bucking problem using network programming algorithms that efficiently find either the shortest or longest path through a network. In the mid 1980's, network analysis was introduced as a potential way to solve the BV problem (Nasberg 1985, Sessions 1988). Sessions (1988) formulated the problem as a network where all the possible bucking points along a stem represented the nodes on a network and the arcs connecting the nodes represent the value of the log that might be cut between them. The objective of this formulation is to find the path of arcs and nodes that gives the maximum value. Sessions implemented an algorithm similar to Dijkstra's node labelling algorithm (Nasberg 1985). Nasberg (1985) also used a longest path algorithm to solve the same network discussed above. Nasberg's formulation was tailored to Swedish conditions; it is now used on the Ponsse's log merchandising computers (Kivinen and Uusitalo 2003).

Bobrowski (1994) applied the branch and bound technique to the optimal log bucking problem. Bobrowski compared the accuracy and solution speed of the branch and bound technique to the traditional dynamic programming approach. He found that as the DP stage length increased, the accuracy and solution speed decreased when compared to branch and bound. However, when the DP stage length is a multiple of all the possible log lengths and the trim allowance, he found that there is no difference in the solution accuracy for the two techniques. The major limitation with this formulation is that waste is not considered.
Many of these formulations have been implemented into software, mostly for educational and training purpose. Examples of these programs are: OSU BUCK© (Sessions 1988), AVIS (Geerts and Twaddle 1984), VISION (Lembersky and Chi 1984), HW Buck, (Pickens et al. 1992) and others. In 1986, Weyerhaeuser reported that the VISION log bucking training and decision simulator had produced operational benefits that exceeded $100 million in increased profits since its implementation in 1977 (Lembersky and Chi, 1986).

In the mid 1990's the idea of placing an optimal log bucking algorithm onto a set of digital calipers for optimizing individual stems on a landing was commercialized by a New Zealand company. Detailed measurements were made of every stem using the calipers. The optimal solution was found using the optimization software and the stem was marked up ready for bucking (Boston 2001). Although initially heralded as a major step forward for the forestry industry, the system suffered a number of set backs which included not being well accepted by logging contractors. It is now only used by a small number of companies within New Zealand.
**Buck-to-Order (BO)**

The objective of buck-to-order optimal bucking is to maximize the monetary value at harvest unit or forest level while meeting market and operational constraints. What is optimal for individual stems is unlikely to be optimal at a unit or forest level. Market and operational constraints can be in the form of the following: target volumes, minimum percentage of volume must be greater than a certain length, minimum average small end diameter (SED) for a product, and minimum percentage of the volume must be of a certain grade (Murphy 1993). This problem can be solved at both an individual stand and at forest level.

In the literature there are generally two approaches that have been taken to solve this problem:

1. Selecting cutting instructions, either before or during the bucking process, for each tree that will produce the required volume for each product
2. Finding the correct price list (in some cases the correct specification) that will be applied to the stand of trees to produce the required volume for each product.

The first published optimal bucking formulation, (Smith and Harrell 1961), was actually solving the BO problem, using linear programming. However, as Pnevmaticos and Mann (1971) stated, the Smith and Harrell linear programming formulation was limited by the requirement that all relationships be linear and by the limited number of cutting instructions available for each diameter class.
The limited number of cutting patterns problem was solved by Nasberg (1985), Mendoza and Bare (1986), Eng et al. (1986) and Laroze and Greber (1997) by using a two stage iterative formulation of the problem. The first stage, or master problem, uses linear programming to solve the constrained market problem and the second stage, or sub-problem, uses a dynamic programming or network algorithm to solve the individual tree problem. The shadow prices from the master problem were used in the second stage to generate new cutting patterns. These were then used to form new columns in the master problem using column generation techniques. This general approach is theoretically correct and computationally efficient (Laroze 1993), but as many authors (Sessions et al. 1989, Laroze 1993 etc) have pointed out, the solutions produced are not particularly practical as they produce large numbers of cutting instructions. Sessions et al. (1989) also noted that the requirement of these techniques to subdivide the stand into stem classes makes these solutions hard to implement.

The second approach does not suffer from these same problems, however, it can not theoretically guarantee that maximum revenue is gained from the bucking of the stand. Duffner (1980) is the first published work on adjusting the price list in a bucking algorithm to meet market demands. There was however, very little detail in the Duffner (1980) paper on exactly how he adjusted the prices.

Sessions et al. (1989) developed a system to adjust prices iteratively using a shortest path algorithm to solve the sub-problem and a binary search to find the price multipliers
to obtain the correct ratio of long logs to short logs. The formulation was designed to overcome the problem of producing too many short logs that plagued optimal bucking in areas where the Scribner volume scaling rules were used.

A number of other approaches have been tried, such as using a LP solution at the upper level to adjust the prices in the DP lower level, or using a heuristic to find the correct prices so the demand constraints are met in the master problem (Laroze and Greber 1993; Murphy et al. 2004). Kivenen and Unsitalo 2002 developed a fuzzy logic controller to adjust the prices specifically for a mechanical harvester.

There are advantages and disadvantages for each of these approaches; however there is little published work on the actual commercial implementation of these systems. To the authors’ knowledge, in most forest regions where buck-to-order is implemented relative prices are determined manually using trial and error and the experience of harvest planners. Scandinavia is one of the few exceptions where adjustments are made to relative prices using computer software.
IN FOREST MECHANICAL LOG MERCHANDIZING (MLM)

In the first half of the 20th century, felling and processing were done manually with axes, bow saws and cross-cut saws. Although the first United States patent for a chainsaw was issued in 1858 it was not until the 1900’s that the chainsaw was used in logging (Silversides 1997). In 1913 Bryant noted that no satisfactory power-driven tree-felling machine had been placed on the market. He did mention two “power log-making machines” which had been used successfully for “bucking-up”. These machines were extremely heavy and were dragged around by cable attached to the engine (Bryant 1913). The first chainsaws, or power saws, required two men to operate them but by the early 1940’s one-man chainsaws were being rapidly introduced (Brown 1949).

The next innovation in log merchandizing was the introduction of slasher or roadside processor units (Silversides 1997, Walbridge 1960). These machines were basically large conveyers on a bench placed on the landing, upon which the stems were placed to be “bucked up”. A chainsaw, large circular saw or shears were used to cut each stem into logs. There were a number of different types of “slasher” available on the market, both in the United States and Canada (Silversides 1997), and in Scandinavia (Hansen and Svensson 1972) in the 1950s and 1960s. The early models, such as the Montague Slasher and “Nesco” Slashmobile took several men to operate (Silversides 1997). Modern slashers now require only one operator.
The next major development in mechanical harvesting was in 1959 with the development of the Busch Combine (Figure 1.2 (b)) and the Pope Harvester. These machines were the first mechanical harvesters that could fell, delimb and buck the stem. The Busch Combine proved to be much more successful than the Pope Harvester which never made it past the prototype stage (Silversides 1997).

The 1960s and early 1970s were interesting times in the development of mechanical harvesting and processing equipment. Logging and equipment manufacturing companies spent much of their time searching for the right combination and design of machine. A number of systems were developed during this time, some of which are still used today, such as stroke delimiters (Figure 1.2 (c)) and flat bed processors (e.g. the Hahn Harvester). In 1966 NESCO, a Canadian company, built the first single-grip harvester (Drushka and Konttinen 1997). During the 1970’s the first grapple processing heads started to appear in Scandinavia, Canada and the USA (Anon. 1975, Folkema and Legault 1976, Heidersdorf 1976). These heads ranged in design from very simple ones which attached a chainsaw to a grapple (Anon 1975) to more complex heavy processor heads (Folkema and Legault 1976, Heidersdorf 1976).

In the early 1980’s Sweden and Finland became world leaders in the design and development of mechanical harvesting systems, first with the development of the double grip harvester and then later with the development of their own single grip harvesters (Richardson 1988, Peltola 1991). In a 1975 publication “Logging in
Sweden”, no single grip or double grip harvesters were described, however, a number of
the processors were starting to evolve into double grip harvesters (Anon 1975). In 1983
SP-Maskiner, a Swedish company, released the SP21 harvesting head which would
truly begin the single-grip harvester era (Drushka and Konttinen 1997). The
development of mechanical harvesting systems in Sweden was driven by the
introduction in 1980 of the vision which stated; “no hand on the saw, no foot on the
ground” (Sewell 1979). The increasing cost of wages and decreasing labor supply in
this area also forced the Swedish industry to turn to mechanical systems (Jonsson 1984).
These Nordic systems were soon introduced into other parts of the world (Richardson

Nordic machines, in particular the single grip harvesters, were not well suited to all
forest types. In New Zealand, for example, these Nordic machines (Figure 1.2 (a)) were
not large enough to process *Pinus radiata* D.Don (radiata pine). This led to the
development of the Waratah harvesting heads (Figure 1.2 (b)) which now have a large
percentage of the market share in New Zealand and North America (www.waratah.net ).
Today a range of mechanical processors and harvesters are used and they have become more reliable and useful. Many modern harvestersprocessors have on-board-computers and self-leveling cabs, which are designed to produce an environment with as little noise and vibration as possible (Gellerstedt 2002).

Single and double grip harvesters dominate the market in Scandinavia with almost 100% of the logging in Finland and Sweden carried out by cut-to-length systems (Nordlund 1996 and Hakkila et al. 1992). It has been predicted in eastern Canada that cut-to-length logging using multifunctional heads will continue to replace full-tree systems (Guimier 1999). In the pine plantation forests of New Zealand and Australia much of the processing was being carried out mechanically by the mid 1990’s. In the USA the use of mechanical processing evolved differently in different regions. In the Pacific Northwest, mechanical processors are becoming the norm with the majority of
the processing been done using single grip harvester/processors, both on the landing and at the stump in the cut-to-length configuration. (pers com. Jeff Wimer 2004). However, in Southeast USA most of the processing is done at the mill. Where mechanical processing is done in the forest, sawbucks or slashers are used (Greene et al. 2001). It is estimated that 10 % of the harvesting in Chile uses cut-to-length systems while 25% uses mechanical processing on the landing. In South Africa the adoption of mechanical harvester/processing has been slow mainly due to the lack of equipment. However, a lack of skilled and healthy workers is also causing South African forestry companies to look into the potential of mechanical harvesting/processing systems (per comm. Henk Stander 2004).

The main drivers for the increasing use of mechanical processors, both on the landing and in cut-to-length systems, are to increase productivity and safety. In the case of mechanical cut-to-length systems there are also environmental advantages. The improvement in safety caused by increasing mechanization of the logging industry is most clearly shown in Sweden. The number of accidents has fallen by about 95 % in the past 20 years. Not all of this drop can be contributed to mechanization, but it is still seen as an important factor (Anon. 1997). A study by Axelsson (1998) determined that there was a 73% risk reduction by mechanization compared to chainsaw-based methods.

Increasing productivity has always been a key driver to increase mechanization of logging. Productivity in logging has increased sharply over the last 50 years. In the
1950’s, productivity in Sweden was less than 2 m³ per man day. At the time that mechanical processors started to appear on the market the productivity had increased to just over 8 m³ per man day. Today the productivity of a fully mechanical harvesting system is over 16 m³ per man day and still climbing (Anon. 1997). A survey of time studies on mechanical harvesters and processors showed that tree size is the most important factor effecting productivity and that it could range between 4 m³/productivity machine hour (PMH) (Makkonen 1992) to 143 m³/PMH (Evanson and McConchie 1996). Along with these dramatic increases in productivity there has been a substantial reduction in the forest workforce, caused in part by the increase in mechanization. Axelesson (1998) referenced a Swedish report that indicated that during the last 40 years the forestry workforce in Sweden has dropped by 90 %.

The capital cost of the Pope Harvester in 1958 was estimated to be $10,000 (Walbridge 1960) (1958 US dollars) which equates to approximately $64,000 today (2003 US dollars). By the 1980’s harvesters and processors had purchasing costs of approximately US$400,000 (in 2003 dollars). Today a single grip harvester still costs around US$ 400,000 - $600,000 (Marshall and Murphy 2003, USFS 2004). Over the last 25 years, prices for harvesters and processors increased at a slower rate than over the previous 30 years.
THE POTENTIAL OF OPTIMAL LOG MAKING ON MECHANICAL HARVESTERS/PROCESSORS

The potential of using optimal log making algorithms in mechanical log making systems was realized early in their development. Pnevmaticos and Mann noted in their 1971 (pg 26) paper that

*this procedure* [a DP optimal bucking algorithm] *can be applied either with the use of tables or a system of computerized control of the slasher.*

In 1973, Ösa, a Finnish company, developed a processor called the Ösa 710. This processor head incorporated a relay-controlled system designed to calculate the optimum use for each tree. However these systems were cumbersome and prone to breakdowns caused by vibration. Five years later, in 1978, the first microprocessor-based measuring systems appeared on Volvo’s new 900 harvesters. This development caused a rapid evolution of automated measuring and bucking technology (Drushka and Konttinen 1997). By 1988, all but a few small farm tractor-mounted models had on-board computers as standard equipment, most had length-measuring systems while only a few had diameter sensors (Richardson 1998).

The use of optimal bucking computer algorithms on Swedish harvesters was first tried in 1986. The algorithm was a simple heuristic model which optimized over nine meter lengths. Four meters of the stem were measured while the next five meters of taper was estimated based on the first measurement (Andersson 1986). In 1987 a range of
different log bucking techniques were used on different mechanical harvesters/processors. Many machines had simple operator selection or predetermined selection of log lengths. Some harvesters/processors used automatic bucking to length, automatic bucking to taper and automatic bucking to value (Sondell 1987).

In 1989, Olsen et al. tried using the OSU-BUCK© software developed by Oregon State University on a Hahn Harvester. The trials showed that a 7.5% increase in value could be obtained through the use of an optimal bucking algorithm.

The latest harvesters have PC based computers with high-resolution color displays, and are equipped with a range of different communication media including printers, floppy disks, wireless connection and cell phones that can connect with the internet. They also have a range of communication ports like serial and USB ports so that other hardware, such as a global positioning system (GPS), can be attached.

**On-board Computers**

The modern on-board computers are capable of running a number of complex applications to control the harvester head, timber measurement and base machine functions. The on-board computer controls, adjusts and monitors the power transmission and hydraulic systems. Others have additional software applications. For example; the Timberjack’s TimberOffice is a suite of software products that can be run on either the machine computer or an office computer. The suite includes a
geographical information system (GIS) and GPS application for navigation; a cost, revenue and budget management application; a system monitoring application for monitoring the performance of the machine and an optimal log merchandising management application (Timberjack 2002). Most of the other large Nordic mechanized harvester/processor manufacturing companies have similar software products (e.g., Valmet’s Maxi (Andersson 2003).

**Internet and Email**

Many of the new harvesters have wireless connection to the internet which provides a platform for better supply chain management in the forestry industry. Wireless communication between the forest machine and the company offices mean that current production can be communicated in real time to the logging company, transportation company and customer. Möller et al. (2002. pg 66) gave the following examples of data exchanges:

*bucking instructions (e.g. customer orders, price lists, and restrictions for different assortments), reporting of production results (volume of logs per assortments and dimensions).*

In Scandinavia, Skogforsk administers StandForD which is a common Nordic and North European Standard for Forest Data and communication (Anon. 2003). All modern harvesters in Nordic countries now operate with the same standard of open data exchange allows production and demand data to be easily exchanged among all members of the supply chain (Möller et al. 2002).
**Measuring Systems**

Modern mechanical harvesters/processors use mechanical sensors, and in some cases photocells, to measure diameter and length. The length measurements are commonly done using a measuring wheel (90% of the time) or the feed rollers that are connected to an encoder (Andersson and Dyson 2002, Gellerstedt 2002). The encoder generates a fixed number of pulses each time the wheel is turned. The wheel is kept in contact with the stem either by using a spring or a hydraulic cylinder (Makkonen 2001). The wheel is either reset using the action of the cut-off saw or in some cases using photocells located near the cut-off saw. The diameter of the log is measured using one or two potentiometers or encoders connected to the feed rollers or delimber arms (Andersson and Dyson 2002, Makkonen 2001). The measuring systems are connected to the on-board computers and the measuring sensors provide them with a continual stream of length and diameter measurements.
Bucking Systems

Most of the literature on the implementation of optimal bucking on mechanical processing systems is based on Scandinavian harvesters/processors. Modern single-grip harvesters employ either buck-to-value or buck-to-order (Sondell et al. 2002 and Uusitalo et al. 2003). As noted earlier in this paper, bucking-to-value means that every stem is cut into logs in such a way that the total value for each stem is maximized. In buck-to-order a stand of trees is bucked so that the fulfillment of orders is maximized.

There are currently two main approaches to buck-to-order optimization (also known as apportionment bucking) that have been developed by the harvester manufacturers. In the “adaptive price list” approach, the value of each log grade is changed in accordance with how well the demand for each product is being met as harvesting progresses through the stand. In the “near optimum” approach a cutting solution is selected from the top 5%, based on value, of the buck-to-value solutions that best fulfills the demand requirements (Uusitalo and Kivinen 2001). The Dasa4, Timbermatic 300, Valmet and Motomit computers all use the near optimum approach; the Ponsses’ computer uses the “adaptive price list” approach (Sondell et al. 2002).

The majority of harvesters use adaptive functions for stem form prediction. These functions are able to “learn” the mean taper in the stand as they work their way through it (Sondell et al. 2002). This allows the stem to be bucked based on only partial
information about stem shape. Uusitalo et al. 2003 states that harvester operators can apply optimal-bucking in three ways:

- **Automatic bucking** – if no significant changes in quality exist within the stem, it can be bucked automatically using the cross-cutting decisions from the optimization system.

- **Automatic quality bucking** – changes in quality are entered into the optimization system, the optimization system then takes the quality changes into account when calculating the optimal cross-cutting decisions. The decisions are then automatically carried out by the harvester.

- **Quality bucking** – In this case, bucking is carried out manually. Pre-selected species and log lengths or diameters (Coyner 2004) are entered into the computer and can be assigned to “hot keys” on the operator’s controls.

When harvesting Norway spruce in Scandinavia, “automatic bucking” is commonly used as there is little variation in quality, and the value differences between lumber-quality grades are quite small. In Sweden “automatic quality bucking” is quite popular (Uusitalo et al. 2003). In other species where there is large variation in quality between trees, and the value of log grades depends heavily on quality, automatic optimization is considered inefficient and has led to economic losses (Uusitalo et al. 2003).
THE PERFORMANCE TO-DATE OF IN FOREST MLM

Despite the new technology that in-the-forest mechanical harvesting/processing has brought to the forest, the performance to-date has been relatively poor with the exception of Scandinavia. In *Picea abies* (L.) Karst. (Norway spruce) mechanical harvester/processors are capable of obtaining near optimal distribution of logs both in terms of the value and order fulfillment. A recent value recovery study in Sweden on five of the most popular merchandising computers, showed that value recovery was all within five percent of the optimal value. However this is not the case in other parts of the world. Figure 1.3 summarizes 60 value recovery studies published in the literature (Murphy 1983, Olsen *et al.* 1991, von Essen and Sondell 1996, Sondell *et al.* 2002, Boston and Murphy 2003, Marshall and Murphy 2004 etc) along with confidential audits of mechanized operations undertaken by the second author in Australia and New Zealand. The results are expressed in percent value loss:

\[
\text{Value Loss (percent)} = \frac{100 \times (\text{Optimal } $ \text{value} - \text{Actual } $ \text{value})}{\text{Optimal } $ \text{value}} \quad (1.1)
\]
Figure 1.3 - Results from a survey of value recovery studies on mechanical harvesting systems.

The average value loss for the 60 studies included in the graph was 18% with a range from 1 to 68%. As an indicator, reported studies (Garland et al. 1989, Murphy et al. 1991, Bowers 1998) and confidential audits of 48 manual log-making operators from South Africa, New Zealand, USA and Canada showed a maximum value loss of 33% and an average value loss of a little over 11%.
Increases in value recovery can come from mechanized felling through a reduction in stump heights, reduced damage to the butt log, and less breakage higher in the tree (Murphy 2003a). Studies have shown that increases could be up to $1450 per ha in South Africa (Kewley and Kellogg 2000). The level of improvement depends on the tree size, markets, and the skill levels of both the manual fellers and mechanized felling machine operators. In thinning operations, mechanical cut-to-length systems have been shown to cause less stand damage than tree length systems (Han 1997, Lanford and Stokes 1995).

There has been little work done on determining how good different operations are at maximizing revenue while fulfilling orders. Once again the Scandinavians are the leaders in this research (e.g. Sondell 1993, Möller and von Essen 1997, Sondell et al. 2002). Percent value recovery, or loss, gives little indication how well the harvesting operation has fulfilled the orders required of it. The most popular measure for determining how well a buck-to-order operation is working is the apportionment degree (AD), the formula for which is given in Eq. 1.2.

\[
AD(\%) = 100 \times \left( 1 - \frac{\sum_{i=1}^{k} |D_{di} - D_{pi}|}{2} \right)
\]  

(1.2)

where

k = number of log grades

\(D_{di}\) = proportion of demand for the log grade

\(D_{pi}\) = proportion of production for the log grade
The latest published information on the performance of the buck-to-order systems was done by Sondell et al. (2002). This study found that, with the exception of one merchandizing computer, all were able to obtain an AD of 80% or greater for Grade 3 Norway spruce.

So why is the rest of the world so far behind the Scandinavian countries in extracting the most from their resources using mechanical processing machines? If the Scandinavian value losses shown in Figure 1.3 are removed from the analysis the average percentage value loss increases to 22.3%. We would conjecture the most probable reasons for the large difference between the Scandinavian countries and other parts of the world are firstly, Norway spruce as a species has few defects and low intra and inter-tree variability (Uusitalo et al. 2003), and secondly the Scandinavian machines and software are designed for processing Norway spruce specifically for the spruce markets.
CHALLENGES TO OBTAINING OPTIMALITY IN FOREST MLM AND POTENTIAL RESEARCH PROJECTS

The value recovery studies from around the world (Figure 1.3) clearly show that there is significant room for improvements in the performance of mechanical harvesters/processors. Obtaining the correct and optimal distribution of logs from a mechanical harvester/processor operation requires the interaction of four different areas; mechanical/computing systems, customer’s and seller’s needs, human nature and stand composition variation (Figure 1.4).

Figure 1.4 - The factors effecting the optimal output distribution of logs in a mechanical processing operation (This is a modified version of a diagram in Uusitalo and Kivinen 2001).
The following sections describe the challenges and potential research projects that exist in each of the boxes in Figure 1.4.

**Measurement Error**

Several studies have looked at the level of measurement error of the length and diameter systems in Sweden, Canada, USA and New Zealand; all conclude that the accuracy levels are unsatisfactory (e.g. Andersson and Dyson 2002, Evanson and McConchie 1996, Sondell et al. 2002). However, few studies have looked at the economic impact of inaccurate length and diameter measurements. Sondell et al. (2002) estimated that measurement error in Norway spruce caused approximately 1% loss in value. Measurement errors have been shown to be much greater in the processing of other species, which would indicate that losses in these species could be considerably greater. Obtaining an estimate of the potential value loss from length and diameter errors would help justify the development of new and improved log measuring systems, such as those proposed by Löfgren and Wilhelmsson (1998), Möller et al. (2002) and Judd (2004).

In most cases, log quality characteristics, such as knot, rot and sweep are visually assessed by the operator. These log quality characteristics are, for some species extremely important for characterizing different log types and their value. There have been few scientific studies looking specifically at how well operators assess changes in either stem quality or form as the stem is being processed. Gellerstedt (2002), however, reported that Scandinavian harvester operators indicated that they have problems seeing
defects in the log at current feeding speeds of 4 m/s and that more “sensing” in the harvester head is required for faster operation and better judgments on stem quality.

**Stem Shape and Quality Forecasting**

One of the problems with true optimal bucking on mechanical processing systems is that bucking algorithms require a full description of the stem. This requires the stem to be fully measured before processing. The head would have to travel along the stem at least twice (three times if it has to return to the butt before bucking can begin) which can have a serious impact on the productivity of the operation. As noted earlier, many of the Scandinavian harvesters/processors are designed to optimize the bucking of a stem by measuring a portion of the stem and then forecasting ahead (Berglund and Sondell 1985, Uusitalo and Kivinen 2001). This procedure has been used to great success in Norway spruce (Sondell et al. 2002), but has little use in the optimal processing of other species in Scandinavia such as Scots pine and birch.

Research done on Scots pine in both Sweden (Möller *et al.* 2003) and Finland (Nummi and Möttönen 2002) on prediction models for accurately forecasting a number of lumber and wood quality characteristics during the stem processing operation is showing promising results. To date there has been limited research on modelling stem characteristics specifically for forecasting during log making on any other species. Although this partial measurement method of bucking is sometimes used in the processing of other species around the world, there has only been one study done
outside Scandinavia on the productivity gains and value losses of using partial stem scanning procedures (Murphy 2003b).

**Market Demand and Log Value**

As forest companies try increasingly to improve their supply chain management, fulfilling orders at the right time is becoming extremely important. A key link in the forestry supply chain are the log makers. They are the people responsible for converting the trees, which required years of investment to produce, into products. This means that log makers have control of the rate of production of these products and their allocation. A study on Temple-Inland sawmills showed that there is an approximate 3.3 % improvement in profit margin through improved valuation of sawtimber and better allocation of sawlogs (Wagner *et al.* 1996). Accurately matching demand to supply allows mills to reduce their log inventories and improve their delivery performance which leads to reduced costs for the entire supply chain (Jones 1999).

Mechanical harvesters/processors have some real advantages in terms of having computers on-board that can monitor and adjust production so demand requirements are met. The communication systems now available allow production data to be passed to the mill and demand information to be passed back to the harvester in real time through the internet and email (Sondell *et al.* 2002). This real time communication allows product specifications and pricing to be changed on the harvester from the mill instantly, while the harvester can send information about the next load of logs to the
mill before the truck leaves the landing. Historical yield information can easily be recorded along with spatial information using GPS and GIS technology which should allow future product yields, in terms of both quantity and quality, to be forecasted.

Much research is still required if the full potential of these systems in helping to manage the forestry supply chain is to be realized. Once again the Scandinavian research and forest industry is significantly more advanced in this area when compared to other forest industries around the world. Many of the Scandinavian harvesters now store and report information in standard formats, meaning that this information can be easily transferred to all members of the supply chain (Möller et al. 2003). The hardware systems to allow harvesters/processors to become a pivotal source of information in the forestry supply chains are available; however, many of the software and information systems have yet to be developed in many parts of the world.

**Harvest Operator Effect**

The human operator is still extremely important, despite the technology and automation that exists on the modern harvesters/processors. The current technology still requires many of the machine controls to be handled by the operator. A study by Gellerstedt (2002) found that operating a harvester requires 4000 control inputs per hour. Another study found that a harvester operator in a thinning operation is making approximately 16 decisions per minute (Forsberg, 2003). Traditional logging has been seen as an extremely physical occupation requiring limited mental power. However, operating a
modern harvester/processor requires knowledge of planning, machine maintenance, merchandizing computers, environmental needs and log specifications (Gellerstedt, 2002). Gellerstedt (2002) points out that perceptual motor skills are still an important part of the tree harvesting operation, but the importance of performing cognitive skills has grown.

To help operators get all the information they require, they need to have a good view of the area around the harvester as well as a good interface between him/herself and the harvester’s computer. Harvesters and processors cabs are generally built to maximize the viewing range of the operator. The modern computers give cross-cutting suggestions by using audible and visual signals as well as the harvester head stopping at the correct location. Research done on the correct layout of the information on the harvester’s computer screen, showed that using symbols, colors and size and positioning in the design can help improve the operator’s ability to obtain information (Forsberg 2003).

Literature in the field indicates that it takes up to two years to become 100% productive in a harvester (Anon. 1990, Cottell et al. 1976). Gellerstedt (2002) noted that to reach an acceptable capacity in log-making, an operator needs theoretical knowledge about log grades and their end use, as well as being interested in learning the skill of assessment, which can take several years to learn. Training is an important part of getting new operators up to their full potential quickly. Gellerstedt and Dahlin (1999) reviewed the training programs for forest workers in Sweden, Germany and USA. They
found that Sweden and Germany had specialty training programs where as the USA training tends to be “on-the-job” training with limited short courses. In Sweden, forestry schools usually own several different types of harvesters solely for training purposes (Packalén 2001). It seems that with the high operating cost of harvesters and the high level perceptual motor and cognitive skills required by harvester/processor operators it would be logical to put potential operators through well designed training programs.

The use of simulators is becoming increasingly popular as a low cost way of selecting and training new operators. A number of harvester manufacturers have built simulators. In total there are 30 Timberjack simulators around the world (Packalén 2001) and Valmet and Ponsse are known to have they own simulators. A study of the benefits of training on a simulator (Freedman 2004) showed that productivity could be increased by 25%, the volume of wood could be increased by 50% and maintenance and repair costs could be reduced by 30%. The main focus of current simulators seems to be to increase productivity. To the authors’ knowledge there is no, or limited, consideration for improving value recovery in the modern harvester simulators. Value recovery, and the evaluation of the trainee’s ability to maximize value in cross cutting, could easily be integrated into harvester simulators.

In 1998 Swedish harvesters worked 2500-2700 hours a year (Gellerstedt and Dahlin 1999), thus shift and night work is on the increase (Gellerstedt 2002). Work has been done in Australia looking at the effect of fatigue on productivity (Nicholls et al. 2004).
A negative effect of operator fatigue on productivity was not shown, however studies in other industries have shown an effect. The authors are unaware of any studies that have looked at the effects of fatigue or increased stress on the quality of the bucking decision made by harvester/processor operators.

**Stand Composition**

The variables which make managing and optimizing the forestry supply chain hard compared to other industries, are the inter and intra natural variability in the stand and forest composition. However, with the use of adaptive modeling techniques, some tree and stand characteristics can be predicted. For example, in harvesters/processors such as the Ponsse harvester, taper is adaptively modeled using the last eight trees. Research has been done on trying to predict stem and wood characteristics spatially through the stand (Möller et al. 2003). Much work still needs to be done. Many of the supply problems in the forestry industry would be solved if the shape and quality of the next tree could be accurately predicted.
CONCLUSIONS

In the past the logging industry has concentrated its efforts on reducing costs in an attempt to maximize profits. In designing mechanical harvesting and processing machines, increasing productivity has been a key motivation for new developments. Today’s machines have faster processing speed and are more reliable than in the past. Logging, however, can be one of the major areas where the potential value of a forest can be lost.

In Scandinavia, where many of the new mechanical harvesters are being developed, the forestry and forest equipment industries have invested and still are investing, considerable amounts of money and time in new hardware and software that can help obtain the optimal distribution of logs both in terms of their value and order fulfillment. However, unlike the productivity improvement technology that seems to have been successfully applied to other areas of the world, the value maximizing technology has not been so successful. This is largely due to differences in tree species, forest types and markets.
As the level of competition in forestry increases, value maximization at the time of harvesting trees is vitally important for improving or maintaining international competitiveness. The Scandinavians have shown that mechanical harvesters/processors provide a great platform from which to better manage the forest supply chain. In many parts of the world, however, the way that the technology is applied will need to be customized for different forest types and markets.
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Chapter 2:

EVALUATION OF THE ECONOMIC IMPACTS OF LENGTH AND DIAMETER MEASUREMENT ERROR ON MECHANICAL HARVESTERS/PROCESSORS OPERATING IN PINE STANDS.

By Hamish Marshall

Glen Murphy
ABSTRACT

Value recovery studies from around the world have shown that on average mechanical log making systems lose 18% of the potential value compared to 11% for motor manual systems. One of the potential reasons for their poor value recovery performance is the level of accuracy of their diameter and length measurements of the stem. Numerous studies have looked at the level of error in both the diameter and length measurements made by mechanical harvester/processors; however, few have looked at the economic impacts of these errors.

The paper investigates the economic impacts in terms of value loss of six different harvesting operations in three different pine species. The accuracy and precision of the measurements recorded in this study were similar to other studies done around the world. A simulation model was developed to estimate the value loss caused by these errors. The results of the simulation model showed that the operations were losing between 3% and 23% of the potential value due to measurement errors. Further analysis showed that the industry should concentrate on increasing the precision of the length and diameter measurements to make the most gains from reducing the measurement error rates.
INTRODUCTION

There is a worldwide trend toward mechanization and computerization in the forestry industry. This is particularly true in timber harvesting operations where the adoption of harvester/processors with on-board computers has increased markedly (Gellerstedt and Dahlin 1999, Godin 2001). The drivers for this trend include productivity/cost improvements (Anon. 1997) and labor-related issues, e.g. to improve worker safety (Axelsson 1998) and to address growing labor costs.

The first automated measurement systems based on relay technology appeared in 1973. They were replaced by more reliable microprocessor-based measuring technology in 1978. Initially log length was the only measure made, however in the mid 1980’s harvesters and processors started to measure diameter as well (Drushka and Konttinen 1997). In 1988 the first automated cubic measuring system was introduced. By that year most Scandinavian harvesters had length-measuring systems, while a few had sensors for measuring diameters (Richardson 1988).

Modern harvesters/processors are commonly equipped with merchandising computers, with high-resolution color display, keyboards, floppy disk drives and remote communications systems allowing the computer to connect to the Internet (Sondell et al. 2002). These merchandising computers are connected to length and diameter sensors
that provide a continuous-stream of stem dimensional data to the computer to assist the operator in making value driven bucking decisions.

The length measurements are commonly done using a measuring wheel (90% of the time) that is connected to an encoder (Andersson and Dyson 2002, Gellersedt 2002). The encoder generates a fixed number of pulses each time the wheel is turned. The wheel is kept in contact with the stem either by using a spring or a hydraulic cylinder (Makkonen 2001). The wheel is either reset using the action of the cut-off saw or in some cases using photocells located near the cut-off saw. Some harvestersprocessors do not have a measuring wheel; instead they use the feed rollers connected to an encoder. The diameter of the log is measured using one or two potentiometers or encoders connected to the feed rollers or delimber arms (Andersson and Dyson 2002, Makkonen 2001).

Figure 2.1. - A common configuration of a single grip harvesting/processing head.
As with all measurements, the length and diameter measurements made by the harvesting head sensors will contain some level of error. Errors are defined as the difference between the measured and true value of a physical variable of an object. There are generally two classifications of error; random/accidental and systematic errors. Mistakes or gross blunders are not errors and should never be called such (Barry 1978).

Systematic errors have a definite magnitude and direction (Sirohi and Radha Krishna 1991); that is, the output readings from the measurement are consistently on one side of the true value (Morris 1996). Random errors tend to be small and many times are mutually compensating. Both the magnitude and direction of the error is random and the probability of a particular error occurring usually follows the normal distribution. Therefore, the measurement of random error is the standard deviation of the error distribution.

There are a large number of causes for measurement error; they include a lack of instrument calibration, changes in environmental conditions, external and internal nature of the subject or object and the skill level of the observer (Morris 1996, Sirohi and Radha Krishna 1991).

Two important concepts in describing error are accuracy and precision. Accuracy (Figure 2.2(b)) describes the agreement of a measurement to the true value of the
measurement quantity. Precision (Figure 2.2(a)) refers to the repeatability of a measuring process, that is the closeness to which measurements of the same physical quantity agree to one another regardless of any systematic error measurements (Sirohi and Radha Krishna 1991). The most desirable measurements are those that are both accurate and precise (Figure 2.2(c)).

![Figure 2.2. - Three targets showing (a) precise shooting but inaccurate, (b) accurate shooting but not precise and, (c) precise and accurate shooting.](image)

Several studies on the accuracy and precision of the measuring systems installed on modern harvesting heads have been carried out in Sweden and eastern Canada. The earliest work was carried out by von Essen and Sondell in 1996. This same study was repeated in the same Swedish stands in early 2001, where five of the six merchandising systems on the market in Sweden at the time were tested. The tests were carried out in a large diameter *Picea abies* (L.) Karst. (Norway spruce) stand and only undamaged trees were processed. The study concluded that although improvements had been made in communications, productivity, and value extraction from the timber, the length and diameter sensors were still largely unsatisfactory (Sondell *et al.* 2002).
Another Swedish report looked specifically at the diameter measurements made on the harvester and at the sawmill. The standard deviations for diameter error from harvester diameter measurement found to be between 5-8 mm. This range included errors arising from inaccurate bark thickness estimates, logs being oval or out of round and the measurement apparatus not maintaining contact with the stem. They concluded that although work still needs to be done on diameter measurement at the mill, the highest priority needs to be placed on the development of improved diameter sensing technology on harvesters, together with equipment and methods capable of providing correct readings of diameter under bark (Moller et al. 2002).

A large investigation was carried out by FERIC on 103 harvesters/processors throughout western Canada from October 1996 to September 1999. All the systems, which included both double and single grip, strokers and roll-strokers harvesters, had microprocessor-based technology which was connected to length measuring systems. Some also had diameter sensors. FERIC reported the length error in terms of meeting company specifications rather than absolute error. It was found that 37% to 100% of the logs processed in 83 cut-to-length operations met the company log length specifications. On the long log operations the percentages were 36% to 95%. FERIC studied the diameter measurement accuracy on 31 of the cut-to-length operations. The errors were expressed as a percentage of the small end diameter that were within the following error ranges; ± 2 mm, ± 4 mm and ± 8 mm. On average, it was found that 19%, 34% and
57% of the logs were within these error limits, respectively (Anderson and Dyson, 2002).

An earlier FERIC study by Plamondon (1999) which looked at only length error, reported results in absolute error terms. In total, 13 different machines with 6 different harvesting head brands were studied. The mean errors ranged from -8.75 cm to +8.44 cm with a standard deviation for the error distribution ranging from 1.28 to 13.3 cm. It should be noted that some contractors in the study adjusted log lengths by modifying the limiting values for the “bucking window” (for example, the values that the computer uses to determine when to cut a log) rather than calibrating the system. In these cases a large mean error is produced but the logs still conform to product standards.

The sources of these errors are both systematic and random. Much of the length error relates to either the measuring wheel that is used and/or the characteristic of the stem surface over which the wheel is traveling. The need to maintain direct contact between the measuring wheel and the stem leads to many possible errors as a result of the wheel losing contact with the stem or slipping on the bark (Makkonen 2001). Often poor calibration of the measuring wheel can cause significant systematic length errors. Systematic length errors are also caused by the stem shape, when a measuring wheel crosses an obstacle such as a branch stub, swelling around the branch whorls can cause the measuring wheel to travel a longer distance, causing a log’s length to be over
measured. Stem taper also causes the measuring wheel to travel a longer distance than the actual length of the stem.

Plamondon (1999) looked at the assumption that the length error increases with log length. He found that increasing log length could not fully explain the variation observed in his results. He concluded that although this effect is probably real, it remains weak by comparison with other sources of variation.

Random length errors also result from disturbances that occur in an unpredictable or irregular fashion. The vibration and shocks from the stem hitting the ground and when handling the fallen tree can induce measurement errors. This is more likely to occur when measuring the butt log, so the length accuracy tends to be more inconsistent for butt logs than for logs bucked from the middle of the stem (Makkonen 2001). Plamondon (1999) showed that the presence of defects such as scars, calluses, knots with a diameter greater than 3 cm, very knotty sections and dry or crooked trees, increased the standard deviation of length-measurement errors by up to 45% compared to logs without such defects. In some species the amount of length measurement error that occurs is dependent on the season; in spring/summer when the sap is running the bark can become looser which can cause the measuring wheel to increasingly slip. Length measurement errors may also increase in species which are difficult to delimb as the operator may have to run up and down the stem to remove the branches, this increases the distance traveled, which could increase the potential for error.
In some cases the trigger used to reset the length measurement does not work, this may cause an error, however it is probably more correct to consider this a mistake or gross blunder.

The level of accuracy and precision of diameter measurements are also affected by the surface characteristic of the stem. The amount of pressure applied to the delimming arms or feed-roller, will effect the diameter measurement. In most cases a maximum of three measuring points lying in different planes are used. This means that the minimum diameter can not be measured accurately on irregular logs (Makkonen 2001).

Another potential source of diameter measurement error is incorrect application of bark thickness equations. The majority of the logs sold around the world are sold on a volume under bark basis, however most diameter measurements made by harvesters are made over bark. Many of the modern harvesters have bark thickness adjustment factors and equations built in; however their level of precision varies. These systems also require the operator to make adjustments to these factors and equations for different forest types.

There have been few studies which looked at the implication of measurement error. Olsen et al. (1989) investigated the effects of accuracy of length and diameter measurements on the optimal bucking solution. Their study was carried out on manual log makers using log tapes for length measurements in second growth Douglas fir
forest. Three different methods of measuring diameter were also used; bucker’s tape, angle gauge, and calipers. The study found that length errors were not significant. Errors in diameter measurement, however, resulted in a substantial loss in potential value: 5.2% when using a logger’s tape, 2.0 % with the angle gauge, and 1.4% with calipers.

There is general agreement in the literature that the length and diameter measuring accuracy of harvesters will have an influence on the precision and quality of the bucking operation (Plamondon 1999, Sondell et al. 1993 and Chiorescu & Grönlund 2001). There is, however, little literature on the effect of measurement error on either the value recovery of a harvester or volume estimates made by a harvester. It has been estimated that in Norway spruce that measurement error could cause approximately 1% loss in value (Sondell et al. 2002).

This paper focuses on single grip harvesters and single grip processors as they are now, or are predicted to become, the dominate type of harvester/processor used in many parts of world (Anon 1997, FERIC 1996, Gellerstedt and Dahlin 1999, Hakkila et al. 1992). Similar problems still exist when double grip harvesters and stroke-boom processors are used; a definition of these terms is given in Kellogg et al. (1992).
Objectives

The objectives of this study are (1) to determine the levels of diameter and length measurement error produced by modern harvesters and (2) to investigate the economic impacts of a range of these errors. This study will look at the economic impacts from a landowner’s perspective; the analyses use the log as the economic unit.
METHODS

There are three main parts to the methodology for this study. In the first part data was collected on machines operating under normal conditions to create length and diameter error distributions. This allowed us to understand the level of diameter and length errors that are occurring in practice. In the second part stem and log specifications were collected from three pine stands. The length and diameter errors distributions and the stem database were then used in the third part to determine the economic impact, in terms of value loss, of length and diameter measurement error. An optimal bucking/error simulation model was developed to help determine these economic impacts.

Part 1: Error Distributions

Descriptions of the Equipment and Study Sites

Table 2.1 gives a description of the equipment, sites and operator experience. All the studies were carried out in pine stands between July 2002 and July 2004. In total six harvesters were studied representing three different harvester head manufacturers. There was no reason for selecting these particular brands of harvesters. Two of the operations were working in *Pinus ponderosa* Lawson & C.Lawson (ponderosa pine (PP)), three in *Pinus taëda* L. (loblolly pine (LP)) and one in *Pinus radiata* D.Don (radiata pine (RP)). Five of the six were operating in a cut-to-length (CTL) configuration at the stump, while the other was operating as a processor of full length stems at the landing (POL).
Of the six sites studied four of them were being commercially thinned; the remainder of the sites were clear felled.

Three of the studies were carried out in Georgia and Alabama and were done as part of a Master of Science thesis by Conradie (2003). One was carried out with the help of Forest Research in New Zealand. The other two were carried out in eastern Oregon.

Table 2.1. - Summary of equipment and study sites.

<table>
<thead>
<tr>
<th>Study</th>
<th>Carrier/Head</th>
<th>Merchandising Computer</th>
<th>Site Location</th>
<th>Species/Operation Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Valmet T500/s52</td>
<td>Valmet Maxi</td>
<td>Eastern Oregon</td>
<td>PP/CTL thinning</td>
</tr>
<tr>
<td>B</td>
<td>Valmet T520/s52</td>
<td>Valmet Maxi</td>
<td>Eastern Oregon</td>
<td>PP/CTL thinning</td>
</tr>
<tr>
<td>C</td>
<td>Ponsse Ergo/H73</td>
<td>Ponsse Opti</td>
<td>Alabama</td>
<td>LP/CTL thinning</td>
</tr>
<tr>
<td>D</td>
<td>Ponsse Ergo/H73</td>
<td>Ponsse Opti</td>
<td>Georgia</td>
<td>LP/CTL clearfell</td>
</tr>
<tr>
<td>E</td>
<td>Ponsse Ergo/H73</td>
<td>Ponsse Opti</td>
<td>Alabama</td>
<td>LP/CTL thinning</td>
</tr>
<tr>
<td>F</td>
<td>Cat 330CL/Waratah HTH 626</td>
<td>Logrite</td>
<td>New Zealand</td>
<td>RP/POL clearfell</td>
</tr>
</tbody>
</table>

The above operations were not selected as a representative sample of the population of harvester operations; each should be seen as independent case studies.
Data Collection

For each machine a series of trees were chosen at random and marked with a number. The trees were then processed into logs according to the onboard computer’s settings. The machines’ measurements were collected in one of three ways: (1) the process was videotaped so that the merchandizing computer screen was visible at all times. The length and diameter measurement displayed by the computer were recorded from the video. The video was also used to determine the location of conditions that may have caused the sensors to miss measure the log. (2) The researcher sat in the machine with the operator and noted the diameter and length measurements when the cut was made or (3) the log file of the log cut from each stem was obtain from the merchandizing computer.

The operator arranged the logs from each individual tree in discrete groups. The length and diameters, in most cases small end diameter only, were then measured using a standard loggers tape and calipers. Although the measurements made by the tape and calipers are not absolutely free of error, the assumption is made that these errors are significantly less than those made by the measuring systems on the harvester.

The operators were informed of the study objectives before starting. The contractors were allowed to calibrate their machines. They were also asked about the calibration procedures in terms of the actual process and timing.
Statistical Analysis of the Error Distributions

The harvester’s measurements and the manual measurements for each log were matched up. It was assumed that the manual measurements made with the calipers and the tape were considered to be the actual measurements. The length and diameter errors ($\epsilon$) were calculated simply by subtracting the harvester measurement from the actual measurement.

$$\epsilon = y - \hat{y}$$  \hspace{1cm} (2.1)

where $y$ is the actual measurement and $\hat{y}$ is the measurement displayed by the harvester. A negative error indicated that the harvester was under-estimating the true measurement and a positive error means that the harvester was over-estimating the true measurement.

The studies by Cossens (New Zealand Forest Research Institute, unpublished data), Plamondon (1999), Möller et al. (2002), Andersson and Dyson (2002) showed that errors are distributed around a mean error level. Plamondon (1999) assumed that the length errors were normally distributed. This assumption is supported by much of the literature on measurement error (Barry 1978, Sirohi & Radha Krishna 1991 and Morris 1996) which states that individual measurement errors are normally distributed. The distribution software BestFit© (Palisade Corporation 1997) was used to determine how well the normal distribution fits the diameter and length errors collected from each of
the harvesters. The Kolmogorov Smirnov test was used to measure how well the normal distribution fitted the sample data. BestFit© was also used to calculate the means and standard deviations for the different distributions.

Regression analysis was used to determine whether the length and diameter errors could be explained by any of the measured stem characteristics. Table 2.2 lists the independent variables tested in the regression analysis. Simple regression analysis was used in most cases; however, for a number of the independent variables multiple regression analysis was used.

Table 2.2. - Independent and dependent variables used in the regression analysis

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Diameter Error</th>
<th>Length Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>height*</td>
<td>height*</td>
<td>log length</td>
</tr>
<tr>
<td>true diameter*</td>
<td>true diameter*</td>
<td>log volume</td>
</tr>
<tr>
<td>log volume</td>
<td>log volume</td>
<td>height</td>
</tr>
<tr>
<td>log quality</td>
<td>log quality</td>
<td>log quality</td>
</tr>
<tr>
<td></td>
<td></td>
<td>change in diameter</td>
</tr>
</tbody>
</table>

* included in a multiple regression analysis.
Part 2: Stem Databases and Log Grade Specifications

Description of the Stem Databases

The stem databases were collected by taking accurate measurements of trees that had been felled. For each tree in the database, overbark diameters were measured at approximately 3 meter intervals up the stem with calipers. In the case of the ponderosa and radiata pine stems underbark diameters were determined using bark thickness equations. The loblolly pine overbark diameters were used in the analysis, as the log grade specifications used overbark measurements. The location of changes in knot size and the presence and severity of other defects were recorded. The form of the stem was also recorded; change in the stem curvature (sweep) was recorded by measuring the location of the start and end of the swept section, the severity was measured relative to the diameter at the top of the swept section. A summary of the three stem databases is given in Table 2.3.

Table 2.3.- Summaries of the stem databases.

<table>
<thead>
<tr>
<th>Stem Database</th>
<th>Species</th>
<th>Average Stem Length (m)</th>
<th>Average Stem Size (m³)</th>
<th>No. of Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP</td>
<td>ponderosa pine</td>
<td>13.3</td>
<td>0.39</td>
<td>100</td>
</tr>
<tr>
<td>LP</td>
<td>loblolly pine</td>
<td>21.1</td>
<td>0.61</td>
<td>60</td>
</tr>
<tr>
<td>RP</td>
<td>radiata pine</td>
<td>29.0</td>
<td>2.34</td>
<td>107</td>
</tr>
</tbody>
</table>
Description of the Log Grade Specifications

The log grade specifications describe the minimum log characteristics required for a log to be sold as a particular grade. The specification also includes the price for which the log grade will be sold. The specifications were obtained from the forest owners of the stands from which the stems were collected. The specifications included characteristics such as minimum and maximum log length and small and large end diameters, minimum acceptable quality features (e.g. maximum branch size), maximum allowable sweep etc. The number of log grades and specifications used differed greatly between the species. Table 2.4 summarizes the log grade specifications used.

Table 2.4. - A description of the log specifications used with each stem database.

<table>
<thead>
<tr>
<th>Log Specification</th>
<th>Stem Database</th>
<th>Number of Log Grades</th>
<th>Length Range (m)</th>
<th>Price Range ($/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PP</td>
<td>ponderosa pine</td>
<td>7</td>
<td>2.4 - 6.7</td>
<td>4.00 – 62.00</td>
</tr>
<tr>
<td>LP</td>
<td>loblolly pine</td>
<td>4</td>
<td>3.0 - 6.1</td>
<td>2.50 - 35.00</td>
</tr>
<tr>
<td>RP</td>
<td>radiata pine</td>
<td>20</td>
<td>1.0 - 12.1</td>
<td>31.20 – 153.40</td>
</tr>
</tbody>
</table>

The price ranges given in Table 2.4 are relative prices and not the market prices. Relative price takes into account not only the market price, but also the market demand. It represents the importance of each log type relative to each other.
Part 3: Determining the Economic Impacts

Description of the Optimal Bucking/Error Simulation Model

To determine the economic impacts of diameter and length measurement errors, an error simulation model with an imbedded optimal bucking algorithm was developed. The model simulated the processes that a harvester goes through in the bucking of a stem. The model assumed that the harvester was operating an optimal bucking system and that each stem was completely scanned before the stem entered the optimization process. However, most modern harvesters do not completely scan the stem before bucking the stem into logs (Sondell et al. 2002, Uusitalo and Kivinen 1999 etc); many such as the Ponsse harvesters (Ponsse 2002), have a taper equation prediction system so a near optimal solution can be generated without scanning the full stem. The assumption to completely scan the stem before bucking was made so the effects of the errors could be determined independently of any stem forecasting system.

The model assumed that the following bucking process was completed by the harvester for each stem; the stem was lifted, and scanned for dimensions, quality and form. This information was used by an optimal bucking algorithm to create an optimal bucking pattern for the stem. The harvesting head then moved along the stem measuring the length and stopping at the location where optimal cuts were to be made. The model simulated a completely automated scanning and bucking operation with no human input. The simulation model was designed to simulate measurement errors that occur, not only during the initial scanning phase, but also when the actual logs were being cut.
In the cutting phase, only length errors were applied as it was assumed that the machine uses the log lengths to cut the stem up into logs. The initial length, diameter and the log length errors could be applied independently of each other or together.

Figure 2.3 is an overview of the whole optimal bucking/simulation model. The model was developed in Microsoft C# programming language. A Microsoft Access database was used to hold the stem descriptions.

![Flowchart](image)

**Figure 2.3.** Overview of the optimal bucking/error simulation model.
The simulation model takes the stem description stored in the stem database and develops a “stem piece”. A “stem piece” is a model of a stem, in which the stem is broken into stages of a set length (0.1 meter). For each stage, the large and small end underbark diameter is calculated as well as the quality and sweep code, the number of defects and volume of that stage. The model randomly generates length and diameter errors from user-supplied error distributions and applies them to each stage of the selected stem piece.

**Applying the Length Error**

When a length error is applied, it is applied randomly to every stage in the “stem piece”. The model attempts to mimic how a harvester on-board computer and measuring system would measure a stem. For example if a harvester measuring system was under measuring every 0.1 meter stage by 0.02 meters then the harvester on-board computer would make diameter, quality and sweep measurements at 0.08 meter intervals while still recording the stage length as 0.1. Consequently a stem that should have only had 300 0.1 meter stages would have, on average, 375 stages and to the computer’s knowledge the stem will be 37.5 meters long rather than being only 30 meters. The simulation model, for a given “stem piece”, creates enough randomly generated stage lengths (i.e. $0.1 + \varepsilon$ where $\varepsilon = N(\mu, \sigma^2)$) so that their cumulative total is equal to the total length of the original stem. The polar method (as described by Law and Kelton 1991) was used to generate random numbers from a normal distribution ($N(\mu, \sigma^2)$) with a mean of $\mu$ and variance of $\sigma^2$. A new “stem piece” was then created with enough
elements to account for the error adjusted length. The next step was to recalculate each stages’ small and large end diameter, quality and sweep code and volume from the original stem database data using the stage lengths \((0.1 + \varepsilon)\). Figure 2.4 gives an example of how the addition of errors effects the stem description used by the optimal bucking computer.

Figure 2.4. - An example of how length measurement error is applied to a stem.
In this example the stage length used to describe the stem is supposed to be 0.1 meter. The first stem (A) is the true stem as it would appear if the machine is making perfectly accurate measurements. The second stem (B) is the actual measurements that are made assuming that the system is under measuring the stage length. The last stem (C) is the stem description that would be used by the optimal bucking algorithm. It can be seen that the stem (A) and stem (C) are quite different in terms of the stage LED and SED, and quality code. The quality and sweep codes change because the quality/sweep code that is applied to a stem is the lowest code that exists in the length of the stem that the stage covers. Due to the changes in the LED’s and SED’s the stage volume will also change. These changes will have an effect on the optimal bucking solution produced.

**Applying the Diameter Error**

Once the length error has been added to the stem description the diameter error can be added (Figure 2.5). This is done by adding or subtracting a randomly generated diameter error term. The diameter errors were generated in the same manner as the length errors but from a different normal distribution. If the diameter adjusted error is less than zero, ie it has a negative diameter and the diameter of that stage is changed so that it is 0. Once the diameters are adjusted for error the stage volumes are recalculated.
Optimal Bucking Solution Generation

The two “stem pieces”, true and error adjusted, are then optimally bucked with an optimal bucking algorithm. The “BUCKIT” optimal algorithm is used in the model. “BUCKIT” uses a dynamic programming (DP) algorithm to determine the optimal cutting pattern given a stem description and a set of log specifications. Dynamic programming was originally developed by the American mathematician Richard E. Bellman in the 1950’s (Dykstra 1984). “BUCKIT” uses a similar dynamic programming algorithm to that contained in AVIS (Geerts and Twaddle 1984) and was developed by the senior author.

Figure 2.5. - An example of how diameter measurement error is applied to a stem.
Processing the Stem Using the Bucking Solution

The next step in the stem processing simulation after the optimal solution has been generated is to cut the logs as specified in the optimal solution. This requires the processor to measure the length of each log, starting most probably at the large end of the stem and making the cuts at the appropriate lengths. The model can also apply a length error to this part of the simulation. It does this by taking the log lengths from the optimal bucking solution and adding a randomly generated length error.

Comparing the Solutions

To make a comparison between the solution produced from the accurately measured stem and the same stem when it is inaccurately measured, it is necessary to determine whether the solution from the inaccurately measured stem is feasible, that is, can it be cut from the stem? To do this the “BUCKIT” algorithm takes the stem and breaks it into “sub stems” using the log length measurement from the optimal bucking solution and rebucks each “sub stem” separately if the original solution for that sub stem was found to be infeasible. Based on the theory of optimality used in DP (Dykstra 1984), if the logs in the optimal solution can be cut from the “sub stems” then those logs will be cut. If the original specified log can not be cut from that “sub stem”, “BUCKIT” will find the solution for the “sub stem” that gives the optimal value. The value of logs from the solution produced once the stem is rebucked is the feasible optimal solution given the inaccurate measurements. If a log is cut from the error adjusted stem that does not meet the specification for that log grade, the log is given the value of the next highest valued
log that could be cut from that “sub stem”. Many companies have a tolerance of \( \pm 5 \) cm around their length measurements and \( \pm 1 \) cm tolerance around the SED and LED measurements. The simulation model has a \( \pm 5 \) cm tolerance for logs being out-of-specification for length but a zero tolerance for diameter measurements.

The simulation model was run on the stem databases listed in Table 2.3 with:

(1) The error distributions measured in the field to determine the value loss associated with each operation. Analysis of Variance was used to determine the level to which the length, diameter and bucking errors interacted with each other.

(2) The simulation model was also run on a range of error distributions with different mean error rates and standard deviations. The results from these simulations were used to produce production surfaces of value recovery. The error distributions collected in the field from the harvesters were used to give guidance in determining the range of the error distribution that needed to be simulated. The following ranges of error distribution were simulated (Table 2.5).
Table 2.5. - Range of error distribution simulated.

<table>
<thead>
<tr>
<th></th>
<th>Means</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length stage error</td>
<td>-0.002 to 0.002 m</td>
<td>0 to 0.09 m</td>
</tr>
<tr>
<td>Diameter error</td>
<td>-1.2 to 1.2 cm</td>
<td>0 to 6 cm</td>
</tr>
<tr>
<td>Bucking error</td>
<td>-0.08 to 0.08 m</td>
<td>0 to 0.6 m</td>
</tr>
</tbody>
</table>

The length errors were collected over a log length; however in the simulation model the length stage errors were applied to each 0.1 meter section (stage) of the stem. Therefore the mean and standard deviation of the length error distribution were adjusted using the following formulas. The assumed average log length used in these equations was 4 meters.

\[ E(\text{length \_ error \_ for \_ stage}) = \frac{x(\text{error})}{x(\log(\text{length}) \_ \text{stage \_ length})} \]  

(2.2)

\[ \text{Var}(\text{length \_ error \_ for \_ stage}) = \frac{\text{Var}(\text{error})}{x(\log(\text{length}) \_ \text{stage \_ length})} \]  

(2.3)

\[ \text{s.d.} = \sqrt{\text{Var}(\text{length \_ error \_ for \_ stage})} \]  

(2.4)
Due to the stochastic nature of this model a pilot study was carried out and the simple sample number formula \( n = \frac{t^2s^2}{e^2} \) was used to calculate the number of replicates required for a 95 % confidence level and a 10 % margin of error. It was calculated that 10 replicates would be required for this confidence level and margin of error.

On each of the six studies the simulation model was run ten times for the eight different combinations of the three error types: length measuring error at the time of scanning the stem \( (L = \text{length error}) \), diameter measuring error at the time of scanning the stem \( (D = \text{diameter error}) \) and length measuring error at the time of bucking the stem into logs \( (B = \text{bucking error}) \). The total value of the logs from the stems contained in each of the databases was added up and averaged over the ten simulations. For each error simulation type the total value was divided by the optimal value to give a percentage value recovery.
RESULTS

The results are presented in two parts; first the diameter and length measurement error distributions for the six studies, and second the impact of these errors on simulated value recovery as produced by an optimal bucking algorithm.


Characterizing the Distribution

The length and diameter error distributions for the six operations are given in Figure 2.6 and Figure 2.7 respectively. All of the distributions have a bell shape to them indicating that these sample distributions, may have come from normal populations, in agreement with the literature on the distribution of measurement errors (Barry 1978, Sirohi & Radha Krishna 1991, and Morris 1996). The sample size for the distributions ranged from 77 to 1413. The large range in sample sizes was due to the nature of the different studies having multiple objectives with different requirements for sample size.
Figure 2.6. - The length error distributions for six different studies.

Figure 2.7. - The diameter error distributions for six different studies.
Table 2.6 shows the mean and standard deviation assuming the length and diameter errors conform to the normal distribution. The Kolmogorov-Smirnov (K-S) goodness-of-fit test values are also given in Table 2.6. All the K-S values are less than the critical value of 0.819 at a 90% confidence level, and hence it was unlikely that the data was produced from a normally distributed population. For most of the error distributions in Table 2.6, the normal distribution was ranked in the top 5 distributions according the to K-S test values. All of the top 5 ranked distributions had similar K-S values.

Table 2.6. - Univariate statistics for the length and diameter errors distribution.

<table>
<thead>
<tr>
<th>Study</th>
<th>Carrier/Head</th>
<th>Length Error (meters)</th>
<th></th>
<th>Diameter Error (cm)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>mean</td>
<td>s.d.</td>
<td>K-S</td>
<td>mean</td>
</tr>
<tr>
<td>A</td>
<td>Valmet T500/s52</td>
<td>-0.01</td>
<td>0.39</td>
<td>0.345</td>
<td>-0.65</td>
</tr>
<tr>
<td>B</td>
<td>Valmet T520/s52</td>
<td>0.04</td>
<td>0.23</td>
<td>0.303</td>
<td>-0.46</td>
</tr>
<tr>
<td>C</td>
<td>Ponsse Ergo/H73</td>
<td>0.03</td>
<td>0.10</td>
<td>0.270</td>
<td>-0.40</td>
</tr>
<tr>
<td>D</td>
<td>Ponsse Ergo/H73</td>
<td>-0.02</td>
<td>0.11</td>
<td>0.246</td>
<td>-0.02</td>
</tr>
<tr>
<td>E</td>
<td>Ponsse Ergo/H73</td>
<td>-0.03</td>
<td>0.23</td>
<td>0.352</td>
<td>-0.31</td>
</tr>
<tr>
<td>F</td>
<td>Cat 330CL/Waratah</td>
<td>0.01</td>
<td>0.25</td>
<td>0.344</td>
<td>0.60</td>
</tr>
</tbody>
</table>
Despite the relatively poor K-S goodness-of-fit values, the error distributions used in the remainder of this paper were assumed to be normal. This assumption was made based on the measurement error literature and because none of the other distributions produced a significantly better K-S goodness-of-fit value.

Regression analysis showed that although some of the independent log characteristics outlined in Table 2.2 were significantly related to diameter and length errors, none displayed a strong relationship. The best correlation coefficient ($R^2$) found in all the relationships was 0.3 between length error and log volume for one of the machines studied, however this result was not consistent throughout the studies. Makkonen (2001) suggested that length error should be related to change in the diameter over the log length. He based this on the theory that, due to the taper of the log, the distance traveled by the measuring wheel is longer than the actual log length. None of the datasets collected in this study demonstrated a good relationship between these two variables. This extra distance traveled may contribute to the length error but clearly other factors cause significant variation in the length errors.

In studies C, D, E and F for which the log products were known, a single factor ANOVA was used to determine whether there was any significant difference in errors between the different log products. Studies C and E showed significant differences in the diameter measurement error between the products, study D displayed significant differences in length measurement error and study F, both length error and diameter
error were significantly different between the products. Given that measurement errors do occur, it would be most desirable if those errors were concentrated on the lower value products. Observations made during the studies indicated that many times the last log in a stem was not measured fully for length. In most cases these log were not included in the error distribution because the harvester measurement could not be obtained.

**Part 2. Impact of Error on Optimal Bucking**

**Value Recovery**

Figure 2.8, Figure 2.9 and Figure 2.10 show the results of the simulations using the error distributions given in Table 2.6. The studies were sub-divided into different graphs by species. The (*) at the top of the bars indicates that the effect is significant at a 95 % confidence level.
Figure 2.8. - Simulated value recovery based on errors found in studies A and B in ponderosa pine.

Figure 2.9. - Simulated value recovery based on the errors found in studies C, D and E in loblolly pine.
The graphs show that, of the three measurement errors, diameter and bucking errors result in the biggest value losses. Value loss due to diameter error is relatively easy to understand; it is greatest when the diameter is under measured, as in studies A-E. Only in study F was the value loss from length error during the stem scanning greater than the loss due to diameter error.
More difficult to understand is the large value loss due to bucking length (B) error, especially when compared to the value loss due to scanning length measurement (L) error given that the same error distributions were used in both sets of simulations. For example in Study F, the study done on radiata pine, the value loss due to length measurement errors (L) during log scanning was 5% compared to 13% from length measurement errors (B) during the bucking process. The easiest way to explain this is to use a simplified example as illustrated in Tables 2.7 to 2.9. This example has three log types; pruned sawlog which has to be 5 meters long with a minimum SED of 25 cm, unpruned sawlog which has an allowable length range of 3.5 to 4.5 meters in 0.1 meter steps with a minimum SED of 15 cm, and pulplog which has a minimum length of 1 meter and a minimum SED of 5 cm.

All three tables (2.7 to 2.9) are laid out in the same format. The second column in the tables gives the scanning length error, the third column is the solution produced by the dynamic programming bucking algorithm. The next two columns give the bucking length error and the cumulative length at which the cuts are to be made along the stem. The final column gives the actual feasible logs produced; in some cases these logs have to be rebucked to meet the log specifications.

The solution without any measurement errors added, is given in Table 2.7. The pruned log is limited by its length and the sawlog is constrained by its minimum SED restriction. The optimal value for this stem is $93.68.
Table 2.7. - The optimal bucking of a simple stem without any errors being added.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Length Error per Stage (L)</th>
<th>Optimal Solution from the Bucker</th>
<th>Bucking Error per Log (B)</th>
<th>Actual Cuts Made (stages)</th>
<th>Regrade Solution of Actual Logs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td><em>Optimal</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>+ 0.00 m</td>
<td>Pruned</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Length (Stages)</td>
<td>Length (m)</td>
<td>SED (cm)</td>
<td>Length (Stages)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>50 5.0 33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>40 4.0 15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>20 2.0 6</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>50 5.0 33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>90 4.0 15</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>110 2.0 6</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.8 gives the solutions when a positive length error, bucking error or combination of both errors are added. When a positive error is added to the stage length during the scanning of the stem, the 15 cm SED restriction is reached in fewer stages than in the error free solution. This means that the sawlog was cut 0.1 metres shorter than the optimal solution and so reduced the value of the stem by 3 cents. However when the same effective error is added as a length bucking error, that means that every log cut will be 0.1 metres longer than in the optimal solution, the value of the stem drops by 90 cents. This is due to over cutting the length of the pruned log at 5.1 metres which in turn causes a sawlog’s SED to be less than the minimum SED constraint. Rebucking of these logs produced 0.3 metres of waste. When both errors were added the value dropped less than when just the bucking errors were added alone. This is due to the errors having a compensating effect on each other.
Table 2.8. - The optimal bucking of a simple stem with positive length (L) and bucking (B) errors added.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Length Error per Stage (L)</th>
<th>Length Error per Log (B)</th>
<th>Actual Cuts Made (stages)</th>
<th>Regrade Solution of Actual Logs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Scanning</td>
<td>Solve DP</td>
<td>Cutting Logs</td>
<td>Regrading to Feasible Solution</td>
</tr>
<tr>
<td>L</td>
<td>+ 0.002 m Pruned</td>
<td>50 5.0 32.95 + 0.00 m Pruned</td>
<td>50 5.0 33 78.55</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sawlog</td>
<td>39 4.0 15.37</td>
<td>89 39 3.9 15.45 14.10</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pulp</td>
<td>21 2.1 6</td>
<td>110 2.1 6 1.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>90.1 11 93.65</td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>+ 0.00 m Pruned</td>
<td>50 5.0 33 + 0.1 m Pruned</td>
<td>51 5.0 33 78.55</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sawlog</td>
<td>40 4.0 15</td>
<td>92 39 3.9 15 13.58</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Waste</td>
<td>2 0.2 14.1</td>
<td>110 2 0.2 14.1 0.00</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pulp</td>
<td>18 1.8 6</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>110 11 92.88</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LB</td>
<td>+ 0.002 m Pruned</td>
<td>50 5.0 32.95 + 0.1 m Pruned</td>
<td>51 5.0 33 78.55</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sawlog</td>
<td>39 4.0 15.37</td>
<td>96 39 3.9 15 13.58</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Waste</td>
<td>1 0.1 14.55</td>
<td>110 1 0.1 14.55 0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pulp</td>
<td>19 1.9 6</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>110 11 92.96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The results (Table 2.9) of the negative errors being added are quite different to those of the positive error results. When the negative stage length errors are added, there is no drop in value from the optimal solution as the exact same logs are cut. However when the negative bucking error is added, the value drops by over $20. This is caused by the 5 meter pruned log being cut 0.1 meter short, meaning that it needed to be downgraded to a 4.5 meter sawlog. When both negative errors are added the errors do not have a compensating effect as was found for the positive errors.
Table 2.9. - The optimal bucking of a simple stem with negative length (L) and bucking (B) errors added.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Length Error per Stage (L)</th>
<th>Scanning</th>
<th>Solve DP</th>
<th>Cutting Logs</th>
<th>Regrading to Feasible Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>- 0.002 m</td>
<td>Pruned</td>
<td>50</td>
<td>4.9</td>
<td>33.04</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sawlog</td>
<td>40</td>
<td>3.9</td>
<td>15.08</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pulp</td>
<td>21</td>
<td>2.1</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+ 0.00 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pruned</td>
<td>50</td>
<td>5.0</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sawlog</td>
<td>40</td>
<td>4.0</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pulp</td>
<td>20</td>
<td>2.0</td>
<td>6</td>
</tr>
<tr>
<td>B</td>
<td>+ 0.00 m</td>
<td>Pruned</td>
<td>50</td>
<td>5.0</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sawlog</td>
<td>40</td>
<td>4.0</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pulp</td>
<td>20</td>
<td>2.0</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>- 0.1 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pruned</td>
<td>49</td>
<td>4.5</td>
<td>35.25</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sawlog</td>
<td>88</td>
<td>3.9</td>
<td>15.9</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pulp</td>
<td>107</td>
<td>1.9</td>
<td>7.35</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Waste</td>
<td>3</td>
<td>0.3</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+ 1.05</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Total 110</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>11.0</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>71.11</td>
</tr>
</tbody>
</table>

Validation of the Model

Validation is the process of testing a model to see that it is a valid representation of reality. The validity can often be assumed if the model is able to accurately mimic reality (Daellenbach 1995). The best way to validate a model is to compare the model’s results against the actual results from the same situation. Both sets of results should be obtained independently of each other.

Two of the studies (C and F) have actual value recovery percentages determined from real value recovery studies which were used to validate the model. One important difference between the actual value recovery values and the simulated ones was that the
simulated results assumed that each stem was fully measured before the solution was
determined. This was not the case for the actual machines; when the operator was
processing the stem the cutting solution was generated as the stem was measured.
Comparing the actual value recovery with that determined by the simulations, gives an
indication of how well the model is modeling reality. For Study C both the actual and
simulated value recoveries were 90 % (Conradie et al. 2003) when all errors were
simulated. For Study F, the simulated value recovery was 86% compared to 79% for the
actual value recovery study (Murphy et al., 2004). These results indicate that the
simulation model is reasonably accurate, although given the following conceptual
mechanical harvester value loss equation, the simulation maybe slightly over predicting
the value loss.

\[ Total \ Value \ Loss = L + D + B + quality \ error + sweep \ error + lack \ of \]
\[ \text{optimization software} \] \\
\[ (2.5) \]

Based on this formula the loss due to quality and sweep error and lack of the use of
optimization software which are not modeled in this paper are much lower than would
be expected. It is postulated that this could be caused by an overestimate of the error
distribution used in the simulation and that experienced machine operators are able to
make adjustment to the cutting pattern that reduces the effects of the measurement error.
The model could not simulate adjustments by experienced operators.
It could be expected that the difference between actual and simulated recovery in Study C would be less than in Study F as Study C had much simpler tree quality descriptions and cutting patterns than Study F. The machine in Study C also used computer assisted bucking. These differences would mean that value losses for the last three terms in Eq. 2.5 would be almost zero for Study C and hence the “total value loss” would equal the value loss caused by measurement error.

The results from the Analysis of Variance showed that the value losses from the measurement error are non additive as suggested in Eq. 2.5. The three factor factorial design tested the following linear model which included both the main effects (L,D and B) and interaction effects (LD, DB, LB and LDB):

\[ Value \ Loss \ (measurement \ error) = L + D + B + LD + LB + DB + LDB + \varepsilon \quad (2.6) \]

The (*) above the bar in Figure 2.8, Figure 2.9 and Figure 2.10 shows that there is not one model to describe value loss due to measurement error for all the studies. The results also show that the three types of error do interact, many times producing a value loss much less than would be expected from a simple additive model. In some cases the interaction between two of the error types gives a value loss less than one of the individual error types.
Response Surfaces for Different Levels of Error

The following series of graphs, in Figure 2.11, show the effects of different levels of accuracy and precision of length and diameter measurements on percentage value recovery. The results show that increasing the precision is of greater importance than increasing accuracy for the distributions that were simulated. The simulation results also indicate that over measuring either length or diameter produce lower value losses than under measuring length. This is simply because over measured logs can generally be rebucked without having to be downgraded to a lower value grade. Under measured logs, however, often have to be rebucked and downgraded meaning that significant value is sometimes lost. The interesting dip in results for the zero standard deviation in the radiata pine length and bucking simulations is due to rounding the bucking error, up and down to the nearest stage. This effect is particularly apparent in the radiata pine study as a number of the grades had only one allowable length.
Figure 2.11. - The effects of different levels of accuracy and precision of length and diameter measurements on percentage value recovery.
Out-of-Specification Logs and Volume Calculations

Most of the large value losses that occurred in the simulations were caused by logs being out-of-specification. In the model, if a log was out-of-specification it would be rebucked into the product with the highest value for which the log met the specifications. In reality, logs being out-of-specification can be much more costly than just the drop in value due to the product change; having to rebuck a log incurs an extra handling cost or, if logs that are out-of-specification are not caught until they reach the mill, loads can be rejected and sent back to the forest.

Figure 2.12. - The simulated percentage of logs out-of-specification for Study F.
Figure 2.12 shows the simulated percentage of logs that were out-of-specification for Study F. When all three error types were simulated (LDB) 58% of the logs were predicted to be out-of-specification, twice what was actually measured (Murphy et al. 2004). However, given that the operator was only partially scanning the stems before bucking, a more reasonable comparison may be, when only the length and diameter errors were simulated (LD). Under this scenario the percentage of logs out-of-specification reduced to 38%. One possible reason for the remaining difference is that the machine operator was probably more conservative when he determined which log products to cut, whereas the simulation model always tried to find the highest value product that could be cut from the stem. The other five studies show similar trends and percentage of logs that do not meet the companies log product specifications.

The volume estimates obtained from harvester’s onboard computer systems have the potential to be used as the bases for logger payments. In Finland 85-90% of all logged forests used the harvester’s volume estimates as a method of payment (Anderson et al. 2004). There is also increasing interest around the world (Stendahl and Dahlin 2002, Judd 2004) for using harvesters for, as Murphy et al. (pg 2, 2004) describes, “pre-inventory harvest systems (where representative swathes are cut through the forest prior to harvest), and just-in-time inventory systems on harvesters.” Stendahl and Dahlin (2002) who introduced the notion of using harvesters during thinning operations to carry out a forest inventory, noted that one of the critical assumptions for the use of harvesters is that they can collect accurate data, most importantly the volume estimates.
Table 2.10. - Percentage volume difference between volume predicted from the inaccurate and the actual measurements.

<table>
<thead>
<tr>
<th>Study</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Volume Difference</td>
<td>-5</td>
<td>-3</td>
<td>-4</td>
<td>1</td>
<td>-1</td>
<td>4</td>
</tr>
</tbody>
</table>

Table 2.10 gives the percentage difference between the volumes calculated from the stem using inaccurate length and diameter measurements and the actual volumes. Negative values indicates an under estimate of volume while a positive percentage indicates an over estimate of volume. These values are within the range that Andersson and Dyson (2002) found on a much larger study.
DISCUSSION

The error distributions found in these six studies were well within the range of other reported studies on harvester measurement accuracy. The means and standard deviations of the length measurement errors were similar to those found by Plamondon (1999). The standard deviation for the diameter errors were much higher than those found by Moller et al. (2002) who suggested a standard deviation for diameter error of 5-8 mm. Although it could not be proved statistically, the errors were assumed to be normally distributed with some bias. Cossens (unpublished report) did however prove statistically that length measurement errors that he measured from a manual log making study were normally distributed, which is consistent with the textbooks on measurement error (Barry 1978, Sirohi & Radha Krishna 1991 and Morris 1996).

Using the same stems as were processed in Study F the simulation model produced more than twice the number of logs that did not meet specification than was actually recorded in Study F. These simulated results are similar to those reported by Evanson (1995) for a Denis 3000, where 47% of the stems measured did not meet the length specifications. The percentages of the logs not meeting the length and diameter specification are well within the range reported by Andersson and Dyson (2002). Boston and Murphy (2003) studied a mechanized harvesting operation where only 7 of the 20 samples had mean sample lengths within a 5 cm tolerance.
The average value loss for the six studies when all three error types (LDB) were applied was 18% which is similar to the average value loss of 21% from value recovery studies on mechanical harvesters from around the world (Murphy 2003). Given that many harvestersprocessors do not fully measure the stem before bucking, a more realistic comparison is with the average value loss when only the length and diameter errors (LD) are included, this value loss is 7%. The difference in these numbers could easily be attributed to incorrectly assessing sweep and quality and the lack of optimization systems.

Length measurement errors during the bucking process had a significant effect on value recovery in all six of the studies. In the five studies where the diameters were on average being underestimated, the losses due to diameter error were much greater than from length measurement error during stem scanning. This is consistent with a study by Cossens (1991) on a Hahn harvester in New Zealand where he reported that conservative diameter measurements were the main cause for the 9.7% value loss, given that 83% of the length measurements were within 5 cm tolerances. Chiorescu and Gronlund (2001) looked at the effect of stem length and diameter measurement accuracy of mechanical harvesters on the value obtained from optimal bucking, sawing, crosscutting and board grading procedures at the saw mill. They found that the harvester's performances on measuring length and diameter are both important, with the accuracy of the diameter measurement being of greater importance. The most surprising result from the simulation in this report, which has not been reported in any of the other
studies on harvester measurement accuracy, was the large value loss that occurs when a length measurement error was applied at the time of bucking. In Study F over 20% of the value was lost, which is significantly greater than the 1% value loss that Sondell et al. (2002) estimated in Norway spruce. This may be because a partial scan system is most often used. In the Sondell et al. (2002) study, all the machines were getting a minimum of 69 % of the logs within 5 cm of the correct length which equates to a standard deviation for length error of 0.05 meters. The diameter accuracy for their study was measured in percentage of trees within 4 mm. The worst performing machine after calibration, achieved a diameter accuracy of 62.2%, which means that the maximum standard deviation for diameter error was around 4.5 mm. In comparison to the machines studied in this paper, the level of accuracy reported in the Sondell et al. (2002) study was considerably higher.

Although not simulated in this study, mismeasured logs can have a significant impact on the revenue obtained by lumber producers or other solid wood processors. Andersson and Dyson (2002) calculated that, when a harvester was manufacturing 20% of its logs below the minimum length specification, a 2.5% reduction in lumber yield and a 1.5% drop in mill productivity would follow. Another study, using a sawing simulator, showed that measurement error distributions with standard deviations for diameter and length of 6 mm and 4 cm respectively could produce between 18 and 37% of boards that were off-grade (Chiorescu and Gronlund 2001).
Percentage value losses of the magnitude reported in this paper can equate to substantial losses in revenue to the forest owner. An indication of the amount of revenue lost by the forest owner for the three pine species included in this study can be calculated by multiplying the percentage value loss from measurement errors by the average tree value and by an estimate of a harvester day productivity (50 trees per scheduled machine hour (Marshall and Murphy 2003)).

Table 2.11. - Effect of value recovery and average tree value on daily revenue loss.

<table>
<thead>
<tr>
<th></th>
<th>Value ($US/tree)</th>
<th>Value Recovery (%)*</th>
<th>Loss in Revenue ($US/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ponderosa pine (Study A)</td>
<td>$ 14.44</td>
<td>82</td>
<td>$ 1,040</td>
</tr>
<tr>
<td>loblolly pine (Study C)</td>
<td>$ 12.41</td>
<td>90</td>
<td>$ 500</td>
</tr>
<tr>
<td>radiata pine (Study F)</td>
<td>$ 144.88</td>
<td>86</td>
<td>$ 8,000</td>
</tr>
</tbody>
</table>

* based on zero mill tolerance on log diameter specifications.

This still suggests that forest owners need to take into account the value of their resource before deciding on methods for increasing the accuracy and precision of length and diameter measurement on mechanized processors. A cheaper method may be suitable in low value forests with simple cutting patterns where monetary losses are small. However, in high value forests with complex cutting patterns where even small error rates can be extremely costly, a more expensive method may be more appropriate.
All measurement systems are likely to be subject to measurement error. The diameter and length measurements made by harvesters are made under very difficult mechanical and environmental conditions. One of the easiest ways of reducing measurement error is to have a regular checking, calibration and maintenance program. A good calibration program such as suggested by Makkonen (2001) should eliminate much of the bias in the error distributions. Length and diameter accuracy checks need to be performed both by the harvester operator and by the forest company. Boston and Murphy (2003) suggested using statistical quality control to monitor diameter and length accuracy. Marshall and Murphy (2003) found that a forest owner’s profitability could be maintained by dropping machine productivity to achieve a high value recovery.

Training and communication are extremely important tools in reducing error. Operators need to understand the measuring system they are using and how important accurate log measurements are to the profitability of an operation. As Andersson and Dyson (2002) suggest, log specifications must be clearly understood by operators, machine owners, and company staff. One measuring unit system should be used and well understood; unlike in one of the studies in this paper where the operator did not realize that the machine was displaying length measurements in metric units.

A number of the new harvesting heads now come with calipers to calibrate the harvesters’ measurement system. The calibration procedure requires a number of logs to be laid out. The harvester’s computers measurements are then downloaded into the
calipers. The calipers are used to measure the diameters and lengths of the calibration logs. The calipers then calculate a range of statistics based on the current measurement errors. The calipers can then be connected back up to the harvester’s computer to perform an automatic calibration (Anon. 2004).

The current measuring sensors for measuring stem length and diameter on most harvesting heads are relatively simple. Large increases in accuracy and precision can be achieved by redesigning the measuring equipment. Two New Zealand studies carried out 12 months apart, showed that by redesigning the length measuring systems the percentage of logs within 5 cm of the target length rose on average by over 10% (Evanson and McConchie 1996). There have been a number of attempts at using more advanced sensing technologies such as laser and digital cameras. In the mid-nineties a Swedish project investigated the development of a touch-free measurement system for diameter. They estimated that the new system could produce 90% of all logs within a 4 mm range and lead to potential increases in revenue between US $ 5,000 and US $ 85,000 per single-grip harvester per year. The estimated purchase cost of the fully developed system was estimated to be about US $ 20,000 (Löfgren and Wilhelmsson 1998). In New Zealand a new system has been developed that consists of a scanning bench using multiple scanning systems and a single grip harvester. This system is still a prototype and little is know about its potential gains (Judd 2004).
The diameter errors simulated in this paper include both a measurement error and error of process. The diameter measurement errors are caused by log shape and mechanical problems associated with the measuring device. The overbark diameter measurements are then, in most cases, converted to underbark measurements by a bark thickness function. This conversion has the potential of adding an error of process. This error can be significantly reduced through the development and implementation of more accurate bark thickness equations.

In some high value stands the “high-tech” solution may not be the best option. In some stands, manual log making may be the most profitable option as manual log making has been found to be more accurate on length and diameter measurements than mechanical harvesting systems (Cossens, unpublished report). In low value stands with simple cutting patterns, maintaining good maintenance and calibration systems may be all that could be justified.
CONCLUSIONS

The trend towards mechanical harvesting of the world’s production harvest has been driven by desires to improve productivity and costs or to resolve labor-related issues; e.g. worker safety or labor shortages. With mechanization comes the use of state-of-the-art communication and measurement technologies, and powerful on-board computers giving this system the potential to increase value recovery at the time of bucking.

Like all measuring systems, these are subject to measurement errors. It was found from studies of six machines that the mean error for length ranged from -3 to 4 cm with standard deviations that ranged from 10 to 39 cm. The diameter error distributions had means ranging from -0.65 cm to 0.60 cm with standard deviations ranging from 0.81 to 3.60 cm. These results are well within the range of other studies done around the world on measurement accuracy of mechanical harvesters.

The simulation model described in this paper showed that the cost, in terms of the percent value loss, for these six harvesters could be significant; ranging 3 to 23 % depending on the type of error, the level of error and the species. It was found that value loss seemed to increase more rapidly with decreasing precision compared to decreasing accuracy. Based on the losses reported in this paper, operators, machine owners, forest owners and researchers need to investigate different methods of reducing the level of error in stem length and diameter measurements. There are a number of different
methods available to the industry, both procedural and technological. Choosing which best suits a particular operation, however, requires a detailed knowledge of the causes and implications of the errors. The amount of investment that can be made in any particular method depends not only on the error rate of the machine but also the value of the forest that the machine is working in.

Measurement error can never be completely eliminated from a system. However, minimizing the magnitude of diameter and length measurement errors at the time of the log manufacturing is extremely important to maximize the value from the forestry supply chain and maintain forestry competitiveness in this global economy.
REFERENCES


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Chapter 3:

ECONOMIC EVALUATION OF IMPLEMENTING IMPROVED STEM SCANNING SYSTEMS ON MECHANICAL HARVESTERS/PROCESSORS

By Hamish Marshall

Glen Murphy
ABSTRACT

Use of mechanical harvesting/processing systems in timber harvesting is increasing worldwide, with advantages in terms of increasing productivity and safety. However, despite these systems giving operators access to advanced computer and measuring systems, their ability to extract the maximum value from a tree is, on average, less than motor manual log bucking systems. The productivity, cost, and value recovery of several simulated procedures for scanning and bucking *Pseudotsuga menziesii* (Mirb.) Franco (Douglas fir) and *Pinus ponderosa* Lawson & C.Lawson (ponderosa pine) trees were evaluated from a log seller’s perspective. The procedures evaluated were (a) conventional operating where quality changes and bucking decisions were made by the machine operator, (b) an automatic full scan of the stem prior to optimization and bucking, and (c) partial scanning where a portion of the stem was scanned and then qualities and dimensions were forecast before the optimal bucking took place. After subtracting costs, the net value improvement for the automated scanning procedures over the conventional procedure ranged from –7% to 8%. The best net value improvement for both species was obtained using the procedure that fully scans the stem prior to bucking. Breakeven capital investment costs for new scanning, forecasting, and optimization equipment ranged between zero and US$2,120,000 depending on tree species, markets, scanning speed, volume scaling rules, and scanning procedure.
INTRODUCTION

The adoption of mechanical timber harvesting systems is increasing worldwide. These systems allow stems to be delimbed, bucked, sorted, and sometimes felled by a single machine. In Scandinavia, almost 90% of logging is carried out using mechanical harvesting systems (Nordlund 1996). Within the last 10 years, the number of harvesters and processors sold in eastern Canada increased from 200 to 900 (Godin 2000). In Australia, by the late 1980s mechanization had almost eliminated motor-manual felling in *Pinus radiata* D.Don (radiata pine) thinning operations (Raymond 1988). Factors causing this shift from the traditional motor manual harvesting systems to mechanical harvesting systems include the need to continually increase productivity and to improve the safety record of forestry operations.

A recent survey of value recovery studies (Murphy 2003a) showed that, on average, mechanical log making systems are losing 21% of potential value whereas manual log making systems\(^1\) are losing on average only 11%. In the mechanical log making studies value recovery losses ranged from 1% to 67%. Losses occurred when logs did not meet log grade specifications (e.g., inaccurate lengths, diameters too small or large, too much sweep, non-allowable quality features) or when the combination of logs cut from a stem was sub-optimal. The worst losses occurred when computerized optimal bucking tools

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\(^1\) Manual log making systems refers to log making that is carried out by a person using a logger’s tape for measuring length and a chainsaw for cutting stems into logs.
were not used (Murphy 2003a). Stand characteristics, market complexity, equipment
design, and maintenance, and operator skill can all also affect the level of loss.

A number of mechanical harvester manufacturers such as Ponsse, Timberjack, and
Valmet have implemented bucking algorithms on their machines. To produce accurate
optimal bucking decisions these systems require highly accurate detailed information on
stem shape and quality characteristics.

Most modern mechanical harvesting systems use mechanical sensors, some combining
these with photocells to measure diameter and length (Andersson & Dyson 2002).
Operators have to visually assess changes in quality along the length of each stem and
determine, with or without the use of “optimal” bucking systems, the log types to be
cut. There have been several studies looking at the accuracy of modern mechanical
sensors used to measure diameter and length. One Swedish study tested five of the most
common measuring and merchandising systems and concluded that, with the exception
of one system, either the length sensor or the diameter sensor was unsatisfactory
(Sondell et al. 2002). There have been few scientific studies specifically looking at how
well operators assess changes in either stem quality or form as the stem is being
processed. Gellerstedt (2002), however, reported that Scandinavian harvester operators
indicated that they have problems seeing defects in the log at the current feeding speed
of 4 m/s and that more “sensing” in the harvester head is required for faster operation
and better judgments on stem quality.
Although improved selection and training of operators may provide one of the higher benefit-to-cost ratios from investments in ways to reduce value losses (T. Evanson, Logging Industry Research Organisation, unpubl. data), there is a limit to human ability to capture and process information and, therefore to the potential improvements from training.

In the future wood users may become increasingly specific about the type and quality of wood that they are receiving. The indications are that they may start placing minimum and maximum specifications not only on external features such as log shape and external quality but also on internal characteristics such as wood density, extractives content, and stiffness (e.g., Walker 2000; Young 2002). These additional specifications will add extra complexity to the already complex task of log making. If the industry wants to increase the value recovery from its mechanical harvesters, it needs to look at investing in improved scanning, forecasting, and optimization systems to assist operators in log making.

For many years, the sawmilling industry has utilized different log scanning technologies for collecting data on external log features (e.g., Dashner 1993; Green 1993; Brisky et al. 2004). The data are used for optimization of bucking and sawing patterns as well as for automated grading. The commercial use of laser and camera scanning technologies is well advanced, while other technologies capable of capturing internal log features
such as computer-aided tomography and nuclear magnetic resonance (NMR) are now being investigated for their potential for log scanning (e.g., Chang et al. 1989; Schmoldt et al. 2000; Gupta et al. 1998) and computer-aided tomography is slowly making its way into the sawmill (Anon. 2004).

If scanning technologies such as laser, optimal scanners, and computer-aided tomography can be used in the sawmilling industry there is little reason why they cannot be used within the forest. Although there have been numerous scientific papers on potential new scanning and measuring systems in sawmills (e.g., Chang et al. 1989; Schmoldt et al. 2000; Gupta et al. 1998; Kaestner 1999; Benson-Cooper et al. 1982; Rayner 2001), there are only a small number on the use of this technology with mechanical harvesting systems (Tian & Murphy 1997; Löfgren & Wilhelmsson 1998; Möller et al. 2002).

Scandinavian researchers and equipment developers invested considerable resources into determining and implementing the best procedures for scanning and optimal bucking on mechanized harvesters for their stand and market conditions. For example, Berglund & Sondell (1985) found that by measuring a portion of the stem of *Picea abies* (L.) Karst. (Norway spruce) and forecasting the taper of the unmeasured portion of each stem, productivity impacts could be reduced and value losses minimized. Näsberg (1985) used a similar forecasting procedure and found that loss in value due to incomplete information was less than 2%. Liski & Nummi (1995) developed a linear
mixed model for predicting stem curve measurements in Norway spruce. Their model used measurements from previous stems plus a number of known measurements on the current stem to predict the diameters of the unknown section. They found that value losses decreased as the length of the known portion of the stem increased. The minimum percentage loss found was 5%. A study by Sondell *et al.* (2002) using modern log merchandising computers suggested that losses could be contained to less than 1% for log value recovery.

Automatic bucking using these forecasting techniques is generally not applied in *Pinus sylvestris* (L.) (Scots pine) forests in Scandinavia. This is mainly because Scots pine has considerably more inter- and intra-stem variation in quality and form than Norway spruce, making accurate prediction of these characteristics less likely (Uusitalo *et al.* 2002). This is also likely to happen in other species such as radiata pine and Douglas fir. In an optimal bucking study done on Douglas fir using a Hahn Harvester where diameters for part of the stem were predicted using a taper equation, the value of the logs produced was 12% less than the optimal solution where all the stem diameters were known (Olsen *et al.* 1991).

Murphy (2003b) looked at the economic potential of different approaches to scanning stem dimensions and quality on mechanized harvesters. His study was based on New Zealand conditions and markets and focused only on the processing of radiata pine. The study used generic productivity, cost, and value recovery figures. He found that for
radiata pine the breakeven capital investment that may be made in scanning systems could, in some cases, exceed the combined cost of the carrier and harvester head.

**Objective**

The objective of this study was to determine, from a log seller’s perspective, the economics of placing advanced scanning and measuring systems on mechanical harvesters/processors to improve value recovery. The study continues work done by Murphy (2003b) by looking at two different mechanical harvesting/processing operations in two different species (i.e., Douglas fir and ponderosa pine) to determine a breakeven capital investment for new scanning, forecasting, and optimization technology for these species. Five simulated procedures for scanning were evaluated for each operation.
METHOD

Field Sites and Tree Stem Data Sets

Two sites, which were representative of the two dominant industrial forest types that exist in the Pacific Northwest, were used for this study – Douglas fir-dominated stands west of the Cascade Mountains, and the dry pine-dominated stands east of the Cascades. Sites were selected based on logistics (location, and crew willingness to be studied) and number of log grades being cut. The studies were carried out during the summer of 2002.

Site 1 was a Douglas fir-dominated stand in southern Washington State. Net stocked area of the stand was 12.18 ha (30.1 acres), with an average stocking of 273 stems/ha. It was on mainly flat ground with an access road through the middle, and was clearfelled. The average tree size was 2.35 m³, and the average diameter at breast height (dbh) was 46 cm. These stand parameters were obtained from the forest owner’s stand record system. They were based on field measurements made in 1997 and grown-on using tree growth models to give the stand parameters at the time of harvesting.

Site 2 was a ponderosa pine stand in eastern Oregon. The slope of the site was not more than 5%. The stand was scheduled for thinning and trees to be removed were marked. The average dbh was 27 cm and the average stocking was 415 stems/ha prior to thinning and 102 stems/ha post thinning. The average tree size for the selected trees was
0.35 m$^3$. The forest owner did not possess any stand records for this stand, and so before the harvesting started 11 pre-harvest inventory plots, each of 0.04 ha, were installed. In these plots diameters at breast height of all trees were measured and their thinning status was noted. The height of one tree in each plot was also measured so that a diameter/height relationship could be developed. These plot measurements were then scaled up to give the stand parameters.

At each site 120 trees were selected and felled; on 100 trees detailed measurements were then made of over-bark stem dimensions and qualities. The bark thickness of the other 20 trees was measured at regular intervals up the stem, and these measurements were used to develop a bark thickness equation to convert over-bark diameter measurements to under-bark.

Once all the stems had been measured, the processor operator delimbed and cut them into logs as usual. The lengths and grades of the logs produced were recorded.

**Markets**

Log specifications and confidential prices that were being used at each site to process each stem into logs were obtained from the forest owners. The Douglas fir market included nine log-types; and each log-type could have multiple lengths ranging from 3.6 to 12.2 m. The highest value log-type was an export-grade saw log with an average stumpage value of US$157/m$^3$. The lowest value log-type was a pulp log with a value
of $22/m^3. The ponderosa pine market included three log-types, each of which also had multiple lengths ranging from 2.4 to 6.7 m. The highest value log-type was a saw log with a value of US$62/m^3. The lowest value log-type was a chip log with a value of $4/m^3.

**Machine Productivity and Costs**

At the Washington site a Logmax 750 harvesting head was operated on a Caterpillar 325C Forest Machine with a bucking computer. The harvester essentially sat at one location processing stems brought to it by a shovel. The operator of the Logmax had over 1.5 years’ experience operating this setup plus over 20 years’ experience in the forestry industry. In eastern Oregon a Valmet T500 with a Valmet 965 s-2 harvesting head and MAXI bucking computer operated as part of a cut-to-length thinning operation. The harvester moved through the stand felling and processing (at the stump) the marked trees. The Valmet operator had 5 years’ experience operating cut-to-length harvesters.

Long-term production studies were not carried out to determine percentage utilization and mechanical availability of the harvesters/processors, but a survey of literature for production studies of harvesters operating in similar situations to those described above was undertaken (e.g., Raymond 1989; Richardson 1989; MacDonald 1990; Jackson *et al.* 1984). A utilization level of 75% was assumed to be appropriate for both sites.
Detailed productivity was determined by video-recording at least 5 hours of each machine working under “normal” operating conditions. The videos were analysed using activity sampling which was first developed in 1934 by Tippett. The technique involves taking snap-readings at either set or random time intervals of the element or activity occurring at the time the reading is taken. Due to the semi-random nature of these operations, snap-readings at set intervals were considered to be appropriate and were taken every 15 seconds. The results of these time studies were used to calculate productivity in terms of trees and cubic volume per hour.

To predict delimbing/processing time for each of the processors working under the different scanning procedures, a mathematical model was developed using scanning/delimbing distance (m), head travel distance (m), and total saw-cut diameter (cm) as dependent variables. The dimensional data used to develop these models were collected from the processor’s on-board computerized measuring system, while the time data were collected using video recorded from inside the cab of the processor. The general form of the model is given below (Eq 3.1):

\[
\text{Processing Time} = \frac{\text{scanning distance}}{a} + \frac{\text{head travel distance}}{b} + c \times (\text{total saw cut diameter}) \times d \quad (3.1)
\]

where:

- a and b are travel speeds of the harvester head (m/s).
- c is the slope coefficient from regressing time to make a saw cut against diameter of the cut (s/cm).
d is the sum of the intercept coefficient from regressing the time to make a saw cut against diameter of the cut and the additional time that was required to process a stem but which was not recorded in the detailed time study. The detailed time study was used only to model the head travel and cut time. It did not provide data on the delays that often occur during the stem delimming and bucking process. The additional time was calculated by determining the difference between the average time to process a stem, as determined from the activity sampling time study and from the model (s).

The costs were calculated using standard costing procedures described by Bushman & Olsen (1988). The machine and scanning equipment were costed out separately. Productivity and cost information were combined to determine a cost per productive machine hour. It was assumed that the productivity of the whole operation was limited by the harvester.
Procedures for Scanning

To determine the best procedure for scanning, five simulated scanning, forecasting, and optimization patterns were included in the study:

1. CONVENTIONAL – stem diameters and length measured mechanically by the processor; the machine operator assesses quality breaks and selects log types to cut with or without computer assistance. The bucking is done as the delimbing is done.

2. FULL SCAN – the processor scans the full stem for changes in stem dimensions and quality, and then optimally determines log types that should be cut to maximize value recovery.

3-5. PARTIAL SCAN – the processor scans a certain length for stem dimensions and quality then forecasts a certain length (Table 3.1), optimizes to the end of the forecast length, cuts a log length, and then repeats to the end of the stem. Three partial scan/forecast combinations were evaluated for both species.
Table 3.1.- The three partial scanning scenarios for each of the species.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Douglas fir</th>
<th>Ponderosa pine</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCAN</td>
<td>6.1</td>
<td>4.6</td>
</tr>
<tr>
<td>SCAN</td>
<td>4.6</td>
<td>3.0</td>
</tr>
<tr>
<td>SCAN</td>
<td>3.0</td>
<td>4.6</td>
</tr>
<tr>
<td>SCAN</td>
<td>4.6</td>
<td>3.0</td>
</tr>
<tr>
<td>SCAN</td>
<td>3.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Scan distance (m) 6.1 4.6 3.0 4.6 3.0 1.5
Forecast distance (m) 6.7 8.2 9.8 2.1 3.7 5.2

These scanning and forecasting lengths were selected so that their combined length would be at least as long as the longest marketable log length for each species. If the “optimal” solution required a cut to be made in the forecast zone, resulting in a log not meeting specifications because of either its quality or diameter, a revised bucking solution was determined based on the new information.

Taper was forecast ahead for the distances given in using the taper over the previous 3 m (approximately) of the stem. Quality (such as knot size, rot, crook, and scars) was forecast ahead based on the last 0.1 m of stem. It was assumed for the simulations that sweep was measured consistently and correctly, regardless of scanning procedure. This assumption was made due to the difficulty surrounding the measurement of sweep when the stem is dangling from a processor head.
Gross and Net Value Recovery

An optimal bucking program (BUCKIT) was developed by the authors for this study; it uses a similar dynamic programming algorithm to that included in AVIS (Geerts & Twaddle 1984). BUCKIT was used to determine gross optimal value for the FULL and PARTIAL scan procedures. The volume scaling model used by BUCKIT to determine the log volume was the same as that used in practice for the two operations. This meant that the Douglas fir logs were scaled using the cubic foot scaling rule and the ponderosa pine logs were scaled using the Eastside Oregon Scribner scaling rules. The log lengths and grades that were actually cut by the processor were used to determine the gross value of the CONVENTIONAL scan procedure (i.e., the logger’s value). The lengths for these logs were recorded from the harvester’s computer which was assumed to be measuring accurately. The trees were numbered so that log lengths cut by the harvester could be matched to the stem description measured manually. These lengths were entered into “BUCKIT” as forced cuts, meaning “BUCKIT” was forced to cut the stem in that location.

The different scanning procedures accrued different log-making costs due to the processing head travelling different distances under the different scanning procedures (Figure 3.1). The net value recovery for the different scanning procedures was calculated by subtracting the log-making costs from the gross value recovery.
Breakeven Capital Investment Costs

The Microsoft EXCEL function “Goal Seek” was used to calculate breakeven capital investment that could be spent on new scanning, forecasting, and optimization systems for the different scanning procedures. The Goal Seek function varies an input value to a formula until the formula returns the result the user wants (Microsoft 2003). The costs associated with operating the processor were kept constant while the capital and associated costs of investing in scanning, forecasting, and optimization systems were increased until net value recovery by implementing the new scanning procedures equaled that of the CONVENTIONAL scanning method.
These breakeven capital costs were rounded down to the nearest US$10,000. They provide an indication of the maximum amount that could be spent on new scanning, forecasting, and optimization systems. Sensitivity of these breakeven costs to changes in net value recovery and scanning speeds was investigated.
RESULTS

Machine Productivity and Cost

Productivity data were collected using activity sampling methods, for a total of 256 and 364 trees at the Washington and eastern Oregon sites respectively. At Washington the productivity was 146 m$^3$/productive machine hour (PMH) which was considerably more than the eastern Oregon site where the harvester had a productivity of 14 m$^3$/PMH. On average the harvester at the Washington site was processing 63 trees/PMH compared to the harvester at the eastern Oregon site which was processing 68 trees/PMH. The difference in productivity between the two sites can be attributed to difference in tree size, operation (cut-to-length versus on-landing-processing), and tree species. For both systems approximately half the harvester’s time was spent processing the stem (Figure 3.2).

Two separate models for the two processors were developed to estimate the processing element under the different scanning procedures. The processor/site-specific coefficients for the generalized equation (Eq. 3.1) are given in Table 3.2.

The relationships between stem diameter and time to cut were generated by regressing the data displayed in the graph below (Figure 3.3). Time to cut a stem increased as diameter increased for both machines; however the rate of increase was much greater at the Washington site than at the eastern Oregon site.
Figure 3.2. - Average time spent on the different elements of processing a stem into logs.
Figure 3.3. - Relationship between cut time and diameter of the cut.

Head travel speed for deliming (a) and simply moving (b) along the stem were both significantly different for both sites. The p-value calculated using two sample t-tests were $P(t_{82}>2.044|\mu_1 = \mu_2) = 0.022$ for the Washington site and $P(t_{82}>3.138|\mu_1 = \mu_2) = 0.001$ for the eastern Oregon site.

The time it takes to process a stem is not totally accounted for by adding travel time and cut time together; these two elements do not take into account the time it takes to cut out a multi-leader, etc. The constant $d$ in Table 3.2 is the sum of the regression intercept from Figure 3.3 and the amount found by subtracting the predicted processing time...
using Equation 3.1 from the processing time recorded using the activity sampling time study. It represented the time per tree spent doing activities other than those captured during the detailed time study.

Table 3.2. - Coefficients for the stem processing model in Eq 3.1.

<table>
<thead>
<tr>
<th></th>
<th>a (m/s)</th>
<th>b (m/s)</th>
<th>c (s/cm)</th>
<th>d (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Washington</td>
<td>1.67</td>
<td>2.02</td>
<td>0.0676</td>
<td>2.57</td>
</tr>
<tr>
<td>eastern Oregon</td>
<td>1.13</td>
<td>1.55</td>
<td>0.0275</td>
<td>10.99</td>
</tr>
</tbody>
</table>

The simulated productivity of the FULL scanning procedure was about a quarter to a third less than that for the CONVENTIONAL operating method (Figure 3.4). Scanning only a portion of the stem reduced productivity impacts but the level of reduction was dependent on species, market type, and stand type.
The capital cost of the Caterpillar 325C Forest Machine with the Logmax 750 was US$560,000 with an operating cost of US$161.65/PMH. The Valmet T500 capital cost was US$438,480 with an operating cost of US$149.02/PMH. The costings assumed a machine life of 6 years, an interest rate of 12%, and cost of repairs and maintenance to annual depreciation ratio of 110%. These costs were calculated assuming that the processors were operating the CONVENTIONAL scanning procedure — i.e., without equipment fitted for scanning quality features. Cost per productive machine hour was combined with machine productivity to determine production costs per cubic metre. The changes in scanning cost for the different scanning and processing procedures were in line with changes in productivity for both operations.
Forecasting Accuracy

To determine the accuracy of the simple forecasting method used, the predicted and actual diameters were recorded for each of the forecast sections. The accuracy of the diameter predictions was evaluated by calculating Root Mean Square Error (RMSE):

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \]  

(3.2)

where: \( y_i \) was the actual diameter at each 0.1-m section and \( \hat{y}_i \) the predicted value. The measures of the diameter prediction accuracy for the species and the different scanning procedures are given in Table 3.3.

Table 3.3. - The RMSE for the forecast diameter for each species and scanning procedure.

<table>
<thead>
<tr>
<th></th>
<th>Washington</th>
<th>eastern Oregon</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCAN</td>
<td>6.1</td>
<td>4.6</td>
</tr>
<tr>
<td>RMSE (mm)</td>
<td>27.4</td>
<td>42.7</td>
</tr>
</tbody>
</table>

The results are similar to those of Liski & Nummi (1995) — RMSE decreases as length of the known section increases. Liski & Nummi found that a low RMSE value for the predicted diameters along the unknown section of the stem does not necessarily guarantee lower value losses.
The accuracy of the quality prediction was expressed as the mean percentage of the forecast section for which quality was inaccurately predicted. These mean percentages are given in Table 3.4 for each species and scanning procedure.

Table 3.4. - The percentage of the forecast stem for which the quality which incorrectly predicted.

<table>
<thead>
<tr>
<th>SCAN</th>
<th>Washington</th>
<th>eastern Oregon</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>6.1</td>
<td>4.6</td>
</tr>
<tr>
<td>%</td>
<td>18</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>22</td>
</tr>
<tr>
<td>%</td>
<td>4.6</td>
<td>3</td>
</tr>
<tr>
<td>%</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>%</td>
<td>1.5</td>
<td>10</td>
</tr>
</tbody>
</table>

The simple forecasting technique used in the study obtained results that were better than expected. It can be seen that as the forecast length increased the level of accuracy decreased. The number of quality codes used to describe the tree is also likely to have an impact on the level of the accuracy using this forecasting technique. In these two examples there were six quality codes for the Douglas fir and four for the ponderosa pine.

**Gross Value and Potential Value Loss**

Difference in tree size and markets meant there were very large differences in gross values for the two species. As an indicator of this difference, the gross value per tree was about US$12 for the ponderosa pine and US$276 for the Douglas fir stand. The eastern Oregon operation was losing 17% of potential value recovery, whereas the Washington operation was losing 8%. In absolute terms the Washington operation lost
more value (over US$2000 per hour, or approximately US$22 per tree) than the eastern Oregon operation (US$200 per hour, or approximately US$2 per tree). The percentage value loss figures were below the international average of 21% (Murphy 2003b).

In comparison with gross value recovery differences, the range in processing cost was small: US$1 to US$3 per tree.

Figure 3.5. - Change in net value recovery from 100 stems using five different scanning procedures in comparison to conventional processing.

At both sites, maximum net value recovery was obtained from FULL scanning (Figure 3.5). This conclusion, however, is dependent on the scaling rules used to calculate the
volume. When the 100 ponderosa pine stems were bucked using cubic scaling rules (Bell 2002) as opposed to the Scribner scaling rules used to obtain the results for the ponderosa pine stems in Figure 5, the SCAN 4.6 obtained a higher net value recovery than the FULL scan (not shown in Figure 5). As the scanning distance reduces and the distance of stem that is forecast increases, value recovery falls to the point where the net value recovery for the 100 stems is less than the value recovery for the CONVENTIONAL scan procedure. This occurred at the Washington site using the SCAN 3.0 scanning procedure and at the eastern Oregon site using the SCAN 1.5 scanning procedure.

**Breakeven Capital Investment Costs**

The breakeven capital investment costs that could be invested in new scanning and optimisation technology are shown in Table 3.5. These were in addition to the capital investment already made in the harvester/processor head and the carrier. These values have been rounded down to the nearest US$10,000. At both sites the breakeven cost was highest when using the FULL scan procedures; however, once again this was dependent on the scaling rules (Bell 2002). When cubic scaling (Bell 2002) was used on the eastern Oregon site, the SCAN 4.6 produced the highest breakeven cost.
Table 3.5. - Summary of breakeven investment cost (US$) for the 5 scanning procedures.

<table>
<thead>
<tr>
<th></th>
<th>Full Scan</th>
<th>Scan 6.1</th>
<th>Scan 4.6</th>
<th>Scan 3.0</th>
<th>Scan 1.5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Washington</td>
<td>$ 2,120,000</td>
<td>$ 1,810,000</td>
<td>$ 800,000</td>
<td>$ -</td>
<td>N/A</td>
</tr>
<tr>
<td>eastern Oregon</td>
<td>$ 80,000</td>
<td>N/A</td>
<td>$ 70,000</td>
<td>$ 10,000</td>
<td>$ -</td>
</tr>
</tbody>
</table>

As in the study by Murphy (2003a), it can be concluded that the breakeven capital investment costs were dependent on stand-type, market, and scanning approach.

To investigate the effects of initial value recovery of the system and the speed at which the stem is scanned, the following sensitivity analyses were carried out on the FULL scan procedure.

(a) Net value losses can vary between different operations (see Murphy 2003b). The breakeven capital investment cost was therefore calculated using initial net value losses of 5, 12.5, and 20%. As the initial net value loss increases, the breakeven capital investment cost also increases (Fig. 6) meaning that the most money can be invested in the poorest performing operations. This conclusion should, however, be treated with some caution as the reasons for some operations performing poorly may not be removed by implementing automatic scanning, forecasting, and optimisation systems.
In the literature, the range of potential scanning speed that a system such as X-ray can achieve is quite large, ranging from a low of 0.04 –0.16 m/s (Schmoldt et al. 2000) up to 3 m/s (Oja 1999). If new scanning technology were to be implemented on harvesting/processing heads, it is likely that scanning speeds would have to be less than current scanning speeds of 1–2 m/s for mechanical harvesters. To simulate the effects of reducing the measuring speed, the breakeven capital investment cost was calculated when the scanning speed was reduced by a half, and by two-thirds (Fig. 7).
Figure 3.7. - Effect of scanning speed on breakeven capital investment (US$) under the FULL scan procedure.

It appears from these simulations that breakeven capital investment cost is relatively sensitive to scanning speed. Given the current scanning speed for X-ray suggested by Schmoldt et al. (2000), the breakeven capital investment for the Washington site would be US$480,000; so at least for the Washington site the scanning speed of current X-ray scanners is sufficient to make its implementation economically viable. Other scanner technologies such as NMR whose scanning speeds are much slower than X-ray would probably not be economically viable.
Along with stand-type, market, and scanning approach, the breakeven capital investment cost is also dependent on the initial amount of net value loss and scanning speed.

**DISCUSSION AND CONCLUSIONS**

Simulations reported in this paper indicate that substantial investment can be made by the log seller into scanning systems to improve the accuracy of stem quality and dimensions measurements. The size of this potential investment is dependent on species, stand-type, markets, the scanning system and procedure, and the current value recovery performance of the operation.

Scandinavian researchers have found that by measuring a portion of the stem, and forecasting taper for the unmeasured portion of the stem, value losses could be contained to less than 2% (Nasberg 1985; Sondell *et al.* 2002). In this study, where quality was forecast as well as taper, gross value losses for the longer scanning distances (6.1 m for Douglas fir and 4.7 m for ponderosa pine) were contained to less than 4%. These losses are similar to value losses found by Liski & Nummi (1995).

The FULL scan procedure produced the highest net value recovery. It was concluded that there was no advantage in only partially scanning the stem when using the simple forecasting procedure used in this paper. This result agrees with experience in Finland where automatic bucking used in Norway spruce is considered economically inefficient
in pine or birch (Uusitalo et al. 2003). This study showed that scanning less than 3 m produces a lower net value recovery than the conventional scanning procedure.

It should be noted that a forecasting system that more accurately forecasts both stem form and quality may yield higher net value recovery results and therefore justify the use of partial scanning in Douglas fir and ponderosa pine harvesting. Research done on Scots pine in Sweden (Möller et al. 2003) and Finland (Nummi & Möttönen 2003) on prediction models for accurately forecasting a number of lumber and wood quality characteristics during the stem processing operation is showing promising results. If the Douglas fir and ponderosa pine harvesting industries want to increase their mechanical log bucking productivity while achieving high levels of value recovery they need to invest time and money into developing more accurate stem forecasting models.

The large difference in breakeven capital investment costs indicates that vastly different scanning; forecasting, and optimisation technologies are likely to be applicable for different stand and market conditions. At the Washington site, where the breakeven capital investment was US$2,120,000, the potential for implementing a new scanning and optimisation system is extremely promising. However at the eastern Oregon site the breakeven capital investment of US$80,000 may limit investment to (1) improvement of current measuring systems, (2) improved training, (3) better calibration procedures, or (4) some combination of the three.
An investment in training, at both operator and managerial levels, may be a simpler and more effective way to improve value recovery than investing in technology. As Gellerstedt (2002) pointed out, however, it takes years for an operator to gain the training and experience to effectively operate a harvester and, even then, there is a limit to how quickly operators can perceive and process information about each tree stem. Increases in machine delimbing/processing speeds and a trend towards matching internal wood properties to markets will probably lead to a greater use of scanning technology and log bucking decision support systems on processors where log value warrants such an investment.

Although US$2,120,000 seems a large investment, in many situations the amount required to invest in new scanning, forecasting, and optimisation systems is of at least this order of magnitude. In the sawmill industry, scanning and optimisation systems cost US$500,000 to US$1,000,000. However, the large body of value recovery studies (Murphy 2003a) shows that significant gains in profitability can be made if the optimal value can be achieved from every stem.

The breakeven values reported in this paper are only an indication of the level of investment that could be made in stem scanning systems. The breakeven values reported will be affected by measurement, prediction, and sampling error. No analysis has been done to determine the effect of these errors, as they will be minimal compared to those caused by differences in stand and market conditions.
Although not considered in this study, many new scanning and forecasting systems are capable of scanning for internal quality features of a stem. Further research is required to determine the effects of alternative procedures for internal quality scanning on productivity, costs, and value.
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Chapter 4:

AN INVESTIGATION OF DIFFERENT APPROACHES TO BUCKING-TO-ORDER

By Hamish Marshall

Glen Murphy
ABSTRACT

A new bucking-to-order planning model using mixed integer programming was developed to determine the optimal production from a stand given different market constraints and forest inventory data. Three different approaches: market prices, target cutting patterns and adjusted price list were tested for generating cutting instructions to fulfill the plan created by the new planning model. The three approaches were evaluated in four test stands. The market prices approach simply applied the market prices to each stand. The target cutting patterns approach applied the sample cutting patterns generated from the planning model to the stand. The adjusted price list used a dynamic programming algorithm embedded in a search heuristic to adjust both the prices and small end diameters of log products to achieve the production goals of the planning models.

The results showed that developing a buck-to-order plan is important in obtaining good order fulfillment. The target cutting patterns and adjusted price list approaches certainly out performed the market prices approach. This paper shows that these two approaches are capable of achieving excellent order fulfillment. Further development and testing is needed to determine which method is the best at generating cutting instructions for buck-to-order merchandizing.
INTRODUCTION

The adoption of mechanical harvesting systems in timber harvesting is increasing worldwide (Raymond 1988; Nordlund 1996; Godin 2000). With these systems, stems are delimbed, bucked and sorted by a single machine. There are a number of factors causing this shift from the traditional motor manual harvesting systems to mechanical harvesting systems. These drivers include economic (the need to continually increase productivity) and social pressures along with the continuing need to improve the safety record of forestry operations. These systems provide a platform for state-of-the-art communication and measurement technology and the application of increasingly powerful on-board PC computers (Sondell et al. 2002). These computers provide the following opportunities:

- reducing the variability in production performance by sorting for niche uses,
- capturing and storing detailed description of stems within each stand,
- reducing the variability in decision-making about which are the best markets to supply for each tree, and
- optimally controlling the bucking of logs at harvesting time (Murphy 2003).

A sometimes overlooked aspect of financial improvement in harvesting is value recovery. Value or revenue can be lost in numerous places along the forest to mill value chain. One process that has been identified as having a large potential for value
loss is the process of bucking trees into logs. A recent survey of value recovery studies has shown that on average, manual log making systems were losing 11% and mechanical log making systems 18% of potential value.

These kinds of figures have spurred significant research in the area of optimal log bucking. Optimal bucking is an effective means of making informed decisions before mistakes are made that result in value loss. A number of mathematical formulations and computer models have been developed to optimize the value in each individual stem, this is commonly referred to as buck-to-value. (Pnevmaticos and Mann 1972; Briggs 1980; Geerts and Twaddle 1984; Sessions et al. 1988). The objective of buck-to-value optimal bucking is to obtain the maximum monetary value from an individual stem. A stem can be cut up into logs in numerous ways; each set of logs will yield a different financial return. However, there is, in many cases one unique bucking pattern that yields the maximum value. The value and logs cut using the optimal bucking pattern depends on the species, diameter, taper rate and quality of the stem plus the properties and relative market values of log grades being cut.

Although the majority of buck-to-value models were developed in the eighties, it has only been in recent years that these models have been implemented into large scale commercial harvesting operations (Boston 2001).
The problem operationally is what is optimal for individual stems may not meet the market and operational constraints at a harvest unit or forest level. To maximize the value coming from a forest, these in-the-field bucking algorithms must be given log specifications which take into account market and operational constraints. Constraints can be in the form of the following: target volumes, minimum percentage of volume must be of greater than a certain length, minimum average small end diameter (SED) for a product, and minimum percentage of the volume must be of a certain grade (Murphy 1993).

The cutting-order problem arises in many other industrial situations, both inside and outside the forestry industry. In sawmilling a significant amount of research has been done on developing algorithms to minimize the total cost of filling an order from a given lumber or log supply (Todoroki and Rönnqvist 2002, Hamilton et al. 2002). In logging, to account for these operational and market constraints a number of different buck-to-order procedures have been developed. The objective of buck-to-order optimal bucking is to maximize the monetary value at harvest unit or forest level while meeting market and operational constraints. In the literature there are generally two approaches to developing the in-the-field cutting instructions for buck-to-order bucking:

   Approach 1: Selecting cutting instructions either before or during the bucking process for each tree that will produce the required volume for each product.
Approach 2: Finding the correct price list (in some cases the correct specifications) that will be applied to the stand of trees to produce the required volume for each product.

The first published optimal bucking formulation, the Smith and Harrell (1961) paper, actually solved the buck-to-order problem using linear programming. However, as Pnevmaticos and Mann (1971) stated, the Smith and Harrell linear programming formulation was limited by the requirement that all relationships be linear and by the limited number of cutting instructions available for each diameter class.

The limited number of cutting patterns problem was solved by Nasberg (1985), Mendoza and Bare (1986), Eng et al. (1986) and Laroze and Greber (1997), by using a two stage iterative formulation of the problem. The first stage, or master problem, uses linear programming to solve the constrained market problem and the second stage, or sub-problem, uses dynamic programming or a network algorithm to solve the individual tree problem. The shadow prices from the master problem were used in the second stage to generate new cutting patterns. These were then used to form new columns in the master problem using column generation techniques. This general approach is theoretically correct and computationally efficient (Laroze 1993), but as many authors (Sessions et al. 1989, Laroze 1993 etc) have pointed out, the solutions produced are not particularly practical as they produce large numbers of cutting instructions. Sessions et
also noted that the requirement of these techniques to subdivide the stand into stem classes makes these solutions hard to implement.

The second approach does not suffer from these same problems, however, it can not guarantee theoretically that maximum revenue is gained from the bucking of the stand. Duffner (1980) is the first published work on adjusting the price list in a bucking algorithm to meet market demands. There was, however, very little detail in the Duffner (1980) paper on exactly how he adjusted the prices.

Sessions et al. (1989) developed a system to adjust the prices iteratively using a shortest path algorithm to solve the sub-problem and a binary search to find the price multipliers to obtain the correct ratio of long logs to short logs. The formulation was designed to overcome the problem of producing too many short logs that plagued optimal bucking in areas where the Scribner volume scaling rules were used.

A number of other approaches have been tried, such as using an LP solution at the upper level, to adjust the prices in the DP lower level, or using an heuristic to find the correct prices so the demand constraints are met in the master problem (Laroze and Greber 1993; Pickens et al., 1997).

Laroze and Greber (1997) used a rule based stem bucking algorithm combined with a Tabu Search heuristic to generate easy to implement bucking rules that are applicable to
the entire stand, while providing the best feasible solution given a set of log prices and market constraints. Laroze and Greber (1997) compared the solution from this algorithm with the linear programming/dynamic programming approach and found that the Tabu Search generated bucking rules that led to profits approximately 2.5% below the linear programming/dynamic programming approach. Laroze (1999) used the approach described above, in combination with a linear programming formulation, to solve the forest level bucking optimization problem. Laroze found that his formulation consistently achieved efficiency levels of approximately 97% compared to the optimal solutions for all of the scenarios analyzed.

Kivinen and Uusitalo 2002 developed a fuzzy logic controller to adjust the prices specifically for a mechanical harvester. The fuzzy logic controller is a set of rules which changes the price of a log type based on the disparity between the target proportion and the actual proportion in each log class and the rate of change in this error. Kivinen and Uusitalo found that for the four stands tested, the output log distribution derived by the fuzzy logic controlled production price matrix was within 92% of the log distribution produced by the desired (target) price matrix.

Murphy et al (2004) developed a two level model where the upper level was a threshold accepting heuristic and the lower level was a dynamic programming bucking algorithm. The upper level heuristic was designed to find the product prices and minimum SEDs that minimized the difference between the target proportion and the actual proportion
while meeting a length and average SED constraint. This algorithm is discussed in more
detail later in the paper.

The buck-to-order process can be split into three stages; buck-to-order planning, cutting
instruction development and adaptive control during the harvesting. This paper
investigates in detail the first two stages of this process, it presents a new methodology
for creating a buck-to-order plan and tests the effectiveness of the two approaches
discussed earlier for creating buck-to-order cutting instructions for implementation of
the buck-to-order plan.
METHODS

The methods section is divided into three parts: the first section describes a new mixed integer programming (MIP) formulation for developing an optimal buck-to-order plan; the second section describes two approaches for implementing the plan, and the third section describes the market requirements and four stands that were used to test the two implementation approaches.

Developing a Buck-to-Order Planning Model

The formulation below was developed to solve the following description of the problem:

The buck-to-order problem, simply stated, is obtaining a log product distribution that will obtain maximum returns while meeting a log demand distribution. Ideally the log demand distribution would be satisfied from the harvest unit given the correct cutting instruction, however, this is rarely the case. In many cases, to meet the log demand distribution a company has to either obtain volume from other sources such as log inventories, other stands, spot market, or reallocate excess volume to other markets, for example selling on the open spot market. Required customer demand volume constraints are not the only demand constraints placed on log producers by log buyers; for example, constraints can also be placed on the
average small end diameter or the percentage of long logs (Sessions et al. 1989; Murphy et al, 2004). There may also be constraints on the amount of volume that can be bought from and sold to the spot market.

Buying in volume and selling volume comes at a cost, but in some cases it may be economically better to produce excess volume of a high value product and sell it on to the open market while under producing a low value product.

An MIP model has been used to maximize the market value of the stand while meeting the market constraints, the customer order book constraints and the spot market constraints, by determining the volume of log products that should be cut from the stand.

The model optimizes the projected stand value, given the different market constraints, by determining the optimal bucking patterns for a sample of trees from the stand. The tree data for these sample trees would normally be collected as part of the pre-harvest inventory. The model satisfies the customer order book constraints either by using the volume produced from the stand or buying volume from other sources at an additional cost. In cases where excess volume is produced from the stand the excess is reallocated to other markets at an additional cost. The mathematical formulation of the model is shown below:
Max \( \sum_{i=1}^{p} y_i \cdot c_i + \sum_{i=1}^{p} w_i \cdot d_i + \sum_{i=1}^{p} z_i \cdot c_i - \sum_{i=1}^{p} z_i \cdot e_i \) \hspace{1cm} (4.1)

subject to:

\[ \sum_{j=1}^{s} x_{ij} = y_i + w_i \quad \forall \quad i = 1, \ldots, p \] \hspace{1cm} (4.2)

\[ y_i + z_i = b_i \quad \forall \quad i = 1, \ldots, p \] \hspace{1cm} (4.3)

\[ w_i \leq UB_i \quad \forall \quad i = 1, \ldots, p \] \hspace{1cm} (4.4)

\[ z_i \leq UB_i \quad \forall \quad i = 1, \ldots, p \] \hspace{1cm} (4.5)

\[ x_{ij} - \text{BigN} \cdot \text{cut}_{ij} \leq 0 \] \hspace{1cm} (4.6)

\[ x_{ij} \geq \text{Min} V_{ij} \cdot \text{cut}_{ij} \quad \forall \quad i = 1, \ldots, p \quad j = 1, \ldots, s \] \hspace{1cm} (4.7)

\[ x_{ij} \leq p V_{ij} \quad \forall \quad i = 1, \ldots, p \quad j = 1, \ldots, s \] \hspace{1cm} (4.8)

\[ \sum_{i} x_{ij} \leq CV_{ij} \quad \forall \quad i \in \{\text{product group}\} \quad j = 1, \ldots, s \] \hspace{1cm} (4.9)

\[ \text{cut}_{ij} \in \{0,1\} \]

where

\( p \) = the number of log products

\( s \) = the number of stems

\( b_i \) = the volume demanded of each product (i) from the markets

\( x_{ij} \) = the volume cut of each product (i) from each sample stem (j)
\( y_i \) = the volume of each product cut from the stand used to fulfill the demand constraints

\( w_i \) = the volume of each product “sold” to other markets.

\( z_i \) = the volume of each product “bought in” from other sources

\( c_i \) = the market price for log-type \( i \)

\( d_i \) = the “sell off” price for log-type \( i \)

\( e_i \) = the “buy in” price for log-type \( i \)

\( UBI_i \) = upper limit on volume that can be bought from other sources

\( US_i \) = upper limit on volume that can be sold to the markets

\( cut_{ij} \) = the number of logs of each log type cut from a sample stem

\( BigN \) = a larger number, for example 200

\( Min_{Vi} \) = the minimum possible volume for a single log of that log product in that stem

(It is found by optimal bucking the stem using only that product and restricting the length of the logs to the smallest possible length for that log product)

\( pV_{ij} \) = this is the maximum potential volume that can be cut from stem \((j)\) of that product \((i)\) (This value is found by bucking the stem using a dynamic programming bucking algorithm, using only the product specifications for that product and waste, where waste has a value of zero)

\( CV_{ij} \) = the maximum constrained volume; this is the maximum volume from a stem when all the products in a particular “product group” are used by the bucking algorithm. A “product group” is defined as those products with the same or more
restrictive over-lapping quality and small end diameter specifications. All products in that “product group” are given the same value.

Table 4.1 gives a simple example of how product groups are defined. The volume in a stem that can be made into Pruned logs can be made into every other product, so it is part of every product’s product group. However, the volume in a stem that can be made into Sawlog 1 logs can be made into all other products, except Pruned and Sawlog 2, because it’s minimum SED is less than 350. This means Sawlog 1 is a part of every log product’s product group except for Pruned and Sawlog 2. The members of Sawlog 1’s product group are restricted by the allowable qualities. The only product, other than itself, that it can be made out of is Pruned, as Pruned is the only product that does not have a lower allowable quality grade (e.g. C, D or E). It is therefore the most restrictive of either the minimum SED or allowable qualities that defines the members of each product’s product group.

Table 4.1. - An example of product groups.

<table>
<thead>
<tr>
<th>Product</th>
<th>Minimum SED (mm)</th>
<th>Allowable Qualities</th>
<th>Member of Product Groups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pruned</td>
<td>350</td>
<td>A</td>
<td>Pruned</td>
</tr>
<tr>
<td>Sawlog 1</td>
<td>200</td>
<td>AB</td>
<td>Pruned, Saw 1</td>
</tr>
<tr>
<td>Sawlog 2</td>
<td>350</td>
<td>ABC</td>
<td>Pruned, Saw 2</td>
</tr>
<tr>
<td>Sawlog 3</td>
<td>200</td>
<td>ABC</td>
<td>Pruned, Saw 1, Saw 2, Saw 3</td>
</tr>
<tr>
<td>Pulp</td>
<td>150</td>
<td>ABCD</td>
<td>Pruned, Saw 1, Saw 2, Saw 3, Pulp</td>
</tr>
<tr>
<td>Waste</td>
<td>10</td>
<td>ABCDE</td>
<td>Pruned, Saw 1, Saw 2, Saw 3, Pulp Waste</td>
</tr>
</tbody>
</table>
The constraints shown above assure that:

Eq. 4.2 The sum of the volume cut from all the stems for each log product, is equal to the volume produced from the stand that is being used towards fulfilling the order, plus the volume being sold onto the spot market.

Eq. 4.3 The sum of the volume produced from the stand that is being used towards fulfilling the order, plus the “buy in” volume, is equal to the demand requirement for each log product.

Eq. 4.4 This constrains the amount of volume that can be sold on to the spot market.

Eq. 4.5 This constrains the amount of volume that can be bought from the spot market.

Eq. 4.6 This is the binary trigger constraint. If $x_{ij}$ is greater than zero then $cut_{ij}$ must be 1. Combining this constraint with the constraint in Eq. 4.7, requires $x_{ij}$ to be greater than $Min_{VI}$.

Eq 4.7 This constrains the volume of log product (i) cut from a stem to be greater than integer multiples of the minimum log product volume.

Eq. 4.8 The total volume of all logs of log product (i) cut from stem (j) must be less than the maximum potential volume for that log product in that stem.

Eq 4.9 The total volume of the “product group” must be less than the maximum potential volume for that “product group” in that stem.
The MIP model was formulated in AMPL mathematical programming language and solved using CPLEX 8.0. The default CPLEX optimizing settings were used. The model was solved on a Pentium 4 laptop with 1 GB of memory. Most of the models took less than one minute in solve.

The solution provides projected volumes that should be (1) cut from the stand, (2) be sold on to the spot market, and (3) purchased from the spot market to satisfy the order book constraints. Solving the MIP formulation also creates cutting patterns for each of the sample trees included in the formulation. These cutting patterns, which are in the form of volume per product \((x_{ij})\) and the maximum potential volumes per product \((pV_{ij})\) for each tree, are used in the Cutting Pattern approach described in the next section.

**Methods for Implementing the Buck-to-Order Plan**

**Approach 1: Market Price**

In this approach the market prices were applied using an individual stem optimal bucking dynamic programming algorithm. This algorithm was develop by the first author of this paper and is similar to that described by Deadman and Goulding (1979). Its aim was to maximize the total value of each stem.

**Approach 2: Target Cutting Patterns**

A new algorithm to apply the target cutting pattern was developed for this paper. As Sessions et al. (1989) pointed out, the two major practical problems with the buck-to-
order formulations that generate target cutting patterns are (1) identifying which stem class each tree belongs to and (2) determining what bucking pattern should be applied to each tree within the stem class.

This algorithm overcomes this problem by allocating the target cutting patterns to a tree using the maximum potential volume \( (pV_0) \) of each log product. The theory is that two trees that are similar in terms of size and quality characteristics will have similar maximum potential volumes and hence should be bucked in a similar manner.

The theory of this formulation is that each of the target trees in the inventory sample represents the same proportion of trees in the total stand and the target cutting pattern will therefore, be applied to the same proportion of trees in the stand. The target cutting pattern to be used on the current stem is found by determining which of the sample trees is most closely matched in terms of maximum potential volumes. A simple distance function as in Equation 4.10 was used to determine the nearest neighbors:

\[
d = \sum_{i=1}^{n} |PTV_i - PAV_i|
\]  

(4.10)

where:

\( i = \text{products } (1..n) \)

\( PTV_i = \text{the maximum potential target volume for product } i. \)

\( PAV_i = \text{the maximum potential actual volume for product } i \text{ for the current stem.} \)
Ponsse harvesters store information on the previous 80 stems harvested and use the “closest” eight trees as the basis for predicting stem taper rather than the taper from the single closest tree. It is possible to use k-nearest neighbors to determine the best cutting pattern to apply to each tree in the stand. The same distance function (Eq. 4.10) would be used to determine the k-nearest neighbors. Trials using different ks showed that no gains were made by using k more than 4 for this application.

The target volumes for each product are then calculated from the k-nearest neighbors. When k is equal to 1, then the target volumes will simply be the volumes for each product from the MIP solution in the planning model. If k is greater than 1, then target volumes are calculated from the k nearest neighbors. The target volumes are calculated in proportion to the distance each of the k-nearest neighbors is from the current stem. The following equation is used to calculate the target volumes for the current stem:

\[
TV_i = \sum_{k=1}^{m} (TV_{ik} \cdot (1 - \frac{d_k}{\sum_{k=1}^{m} d_k})/(m - 1))
\]  
(4.11)

\(i = \) products (1..n)
\(k = \) nearest neighbors (1..m)
\(TV_i = \) the target volumes for the current stem
\(TV_{ik} = \) the target volumes from the k nearest neighbor
The target volumes for each product are then used in an heuristic allocation model that uses the same structure of a forward recursive dynamic programming algorithm to minimize the deviation from these target volumes. Dynamic programming relies on the principle of optimality that states (Dystra 1984, pg 298):

*Given the current state of the system, an optimal policy for the remaining stages is independent of any policy adopted in previous stages.*

The decision whether to cut a product at a particular state in this problem depends on what products have been cut before, hence breaking the principle of optimality. Although the heuristic procedure used does not guarantee an optimal solution it did provide the best solution of the different procedures tried.

The algorithm attempts, as closely as possible, to cut the same volumes out of the current tree as the sample cutting pattern. This is achieved by replacing the maximize revenue objective function with a minimize the weighted volume deviation from the target volume function. The minimize volume deviation requires the addition of “i” more state variables; where i represents the number of products. These new state variables contain the volume of each product that has already been cut at the state.

The volume deviations from the target of each product are weighted to encourage the algorithm to meet the targets for higher value products. This is done using the market prices for the products. If the current cut volume of that product at that stage is less than
the target volume for that product, the market price for that product is used as the weight. However, if the current cut volume of that product at that stage exceeds the target volume then the market price list is applied in reverse. Table 4.2 gives a simplified example of the weighting scheme used.

Table 4.2. - A simplified example of the weighting scheme used.

<table>
<thead>
<tr>
<th></th>
<th>Market Price</th>
<th>&lt; Target</th>
<th>&gt; Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pruned</td>
<td>100</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Saw</td>
<td>50</td>
<td>50</td>
<td>20</td>
</tr>
<tr>
<td>Pulp</td>
<td>20</td>
<td>20</td>
<td>50</td>
</tr>
<tr>
<td>Waste</td>
<td>0</td>
<td>0</td>
<td>100</td>
</tr>
</tbody>
</table>

During the early testing of this algorithm it was found that the pulp and waste products were being over produced. In an attempt to reduce this, the target volumes for all the target cutting patterns for pulp and waste were set to zero. This changed the objective function of the algorithm to minimize the volume deviation from the target volumes (for all products except pulp and waste) while minimizing the production of pulp and waste volumes. This change significantly improved the performance of the algorithm.
Approach 3: Adjusted Price List

The adjusted price list algorithm that has been used in this paper is FASTBUCK which was developed by G. Murphy and H. Marshall. A full description of the algorithm is given in Murphy et al. (2004).

In summary, the algorithm was developed by imbedding an individual stem optimal bucking dynamic programming procedure in a threshold accepting algorithm which adjusts the relative prices and minimum small-end diameter specification to meet order book constraints. The threshold accepting algorithm tries to optimize the order fulfillment and not the market value of the volume produced. The objective function is to maximize the apportionment degree (%), which is a measure of how well the production is meeting the orders. Apportionment degree (AD%) is defined as:

\[
AD(\%) = 100 \times (1 - \frac{\sum_{j=1}^{k} |D_{di} - D_{pi}|}{2})
\]

where:

- \( k \) = number of log grades
- \( D_{di} \) = target proportion demanded for the log grade
- \( D_{pi} \) = actual proportion produced for the log grade
In this paper the target proportion of the total volume for each product was determined using the results from the buck-to-order planning model. The projected volume production for each product was divided by the total projected volume. The FASTBUCK algorithm was applied to the pre-harvesting inventory, the resulting relative prices and minimum SED were then applied to the whole stand to simulate the harvesting process.

The threshold accepting algorithm was set up with the search parameters suggested in Murphy et al. (2004), where the AD% was penalized for not meeting an average SED and length constraint. In this paper no penalties have been added.

**Calculating the Effectiveness of the Approaches**

The production from the simulated harvest from each approach was then adjusted using the projected “buy in” and “sell off” volume from the Buck-to-Order planning model. The effectiveness of the different approaches where measured using 1) the level to which the orders were fulfilled and 2) the monetary return from harvesting the block. The metrics that will be used are described below:

**Order Fulfillment**

To evaluate the goodness of fit between the demand and production vector/matrix the AD (%) was used. It was originally developed by a Skogsarbeten (now know as Skogforsk) researcher in the 1980s (Bergstrand 1989). This is a commonly used
measure for evaluating the fit between an actual output distribution of logs and the desired log distribution. The equation for the AD(%) was given earlier in the paper.

**Monetary Return**

The monetary return is calculated by determining the gross value gained by harvesting the unit, given that the volume of the over produced products is sold on to the spot market at a discounted price (Table 4.4), and the orders that are undersupplied have to be fulfilled using volume bought from the spot market at a inflated price. The monetary return (MR) is determined using the following equation:

\[
MR = \text{Max} \sum_{i=1}^{p} y_i \cdot c_i + \sum_{i=1}^{p} w_i \cdot d_i + \sum_{i=1}^{p} z_i \cdot c_i - \sum_{i=1}^{p} z_i \cdot e_i
\]  

(4.13)

where the coefficients are the same as those defined for Equation 4.1.

The formula gives the monetary return of the solution, given that the log demand distribution has been completely fulfilled, either from the stand, or from the planned sales and purchases from the spot market. However, given that perfect information is not available, it is possible that additional volume will have to be purchased from the spot market during or after the harvest. These purchases come at a significant cost to the company. In this paper, it has been assumed this cost will be 125% of the original market prices. Any volume produced in excess of the originally projected production is valued at the price of pulp, regardless of its original value.
Test Stands

Four stands were used to test and evaluate the performance of these buck-to-order approaches. For comparison purposes these four stands were the same as those used in Murphy et al. (2004). All stands had been pruned and were of similar mean diameter at breast height (DBH), details of which are provided in Table 4.3. Only one of the four stands was a “real-world” stand; this stand (WHAKA) was a Pinus radiata plantation stand in the North Island of New Zealand. Every tree in this irregular shaped stand was located, measured and described using the MARVL inventory system (Deadman and Goulding 1979).

The other three stands were virtual stands and were rectangular in shape (500 m × 200 m). These were based on growth and form characteristics of Pinus radiata and were generated to represent a variety of forest conditions. The lower limbs had been removed (pruned) from all trees to a height of approximately 6 m in the EVEN stand. Selection for pruning was uneven in the UNEVEN stand; 100% of trees were pruned in the middle of the stand decreasing to 70% at the edges of the stand. This mimicked situations where the pruning contract supervision or funds were inadequate to ensure all final crop trees in the stand were pruned. The EVEN and UNEVEN stands were generated to have diameter distributions which ranged from 20 to 70 cm with a DBH of approximately 45 cm and standard deviation of 5.9 cm.
The FROST stand mimicked a situation where there was a frost effect in the center of the stand; tree size was small in the center and increased toward the edge of the stand. All trees were pruned in the FROST stand.

Table 4.3. - Characteristics of test stands.

<table>
<thead>
<tr>
<th></th>
<th>EVEN</th>
<th>UNEVEN</th>
<th>FROST</th>
<th>WHAKA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Area (ha)</td>
<td>10.0</td>
<td>10.0</td>
<td>10.0</td>
<td>1.9</td>
</tr>
<tr>
<td>Density (stems per ha)</td>
<td>375</td>
<td>375</td>
<td>375</td>
<td>249</td>
</tr>
<tr>
<td>Mean DBH (cm)</td>
<td>45.0</td>
<td>44.8</td>
<td>45.2</td>
<td>48.5</td>
</tr>
<tr>
<td>Total Volume (m3)</td>
<td>5990</td>
<td>6136</td>
<td>6554</td>
<td>1066</td>
</tr>
</tbody>
</table>

Fifteen circular pre-harvest inventory plots were systematically located in each of the EVEN, UNEVEN, and FROST stand and five square plots were located in the WHAKA stand. The inventory plots occupied 3% of total area in each stand.

**Product Requirements for Test Stands**

The same product requirements were applied to all four test stands (Table 4.4). There were five log-types (Pruned Domestic Sawlogs, Unpruned Export Sawlogs, Domestic Sawlogs #1, Domestic Sawlogs #2, and Pulp) plus waste. Most log types allowed multiple lengths; some in multiples of 0.3 m, others in multiples of 0.1 m. A total of 51 lengths were included in the analyses. Each log-type had target proportions of volume
that were required. For example, the demand target proportion for Pruned Domestic Sawlogs was 0.15, or 15%, of the total volume harvested.

Three different prices are included in the specifications for each log type:

- The market prices, which are the prices for the volume of each log type with confirmed markets.
- The “sell off prices” that can be thought of as, either a transfer cost into log stocks, or the price received for selling excess volume on the spot market. These prices are 5% less than the market prices rounded to the nearest integer.
- The “buy in prices” can also be thought of as a transfer cost out of log stocks, or the price for buying volume from the spot market. These prices are 10% greater than the market prices rounded to the nearest integer.
Table 4.4. - Market requirements and constraints for the four test stands.

<table>
<thead>
<tr>
<th>Log-types</th>
<th>Lengths (m)</th>
<th>Minimum SED (mm)</th>
<th>Market Prices ($/m³)</th>
<th>Sell off Prices ($/m³)</th>
<th>Buy in Prices ($/m³)</th>
<th>Target Proportions (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pruned Domestic Sawlog</td>
<td>3.7-6.1</td>
<td>350</td>
<td>145</td>
<td>138</td>
<td>160</td>
<td>15</td>
</tr>
<tr>
<td>Unpruned Export Sawlog 12.2 m</td>
<td>12.2</td>
<td>260</td>
<td>97</td>
<td>92</td>
<td>107</td>
<td>20</td>
</tr>
<tr>
<td>Unpruned Export Sawlog 8.2 m</td>
<td>8.2</td>
<td>260</td>
<td>88</td>
<td>83</td>
<td>97</td>
<td>6</td>
</tr>
<tr>
<td>Domestic Sawlog #1</td>
<td>3.7-6.1</td>
<td>200</td>
<td>68</td>
<td>65</td>
<td>75</td>
<td>12</td>
</tr>
<tr>
<td>Domestic Sawlog #2 Longs</td>
<td>4.9-6.1</td>
<td>200</td>
<td>48</td>
<td>46</td>
<td>53</td>
<td>8</td>
</tr>
<tr>
<td>Domestic Sawlog #2 Shorts</td>
<td>3.7-4.6</td>
<td>350</td>
<td>46</td>
<td>44</td>
<td>51</td>
<td>7</td>
</tr>
<tr>
<td>Pulp</td>
<td>3.7-6.1</td>
<td>100</td>
<td>25</td>
<td>24</td>
<td>28</td>
<td>24</td>
</tr>
<tr>
<td>Waste</td>
<td>0.1-0.6</td>
<td>0</td>
<td>0</td>
<td>-1</td>
<td>1</td>
<td>8</td>
</tr>
</tbody>
</table>

Waste is given a negative “sell off” price of $1 and positive “buy in” cost of $1 to represent the cost of handling under and over production of waste volume.
Market Scenarios

To test the robustness of the different approaches four different test market conditions were used:

1. **Unconstrained Spot Markets (Unconstrained Spot)**

   This is the base scenario; it uses the prices in Table 4.4. The scenario has no constraints on the volume that can be brought in from, and sold off to, the spot market.

2. **High “Buy In” for “Unpruned Export Sawlog 12.2 m” (Hi-Price Exp 12)**

   In this scenario the “buy in” price for the “Unpruned Export Sawlog 12.2 m” was increased from $107 to $147 which is greater than the “Sell Off” price of “Pruned Domestic Saw”. This is to simulate an increase in price on the spot market due to limitations in the supply of “Unpruned Export Sawlog 12.2 m”.

3. **Spot Market Availability Constraints (Spot Constraints)**

   The volumes for EVEN, UNEVEN and FROST stands of “Unpruned Export Sawlog 12.2 m” and “Domestic Sawlog #2 Shorts” that was available on the spot market is limited to 575 m³ and 300 m³ respectively. The available market for the surplus “Pruned Domestic Saw” volume was limited to 175 m³. The numbers were reduced to 30, 13 and 70 for the WHAKA stand. These volumes were chosen arbitrarily, solely to constrain the model.
(4) Minimize “Buy In” and “Selling Off” volume. (Buy/Sell Min)

To test the robustness of the model, the objective function of the buck-to-order planning model was changed from maximizing return to minimizing the amount of the volume that was brought in and sold off. To stop that model just producing lots of “Waste”, the objective function was formulated to minimize the production of waste as well.

\[
\begin{align*}
\text{Min} & \sum_{i=1}^{p} w_i + \sum_{i=1}^{p} z_i + y_7 \\
\end{align*}
\]

\( y_7 = \text{volume of waste.} \)
RESULTS

Buck-to-Order Planning Model

The buck-to-order MIP planning model was run on all four stands under the four different market scenarios. Figure 4.1 shows the projected maximum value objective function for the different stands under the four marketing scenarios.

Figure 4.1. - The projected objective function from the buck-to-order planning model for each stand under the different market scenarios.

The constraint on “buy in” volume of Unpruned Export Sawlog 12.2 m had to be relaxed for the UNEVEN stand under the Spot Constraints scenario, as the model was infeasible with the original constraints. The chance of obtaining an infeasible solution is
significantly increased as the number of hard constraints that are placed on the amount of available “buy in” and “sell off” volume increases.

The objective function produced by the model shows the operational planner and marketers in a company, the trade-offs from placing more market constraints on a stand. For example, trying to minimize the “buy in” and “sell off” cost 5% of the unconstrained spot market value of the forest for the UNEVEN stand.

Figure 4.2. - The projected proportion of the different products being cut from the EVEN stand, under the different market scenarios.
The effect on the volumes that are cut from the EVEN stand, under the four market scenarios is shown Figure 4.2. The graph shows the change in the proportion of the total stand volume that is projected to be cut for each product from the stand in comparison to the original order book constraints given in Table 4.4. Increasing the “buy in” cost of the Unpruned Export Sawlog 12.2 m causes the model to cut more of that volume from the stand, reducing the volume of Pruned Domestic Saw log, and the overall return from the stand by 7%. Minimizing the amount of “buy in” and “sell off” is the most costly scenario of the four market scenarios for all four stands.

Implementing the Buck-to-Order Plan

Order Fulfillment Effectiveness

The AD(%) from simulating implementation of the different approaches to carrying out the plans for each market scenario is given in Table 4.5. All three approaches did well in scenario 1. This is because this scenario represents an unconstrained spot market in which using the market prices would maximize the value of the stand. The order book constraints can simply be fulfilled by buying in needed volume and selling off excess volume to the spot market. As the additional constraints are included in the order fulfillment, performance of the Market Price approach reduced while the other two approaches continued to produce high AD(%). The Market Price approach has no way to adapt its cutting instructions to take account of the additional constraints.
Table 4.5. - Apportionment degree for three approaches for implementing a buck-to-order plan.

<table>
<thead>
<tr>
<th>Stand</th>
<th>Scenario</th>
<th>Approach</th>
<th>Market Price</th>
<th>Cutting Pattern</th>
<th>Adjusted Price List</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVEN</td>
<td>Unconstrained Spot</td>
<td></td>
<td>92.5%</td>
<td>93.6%</td>
<td>95.4%</td>
</tr>
<tr>
<td></td>
<td>Hi-Price Exp_12</td>
<td></td>
<td>88.0%</td>
<td>92.1%</td>
<td>95.1%</td>
</tr>
<tr>
<td></td>
<td>Spot Constraints</td>
<td></td>
<td>87.8%</td>
<td>91.6%</td>
<td>94.0%</td>
</tr>
<tr>
<td></td>
<td>Buy/Sell Min</td>
<td></td>
<td>86.2%</td>
<td>94.1%</td>
<td>96.4%</td>
</tr>
<tr>
<td>UNEVEN</td>
<td>Unconstrained Spot</td>
<td></td>
<td>94.6%</td>
<td>92.4%</td>
<td>92.4%</td>
</tr>
<tr>
<td></td>
<td>Hi-Price Exp_12</td>
<td></td>
<td>90.0%</td>
<td>91.3%</td>
<td>95.2%</td>
</tr>
<tr>
<td></td>
<td>Spot Constraints</td>
<td></td>
<td>90.0%</td>
<td>91.3%</td>
<td>96.0%</td>
</tr>
<tr>
<td></td>
<td>Buy/Sell Min</td>
<td></td>
<td>89.5%</td>
<td>94.2%</td>
<td>95.2%</td>
</tr>
<tr>
<td>FROST</td>
<td>Unconstrained Spot</td>
<td></td>
<td>91.0%</td>
<td>88.1%</td>
<td>90.5%</td>
</tr>
<tr>
<td></td>
<td>Hi-Price Exp_12</td>
<td></td>
<td>82.4%</td>
<td>86.5%</td>
<td>88.0%</td>
</tr>
<tr>
<td></td>
<td>Spot Constraints</td>
<td></td>
<td>82.4%</td>
<td>84.9%</td>
<td>89.4%</td>
</tr>
<tr>
<td></td>
<td>Buy/Sell Min</td>
<td></td>
<td>84.8%</td>
<td>91.1%</td>
<td>86.6%</td>
</tr>
<tr>
<td>WHAKA</td>
<td>Unconstrained Spot</td>
<td></td>
<td>59.0%</td>
<td>74.8%</td>
<td>80.5%</td>
</tr>
<tr>
<td></td>
<td>Hi-Price Exp_12</td>
<td></td>
<td>57.6%</td>
<td>67.6%</td>
<td>75.2%</td>
</tr>
<tr>
<td></td>
<td>Spot Constraints</td>
<td></td>
<td>52.0%</td>
<td>52.3%</td>
<td>77.8%</td>
</tr>
<tr>
<td></td>
<td>Buy/Sell Min</td>
<td></td>
<td>65.3%</td>
<td>73.0%</td>
<td>81.5%</td>
</tr>
</tbody>
</table>

The effect of the increased variation in the stand can be seen in all three approaches. The AD(%) is much lower in the FROST stand than the EVEN stand. Adjusted Price List generally outperforms the other two approaches. It produced substantially better results in the WHAKA stand, although this may be as much a function of the small
inventory sample size as a function of the algorithms. To summarize the above table, Table 4.6 was created to show which approach produces the highest AD(%) .

Table 4.6. - The best approach in terms of AD(%) for each market scenario and stand combination.

<table>
<thead>
<tr>
<th></th>
<th>Unconstrained Spot</th>
<th>Hi-Price Exp 12</th>
<th>Spot Constraints</th>
<th>Buy/Sell Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVEN</td>
<td>Adjusted Price List</td>
<td>Market Price</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
</tr>
<tr>
<td>UNEVEN</td>
<td>Market Price</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
</tr>
<tr>
<td>FROST</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Cutting Pattern</td>
</tr>
<tr>
<td>WHAKA</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
</tr>
</tbody>
</table>

**Monetary Return**

The monetary return achieved by the different approaches differed for each stand under each marketing scenario. Having the highest AD(%) does not guarantee the highest monetary return from the stand. This is because the AD(%) treats every log product equally, however, rarely is the importance of fulfilling every order the same.

Table 4.7 summarizes the monetary return results, showing which approach achieved the highest monetary return for each stand under the different scenarios. Using this metric to evaluate the performance of the different approaches, the Cutting Pattern
approach generally outperforms the other approaches but may be stand and market scenario dependent.

Table 4.7. - The best approach in terms of monetary return for each market scenario and stand combination.

<table>
<thead>
<tr>
<th></th>
<th>Unconstrained Spot</th>
<th>Hi-Price Exp_12</th>
<th>Spot Constraints</th>
<th>Buy/Sell Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>EVEN</td>
<td>Cutting Pattern</td>
<td>Market Price</td>
<td>Cutting Pattern</td>
<td>Cutting Pattern</td>
</tr>
<tr>
<td>UNEVEN</td>
<td>Market Price</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
<td>Adjusted Price List</td>
</tr>
<tr>
<td>FROST</td>
<td>Market Price</td>
<td>Cutting Pattern</td>
<td>Cutting Pattern</td>
<td>Cutting Pattern</td>
</tr>
<tr>
<td>WHAKA</td>
<td>Adjusted Price List</td>
<td>Cutting Pattern</td>
<td>Adjusted Price List</td>
<td>Cutting Pattern</td>
</tr>
</tbody>
</table>

The advantage of developing a buck-to-order plan is shown in Figure 4.3. It shows the percentage increases in the monetary return of the three different approaches under Buy/Sell Min above simply running with market price without any planning.
Figure 4.3. - The percentage increase in return using the different approaches under the marketing scenario 4.

Only the Adjusted Price List approach in the WHAKA stand does not produce a positive percentage increase in revenue. This is because, in order to maximize the AD(%), it has chosen to under produce the high value products and over produce the low value products. In this case the two objectives, monetary return and order fulfillment, are in conflict with each other.
DISCUSSION

The results show the advantages of planning to determine the volumes that can be optimally cut from each stand given market constraints. An example of this, is when the FASTBUCK algorithm (used in Adjusted Price List) was run using the original market proportion in Table 4.4, the best penalty free AD(%) achieved was 88.1 %. This is significantly lower than the 96.4% achieved using the buck-to-order planning model and the FASTBUCK in combination under the “Buy/Sell Min” market scenario for the EVEN stand.

It is important to be able to have predictions of the required extra volume and the surplus volume before starting to harvest the stand. Having this information means that good markets can be found for the surplus volume as well as potential sources for the volume that is going to be in short supply. Having to buy volume off the spot market can sometimes be extremely costly. Equally as costly is having surplus volume that can not be sold. Often, unsold volume has to be downgraded to a lower value product that can be sold.

The buck-to-order planning model gives harvest planners the ability to analyze different market and operational conditions before harvesting the stand. It enables the planner to determine costs of forcing the stand to produce different products. The formulation presented in this paper is for a single harvesting/processing machine, however the formulation could be modified to provide plans for multiple harvesters. There is also the
potential to integrate the crew scheduling concepts presented in Murphy (1998) and Mitchell (2004). Both these extensions to this problem would increase the problem size dramatically, and may require the use of column generation techniques to solve the problem.

The paper showed that both the Cutting Pattern and Adjusted Price List approach out perform the use of Market Prices. In some companies, harvest schedulers will adjust the market prices to take into account market constraints. The performance of human brains in determining the correct relative prices to use has yet to be determined but is currently being investigated.

The Adjusted Price List approach seems to out perform Cutting Pattern approach when AD(%) is used as a metric. This is reversed when the monetary return is used as the metric of performance. This is largely due to the objective function in the two algorithms. Cutting Pattern approach weights the volume deviation to place a high importance on cutting the higher value products, where-as the Adjusted Price List approach simply tries to maximize the AD(%).

The setting of the pulp and waste volumes in the target cutting patterns for the Cutting Pattern approach to zero produced significantly better order fulfillment for all the scenarios tested in this paper. However it is difficult to know, without further testing, whether this is a universal rule or just applies to the stands/market scenarios used in this paper.
The low AD(%)s for the WHAKA stand are probably more a function of the small sample size of the inventory than the cutting instruction generation. Further work is required in determining the optimal sample size for generating the buck-to-order plan and the cutting instructions for fulfilling the plan. It is important to remember that the buck-to-order problem is relatively easy to solve with perfect information on all the trees in the stand, however obtaining this information is extremely costly.

Order book constraints that constrain the total volume of the different log products are not the only type of market constraints. Other log mix constraints, such as minimum average SED and percentage long logs etc, are required by some customers. These types of constraints were not included in the analysis carried out in this paper. However, the FASTBUCK algorithm (Murphy et al., 2004), however was developed so these types of constraints could be included. It is feasible, yet not tested, that these constraints could be included into the formulation of Cutting Pattern approach. The minimize volume deviation objective function in the dynamic programming algorithm could be penalized if a particular log caused the constraints to be violated.

Many harvesters on the market have adaptive buck-to-order systems installed. These systems adjust the cutting instruction while working through the stand. For example, the Ponsse’s computer uses an adaptive-price–list where the value of each log grade is changed, as the harvesting progresses through the stand, in accordance with how well the demand for each product is being met. (Sondell et al. 2002). Other harvester
computer manufacturers, such as Dasa4, Timbermatic 300, Valmet and Motomit, have implemented an approach called “close-to-optimal”, where a cutting solution is selected from the top 5% of the buck-to-value solutions that best fulfills the demand requirements (Sondell et al. 2002; Uusitalo and Kivinen 2001).

As mentioned in the introduction to this paper, Uusitalo and Kivinen (2001) developed a fuzzy logic algorithm that found a good starting price list based on stems from previously harvested stands. They generated the initial price lists with their new algorithm on four stands and then used these price lists in a Ponsse Opti Simu bucking simulator to simulate the harvesting of the stand. Opti Simu uses an adaptive-price-list which is adjusted throughout the harvesting of the stand. They found that using inventory data in the fuzzy logic algorithm to find the initial prices gave the highest AD(%) for only one of the four stands tested. In the other three stands, using only the Opti Simu to adjust the prices produced the best AD (%).

Murphy et al. (2004) investigated using a FASTBUCK algorithm adaptively on the same four stands used in this paper. The four stands were broken into even sized blocks. The FASTBUCK algorithm was then used on each block using the stems from the previously harvested blocks. The gains in AD(%) ranged from 0.7 to 7.6 AD percentage points from using previously harvested block data compared with using pre-harvest inventory data.
Further research work is required to determine the additional gains that can be made by applying the adaptive approaches already implemented on the harvesters, particularly in species grown outside Scandinavia.
CONCLUSION

There are three important parts to the buck-to-order problem; buck-to-order planning, developing of cutting instructions to carry out the plan, and adaptive control of the cutting instructions during harvest. All have the potential to substantially improve the buck-to-order performance of mechanical harvesting machines.

This paper showed that significant gains can be made by determining the optimal volume that should be cut from the stand. Both the Target Cutting Pattern and Adjusted Price List approaches out performed the simple Market Prices approach. Further testing is required to determine the potential gains in order fulfillment with the use of adaptive control of the bucking process during the harvesting of the stand.
REFERENCES


OVERALL CONCLUSIONS FROM DISSERTATION RESEARCH

The work presented in this dissertation concerns the area of obtaining the optimal output distribution of logs from mechanical harvesting/processing systems. The use of mechanical harvesting/processing operations is increasing around the world. This is driven by factors such as the need to continually increase productivity and to improve the safety record of forestry operations. There is growing evidence that the gains made in productivity by switching to mechanical log merchandizing may be lost due to incorrect decisions in converting stems to logs. The first chapter of this dissertation presented an overview of mechanical log merchandizing and the techniques used to optimize this process. A survey of value recovery studies showed that, on average, mechanical log merchandizing, systems were losing 18 % compared to only 11% for manual log making systems. The first chapter concluded by investigating the challenges and potential research projects for improving the output log distribution of mechanical harvesting/processing systems. From the many and complex research project identified, three areas were selected for the focus of this dissertation focused on three of the areas; stem measurement error, stem scanning and forecasting and the development of optimal buck-to-order systems.

The dissertation presented, in Chapter 2, a unique simulation/dynamic programming approach to estimating the potential value loss from stem length and diameter measurement errors made by mechanical harvesting/processing systems. There have been numerous studies looking at the diameter and length accuracy of modern
measuring systems, however few have looked at the value loss caused by these measurement errors. The results of the simulation showed that value loss from six operations in three pine species ranged from 3 to 23%. This is a substantial value loss and highlights the importance of trying to reduce error rates. Further analysis showed that increasing the precision of a measurement is more important for value recovery than increasing the accuracy of a measurement. There has been little work done on the causes of measurement error. There are many unanswered questions, such as; are measurement errors solely mechanical, does production rate effect the level of error, how much do measurement errors vary between operators, etc. Answering any of these questions would provide a significant step forward in reducing measurement error.

There are a number of possible methods for increasing the accuracy and precision of harvesters/processors. These include: training, increased calibration of equipment and the development of new log scanning procedures and systems. Additional research work is required to determine the effectiveness of these different approaches. Only the effect of length and diameter errors were investigated in Chapter 2. However, for many species, log quality characteristics are also important in determining their value. Currently these are assessed by the human eye. There have been few studies on the accuracy of these human assessments so it is difficult to predict the value loss caused by these errors.
Chapter 3 is an economic investigation of different scanning procedures and systems. The potential capital investment that could be made in new scanning technology was determined for two operations in the Pacific Northwest of the United States; one in Douglas fir, and the other in ponderosa pine. The calculations accounted for not only changes in value recovery due to the implementation of improved scanning systems but also the changes in the productivity of the operations. Chapter 3 concluded that (1) there was no advantage in only partially scanning each stem before optimal bucking in these two species and (2) the breakeven capital investment that could be made in new scanning/measuring technology for each harvester was $2,100,000 for the Douglas fir stand and $80,000 for the ponderosa pine stand. Although Chapter 3 showed that there was no economic advantage in using partial scanning and forecasting techniques, there is the potential that, with improved forecasting techniques, partially scanning a stem before optimal bucking may lead to increased productivity to increase without effecting value recovery.

Even with perfect information about the stem, the computer that controlling the bucking solution still requires the correct cutting instructions. These are needed to obtain the optimal output log distribution that will maximize the return while still meeting market and operational constraints. Chapter 4 describes different approaches to solving this problem. A new bucking-to-order planning model, using mixed integer programming, was developed to determine the optimal production from a stand given different market constraints. Three different approaches were tested in four stands for generating cutting
instructions to fulfill the plan created by the new planning model: market prices, target cutting patterns and adjusted price list. The market prices approach simply applied market prices. The target cutting patterns approach applied the sample cutting patterns generated from the planning model to the stand. It has been commented in the literature that an approach that uses target cutting patterns is difficult to implement in the field. Chapter 4 outlines an algorithm that could be used in the field for the implementation of a buck-to-order plan using target cutting patterns. The adjusted price list approach used a dynamic programming algorithm embedded in a search heuristic to adjust both the prices and small end diameters of log products to achieve the production goals of the planning model.

The results showed that developing a buck-to-order plan is important in obtaining good order fulfillment. The target cutting patterns and adjusted price list approaches outperformed the market prices approach. Chapter 4 showed that these two approaches are capable of achieving excellent order fulfillment. Further development and testing is needed to determine which methods are best suited for generating cutting instructions for buck-to-order merchandizing under various stand, market and management situations. Research is also required to determine the potential gains from adaptively controlling the bucking process during the harvesting of a stand.
If the forestry industries around the world want to remain competitive with each other and with other industries, such as the steel and concrete industries, they need to look for new and innovative ways to not only reduce costs but also to increase value during the log merchandizing operation. This dissertation presented three studies which investigated either unstudied areas or applied new problem solving techniques to previously defined problems. Knowledge from these studies could be expected to improve value recovery and forest industry competitiveness.


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