# AN ABSTRACT TO THE THESIS OF

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Training of woodsworkers is described as important for the logging industry in Oregon. There has been little documentation of training gains or research that measures the effects of training from the perspective of the logging firm. Learning theories are evaluated and Towill's form of learning curves are selected for an experiment. A decision model is developed to assess the training gains in complex chokersetting tasks. Thirty subjects are matched and split into a control and experimental group based on initial task performance. Designed training is provided to the experimental group while the control group learns the way industry commonly performs training. Results are presented after six weeks of the experiment. Training gains are significant -- eighteen percent time savings in favor of the experimental group. Other statistical results were suggested by learning theory.

Results of the experiment are incorporated and translated into the decision model developed. A simplified approach is described for logging firms. Simulation and sensitivity analysis are used to examine parameters of interest which include training gains, training costs, job change characteristics of workers, and recovery points of training costs. Summary discussions identify implementation obstacles and future research needs.

A Model for the Economic Evaluation of
Training Alternatives for Complex Logging Tasks

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# A Model for the Economic Evaluation of Training Alternatives for Complex Logging Tasks

## INTRODUCTION

The purpose of this treatise is to develop a decision model which evaluates training alternatives for the repetitive tasks found in logging. Because no prior studies using a matched control and experimental group have been conducted for logging tasks, it has been necessary to first document the magnitude and timing of training gains in a designed study. A methodology has been utilized that expresses training gains as a reduction in cycle time, e.g. a learning curve for a logging task. The training gains have been combined with other criteria into a proposed economic model that allows logging firms to allocate financial resources to logging training. Results have been extended through simulation to explore parameters and assess questions of interest.

## Significance

Oregon has approximately 1300 firms in the logging sector of the Standard Industrial Classification System (SIC code 241, logging camps and logging contractors). Those firms collectively employ between 12,000 and 16,000 person-years in firms which average ten employes, excluding office and management personnel. In 1988, 13,800 were employed as wage and salary earners (Greber, 1989). A few large, corporate logging divisions and large contractors employ over 200 workers, but most firms are small businesses composed of one or two production units (logging sides). The value-added to the Oregon economy by the logging sector amounted to 215 million dollars in 1972 and 439 million dollars in 1982. (Brodie, et. al, 1980, 1982 Census of Manufacturers). Associated Oregon Loggers, an association of contract loggers

representing firms with about half the employment in the logging industry, has estimated the average capital investment for its member firms at $824,000 (Associated Oregon Loggers Survey, 1980).

Safety Record in Logging

Nationwide, the logging industry employed over 165,000 workers in 1980 (U.S. Census, 1988). In 1970, the figure was reported as 124,000 workers (Wolf and Nolley, 1977). This low employment base had the second highest injury and illness rate of lost workdays of any national industry in 1976. Over 287 workdays were lost for every 100 full-time workers (U.S.D.L., 1978). Logging is identified as the most dangerous occupation in the U.S. (Parade Magazine, 1989).

Oregon's safety record in logging is equally dismal. During 1977, the number of injuries and illnesses per 100 full-time workers was 33.6, and over 367 workdays were lost. Currently each year about 20-25 loggers die and over 1500 suffer lost-time injuries (Oregon Occupational Injury and Illness Survey 1987, 1989). Logging typically ranks within the worst five industries of all industries both in Oregon and the United States from an injury standpoint.

While the relationship between the poor safety record in logging and the lack of training within the industry has been observed, designed studies have not been conducted to determine the nature of the relationship. This study has not attempted to assess the relationship between safety and worker training either, but because such relationships are thought to exist, regulatory agencies and others have called for mandatory training.

The revised Oregon Safety Code for Logging in 1980 required a formal, written job training program for five positions where workers might begin with the firm:

chokersetters, fallers, buckers, log truck drivers, and the landing crew (State of Oregon, 1980). The safety code called for prior approval of the plan by the Accident Prevention Division, and its field enforcement division monitored compliance by firms. The non-entry level occupations in logging were covered by the same code as of March 1, 1981.

The effectiveness of the regulations from a safety standpoint has not yet been evaluated, but the implication is clear. Logging firms should train their workers in some fashion acceptable to the Oregon Accident Prevention Division. At the federal level, proposed safety rules also call for training requirements although details are not specified (Federal Register, May 2, 1989). The question remains for firms to decide what level of resources to commit to training. Firms may meet the safety code requirements by minimal training efforts or they may view training as an opportunity to achieve productivity gains as well as compliance with the safety code.

Recent History of Logging Training

It is inaccurate to say that there is little logger training taking place; workers are entering the industry or changing jobs and acquiring the skills through informal ways to make them acceptable workers. However, it is accurate to say that the history (and documentation) of designed logging training programs in Oregon and the nation is a fragmentary record of program starts and stops. Two general approaches are apparent: institutional training and on-the-job training within firms. Much of the impetus for institutional training in logging came from the Manpower Development and Training Act of 1962 administered through the U.S. Department of Labor. The American Pulpwood Association has chronicled some of these programs in the Eastern and Southern United States (American Pulpwood Association, Technical Releases, Various

dates). In Oregon, several community colleges offered logging training programs during the period 1962 to 1978 but none are currently active (Garland, 1979). Several special logging training programs have been established outside of institutions, but they have not remained viable (Sorenson, et al, 1979). Lack of adequate instructors, low enrollment (cyclical), and high training costs are among reasons for the termination of these programs.

One segment of institutional training in logging offered some promise during the decade of the seventies. There were once over 40 high school vocational programs in Oregon that emphasized logging skill development. However, during the recessionary period of the early eighties in Oregon's forestry sector, the number of high school vocational logging training programs dropped dramatically. Currently only twelve programs are nominally available with eight operating at effective levels of staffing and enrollment.

Institutional training programs have been most successful in Scandinavia (Sweden, Norway, Finland) where adequate funding and stringent selection procedures are utilized. Five levels of training are generally available: forest workers, supervisors, forest technicians, graduate foresters, and doctors of forestry. Selection tests are used to select machine operators and progressions to higher levels of training depend on past performance in prior training experiences and field practice environments. In commenting on the applicability of the Scandinavian training to Canadian operations, Scott and Cottell note:

> ... logger training, as a complete system, probably cannot be easily adopted by the Canadian logging industry ... logger training is closely integrated with the ... education system, which provides both an overall structure and readily available training facilities. The training system ... is based upon different social conditions and institutions from those in Canada, different industrial methods, and even different (more homogenious) forest and terrain conditions.
> (Scott and Cottell, 1976, p. 19)

European emphasis on institutional training continues through many countries at high levels compared to the United States and developing countries (ECE/FAO/ILO, 1989). The major benefit to logging training in the United States from the European experience is the adoption of training techniques and ideas which are not entirely dependent on the cultural and social circumstances of the country of origin.

Obstacles to Logging Training

The level of designed training programs within Oregon logging firms was at a low level in 1978. A survey by Oregon State University's Institute for Manpower Studies and the Forest Engineering Department provided information on the amount of structured training within logging firms and some obstacles to training by firms (Sorenson, et al, 1979). Of the 81 firms responding to the question, over 90% did not have a structured program of logging skill training; only two firms had written documents describing their program. Reasons cited for the lack of training included: lack of time (33%); too expensive (17%); preferred traditional informal way (8%); lacked personnel to conduct training (6%); union problems (5%); turnover of trained personnel (3%); and other reasons (12%).

A recent workshop on logging safety asked loggers to identify obstacles to training within firms and a list similar to that above emerged, except turnover had risen higher in importance because of current labor shortages (Logging Safety Workshop, 1988). A survey of firms with mechanized harvesting operations explored selection and training issues as well and found little designed training efforts in the western United States (Schuh and Kellogg, 1988).

Societal Relevance

Pertinent Characteristics of the Logging Labor Force

Certain characteristics of the logging labor force are important considerations when reviewing logging training program benefits and costs. Demographic statistics of the workforce are useful to capture a comparative picture of the labor force on a national, regional, or state basis. However, design of training requires detailed knowledge of the target population beyond demographic variables. Descriptive data on the logging labor force (age, education, and other demographic characteristics) can be found in various publications (Wolf and Nolley, 1977; LIRA, 1980; Teikari, 1979; White, 1978; Cottell, 1974; Goodwin, 1978; White and Bard, 1979; Garland, 1979; Sorenson, et al, 1979; U.S. Census, 1983). Commonalities are found worldwide in developed countries. Stevens (1978) found a core and peripheral labor force to exist in a detailed survey of workers in the Oregon lumber industry (including 69 loggers). The core labor force in logging numbered 16,000 workers while peripheral workers numbered 9,700 workers for the 13,400 person-years worked in 1972. Core workers remained in the labor force for the entire year and worked exclusively in wood products while peripheral workers were mobile workers, students, and others. These part-time participants in the labor force contribute to the high rates of job changing in logging; however, Stevens notes that one third of the core loggers worked for more than one employer in the study year.

Stevens used a human capital approach to show the rational basis for the job changing behavior of workers in the lumber industry. Discounted income streams were compared for changing employers versus remaining in the present job. Job changing behavior produced higher income. Core loggers in Steven's study received little job training; 74% never received any training or at most received training once in a year.

Motivation for Logging Training

Why should logging firms be interested in training? The absence of institutional options suggests that the firm is the likely location for logging training. It will be necessary for firms to train workers to assure a feasible operation. With workforce availability declining in logging, firms will have to consider development programs of various types to recruit, train, and retain sufficient workers for the enterprise.

The requirement for training in the Oregon logging safety code would seem to stimulate increased training by the industry, but there is little evidence to suggest that training actually increased when this restriction was imposed in 1980. Financial motivation for the individual firm to undertake safety training is hampered by insurance rate determination that only partially reflects the safety performance of the firm (Logging Safety and Health Action Planning Committee, 1989). Still, training is seen as the best approach for a long term solution to severe fatality and injury statistics in logging.

Other economic motivations for firms to commit resources to training woodsworkers are based on current trends in the logging industry. The Pacific Northwest is experiencing a reduction in the size of timber harvested. By the year 2000, the average log size will drop from over 27 inches to 14 inches on private lands (Tedder, 1979). Other trends indicate that harvesting mechanization which started in

the 1950's will accelerate, and trained workers will be needed to make expensive capital equipment achieve its expected productivity (Schuh and Kellogg, 1988; Garland, 1989; Silversides, 1972; Saucier, 1977).

Smaller timber may also mean smaller logging crews on production units (and perhaps more crews). A two-person yarding crew might be arranged to have a yarder operator switch roles with a chokersetter at times to maintain productivity (Olsen, 1981). Cross-training on jobs would be necessary in that kind of work arrangement and would be prudent for mechanized operations as well. While these trends will affect individual firms differently, they are visible industry-wide in the Pacific Northwest (Garland, 1989).

Yet other motivations may initiate some training efforts by firms. These might include training efforts to maintain or improve wood quality during harvesting practices. Training may also be required to harvest trees without damaging the residual timber or regeneration left after harvest. Also, strict regulations for environmental protection may require training of loggers in order to meet regulations. Connections between environmental training and productivity or safety training may not be so obvious, but a training delivery system would be needed and no system currently exists in logging.

Documentation of Training Gains

The major motivating force for the firm to commit substantial resources to training remains the economic gain of productivity improvement (in the absence of increased accidents). Prior studies have hinted at this potential but it has not been documented through designed experiments applicable to logging in the Pacific Northwest. Trzesniowski (1976) in Central Europe notes a time of 19.3 minutes per cubic meter for

a well-trained crew versus 43.5 minutes per cubic meter for an untrained crew (on-the-job training) in a yarding situation. Lehtonen (1975) reports learning curves of two training techniques for grapple loading operation in two Finnish logging training schools. One technique produced 34% reduction in loading time at the end of 140 hours of training. Scott and Cottell (1976) report the time to achieve an average level of production after logging training within firms for various courses: highlead (19 weeks); cut/skid (25 weeks); machine operator (7 weeks); mechanical harvesting (19 weeks); supervisor (8 weeks). Presumably these times are significantly less than raw recruits without training, although no evaluation or control comparison is made.

A designed study to estimate the magnitude of training gains has long been needed for logging tasks. Training gains of processor operators have been documented by Hall, Persson, and Pettersson (1972). During the first week of training over half the operators reached the goal set for training (75% of the productivity of "experienced" operators). One month later 26 of 28 operators reached the training criterion. Individual deviations in time per task were reduced as training took place. With a homogenous group, efforts at relating psychological and psychomotor selection instruments were not successful. As part of "rationalization" in Sweden, which was largely followed by other Scandanavian countries, training figured prominently in the projected ten percent reduction in harvest costs over three years (Skogsarbeten, 1984). However, the studies above have not utilized a control and experimental group to assess training differences.

## Engineering Significance

Training of labor to achieve productivity gains was a necessary practice before the industrial revolution going back to the guilds and craftsmen of Europe. In the United States, training for productivity was significantly advanced by Frederick W. Taylor in

his Scientific Management movement (Taylor, 1911). Taylor and his contemporaries,

Gantt, the Gilbreths, and others used a variety of techniques to improve the productivity

of industrial systems. Using the broadest definition of learning as the planned change in

behavior, it is evident that training and learning are imbedded in any systematic attempt

to improve productivity whether it is overall systems design, machine design, or

specific job design.

Not all industries have progressed equally in the advancement and use of training

as an approach to productivity improvement. Greatest development has taken place in

industries related to military material, i.e. air frames, heavy industries, auto factories,

etc. and high technology industries, e.g. electronics, computers, etc. There are

significant reasons why the logging industry in particiular is just now focusing on

training as a potentially significant factor in productivity increases. The explicit

recognition of human capabilities through human factors engineering in logging is

important given certain characteristics of the industry.

1. The lack of time standards for nearly all the complex tasks in logging.

2. The costs of labor may contribute as much as 80% to the costs of production.

3. The pace of production is limited by humans, not machines; seldom are machine capacities fully utilized.

4. Because of the variability in the production system at many stages of production, humans are placed in the role of interactive controllers and decision makers.

5. Because the state of knowledge in employe selection is not developed, the employers must focus on training as a means of obtaining productivity capacity in the work force.

The characteristics above are not too dissimilar from the characteristics of many

industries that have made productivity gains through training. Yet, in the author's

judgement, changes in the logging industry depend on the motivation of owners and

managers. The best opportunities are likely to be changes that are only incrementally different from existing practices within firms. The motivations for training are increasing; safety, expected productivity gains, application of human factors engineering to logging machines and systems, and improved management systems are all gaining momentum. That a major industry has taken so long to focus on structured training for its workers may surprise some readers. Research in this treatise and future research is needed to apply principles of human factors engineering to logging.

## Scope of Research

The Dictionary of Occupational Titles includes over 40 titles that describe some of the functions in logging (Sorenson, et al., 1979). These are job descriptors not task descriptions. The fundamental unit of training is the task not the entire job. Job descriptions may not be the most useful classification for training purposes because a common task, e.g. use of a chainsaw, may be found in ten or more occupational titles. If additional research funds were available it would be appropriate to study logging tasks that involve man-machine interface and crew member interactions. Funds were only available to study a task involving one worker and no complex machinery.

The scope of this research is limited to assessing training gains from the chokersetting task in logging. This task is found throughout logging operations worldwide which employ either cable yarding or skidding by surface vechicles. The emphasis in the training will be on principles incorporated in chokersetting tasks. It is possible to isolate the chokersetting function in one worker for training and assessment purposes. The chokersetting function is represented by approximately 22% of the work force in Oregon's logging industry (Sorenson, et. al., 1978). The chokersetting task is the common entry level work performed by new entrants to the logging industry.

There is considerable regional variation within the United States and Oregon in the types of logging tasks performed. While the chokersetting task is common to many types of logging, the ground, timber, brush, and system conditions vary significantly between the Pacific Northwest and the South, and between Western Oregon and Eastern Oregon. The chokersetting task in this research is typical of cable thinning operations in Western Oregon.

# FOUNDATIONS FOR LEARNING

If logging training is to contribute to the firm's productivity, three elements must be present. First, the training activity must be within the resources of the logging firm. The firm with some assistance should be able to carry out the training as opposed to sending its workers "off to school". Second, the appropriate framework and theory from the research on learning and training should be brought to the logging environment. Third, the training gains must be quantified and incorporated into an economic decision model. The first element is described later in this treatise as the documentation of training given in the experiment. The second and third elements are discussed in this chapter as they relate to training in logging.

## A Cultural Perspective

Few can dispute the significance of learning as a human activity. The largest frame to analyze learning activity is from a cultural perspective. Anthropologist Edward T. Hall identifies three crucial levels of human activity as formal, informal, and technical. He notes that "man progresses from formal belief to informal adaptation and finally to technical analysis, a theory of change is ... implied in this tripartite division ..." (Hall, 1959, p. 37). Hall further distinguishes three levels of learning:

> Formal learning ... activities are taught by precept and admonition ... Formal patterns are almost always learned when a mistake is made and someone corrects it ... The details of formal learning are binary, of a yes-no, right-wrong character.
>
> Informal learning is of an entirely different character ... The principal agent is a model used for imitation. Whole clusters of related activities are learned at a time, in many cases without the knowledge that they are being learned at all or that there are patterns or rules governing them.
>
> Technical learning ... is usually transmitted in explicit terms ... Often it is preceded by logical analysis and proceeds in coherent out-line form ... skill is a function of ... knowledge and ... analytic ability. (Hall, 1959, p. 69-72).

From a cultural perspective, issues of learning and training in the logging industry can be viewed from Hall's three levels. New entrants to the logging labor force come to the firm with a background developed by formal learning in life experiences. However, this learning may not be sufficient in the logging environment and culture. New workers are commonly assigned to experienced workers for training. The new worker models behavior after the experienced worker. Much of this informal learning can be termed "work socialization". New workers learn the job patterns including role expectations rooted in a specific logging culture, i.e. special clothes, work environment, job hierarchies, etc. In a largely informal mode, the skills required for specific logging tasks are acquired from the role model of the experienced worker.

It has already been shown that technical learning and training in logging is just now receiving attention. The emphasis in this treatise will be on specifics of technical learning and training in logging tasks.

## Approaches to Learning Theory

Adapting learning theory to a particular cultural setting, e.g. training in the logging industry, is a matter of characterizing activities and behavior in a meaningful fashion. Because no singular learning model or format has shown universal success over others, training must be conducted in a fashion that makes sense to those within the culture associated with logging.

### On the Job Training

The reasons why people don't send their workers "off to school" and prefer training on the job is "work socialization" and a strategy to enhance transfer of training. Transfer of training refers to the learning experience enhancing job performance.

Positive transfer occurs when training results in better performance; negative transfer occurs when training activities result in poorer performance than if no training had occurred. Neutral transfer of training indicates that training had no effect on performance (Wexley and Yukl, 1977).

An example of transfer of training effects may be seen in the control levers of a log loader. If the control system used in training were exactly like those on machines currently used, then positive transfer of training might be expected. If the controls used in training were quite dissimilar or provided opposite responses than those of current machines, then negative transfer might be expected from concentrated training on the controls. If during training several control patterns were used and if several control patterns are used in actual service, then neutral transfer might be expected.

Bass and Vaughan (1966, p. 87) describe why there may be such a preference for on-the-job training:

> ... the problem of transfer of training is virtually eliminated when the trainee is taught in the physical and social environment which he will perform his new tasks.

Bass and Vaughan further emphasize that the reward system during training is also essentially the same after training with on-the-job training. Because of the expensive logging equipment production is needed while learning and the on-the-job approach is preferred by logging firms.

Transfer Through Principles

Bass and Vaughan (1966) have identified two separate but not incompatable theories for achieving transfer of training: the identical-elements theory and the transfer through principles theory. When the trainee is faced on the job with stimuli similar to those faced in training, the identical-elements theory predicts positive transfer of

training. The transfer through principles approach would achieve positive transfer by applying principles learned in past situations to the class of stimuli encountered on the job.

At present in the logging environment, the transfer of training is generally achieved by the identical-elements approach. Only in rare individual instances does the on-the-job training identify the principles that govern behavior for a class of stimuli. Identifying principles to aid transfer of training is a major activity in designing structured training.

Presenting the Whole or Parts of the Task and Job

Current logging industry practice of training through modeling on the job begins with the parts of the entire job presented to the learner. The trainee is expected to not only become proficient at the parts but to classify and integrate the parts into a whole concept of the task, the job, and a logging organization. Fitts and Posner (1971, p. 11) describe the early or cognitive phase behavior of the adult learner as trying "to 'understand' the task and what it demands". For the purpose of this treatise, a combined whole and parts approach is used. The training is on logging tasks versus the whole job; thus, the parts of the job (tasks) are presented separately.

Massed versus Distributed Practice

During on-the-job training in logging, practice in new learning situations is massed as opposed to distributed. Fitts and Posner (1971, p. 13) identify a hazard appropriate to logging:

> There is no single optimal schedule for all skills, but frequent rest periods seem to facilitate performance. This is particularly true where the skill requires much motor activity, since the tendency to practice incorrect response patterns may increase as the muscle groups involved tire.

Logging tasks such as chokersetting are physically demanding in the logging environment, and fatigue can effect how workers learn motor skills in the "work-by-me" approach.

Duration of Training

Ideally, an assessment is made during the training period to determine the level of performance needed. Typically, the competency assessment identifies the trainee's level against:

1. The level or standard output average of experienced workers
2. Errors measured and compared to a standard level
3. Scores on a test or rating form
4. Various time measures, i.e. time per cycle, time to feasible level, etc.
5. Progress along a charted form i.e. a learning curve
6. Psychophysical criteria, i.e. thresholds
7. Subjective judgements of trainers, supervisors, trainees, others

There are few competency assessment measures for logging because of certain characteristics of the logging environment (described more fully later) and the absence of a systematic effort to develop competency measures. Without objective competency measures, the subjective judgement of trainers, supervisors, and others will determine the duration of training, especially on-the-job training. Also, the availability of training resources, the interruption of production, and various scheduling problems determine the duration of training. Until objective competency assessments are available for logging, the duration of training will be made subjectively by the designer of the training. Use of the learning curve as a descriptive tool is further described in this treatise; however, other competency measures merit investigation within the logging environment, especially behavioral observation scales (Latham and Wexley, 1981).

## Quantification of Learning

The above discussion of logging training and learning follows a "functionalist" theory of learning (Hilgard and Bower, 1966). Important variables of learning and training have been proposed; and the scientific method and experiments provided generalizations about those variables or situations. No fully encompassing theory is suggested as in stimulus-response or cognitive theories; generalizations follow from quantitative descriptions of data. The strength of functionalism is that specific questions useful to training and learning are addressed; the weakness is that experimental results are specific to the environmental and experimental conditions. Until a universally accepted learning theory is developed, experimentation will add useful information to a framework of learning lacking principles universally applicable.

A central part of learning theory is the desire for quantification and goes back to Ebbinghaus in 1885 (Hilgard and Bower, 1966). Early theorists progressed from observation, to the statement of laws, to the design of experiments to test the laws. When the power of mathematics emerged to provide the accurate prediction of human behavior, the functional mathematical forms or "curves" appeared. Many functional forms have been proposed for specific experimental conditions, subjects, and for types of tasks.

### A Recurring Form

Given the abundant model forms, it is possible to review curve fitting in psychological research and industrial learning applications. Hilgard and Bower (1966) contrast the early work of Ebbinghaus in finding the logarithmic form of his retention curve through empirical curve fitting with his later rational curve fitting. Empirical curve fitting selects the form based solely on the basis of goodness-of-fit, while rational

curve fitting is based on a form suggested by theory. Parameters from rational curve fitting should have a quality of interchangeability between experiments or <u>combine</u> in some predictable fashion.

Levine and Burke (1972) want the theoretical base for learning to suggest both the parameters and the specific form of the learning model. Mere selection of models based on goodness-of-fit to experimental data sets lack the psychological rationale to be useful in a generalized sense (Hilgard and Bower, 1966).

Clark L. Hull spent a lifetime combining theory and empirical curve fitting into a quantitative, deductive system first with definitions and postulates, and then with experimental verification and refinements. While this effort has not been accepted universally, the approach is a significant achievement. Hull's system predicted and later experiments supported an ogive form ("s" shape) for memorization of nonsense syllables plotted in a particular form (Hilgard and Bower, 1966). Another form from Hull's system is of interest because it is similar to some common learning curve forms:

$$_sH_R = M(1-E^{iN}) => 100(1-10^{-iN})$$

where,

$_sH_R$ = habit strength measured in arbitrary units
 N = number of reinforced repetitions
 i = constant related to the fractional amount remaining to be learned that is acquired through reinforcement (i = log 1/1-F)
 E does not equal 10 in the absolute sense, but Hull used an arbitrary scale of 100 and the base of 10 rather than E = 2.71828+
 M = maximum amount to be learned, i.e. standardized at M = 100%
 F = fraction of the amount remaining to be learned that is acquired with each reinforcement

The basic question is whether the influence of reinforcement occurs after one trial or whether there is an increment to habit strength, ($_sH_R$, the tendency for a stimulus to evoke an associated response) after each reinforced repetition. The increment to habit

strength is a constant fraction of the amount remaining to be learned. Hull's form is significant because it is derived from a systematic theory and is found in many learning curve forms.

Early Approaches in Industry

A 1936 article by Wright (describing the improvement in airframe construction patterns with a cumulative average curve) set in motion more than four decades of research and applications with various learning curves or models. Nanda describes the range of the types of models and applications within industries for learning curves. Ten types of models are identifiable as distinct forms and a wide variety of uses are found across firms in different industries and within firms for various functions from training to marketing (Nanda and Adler, 1977). Several commonalities can be identified among the various forms of learning curves:

1. A dependent variable of some form, e.g. total time, cycle time or a production measure of some form, or cost terms (marginal cost), etc.
2. An independent variable of the number of trials, cycles, production units, or days of practice arranged in an increasing order of time.
3. One or more parameters (constants) or variables associated with the subject (worker), the task, or both.
4. An acknowledgement that learning may not lead to infinite improvements. Asymtotic levels of production or cycle times are theorized and achieved practically.
5. For some situations, a sigmoid, "s" shaped, or ogive form has been observed, acknowledging slow progress initially, rapid improvement, and later slowing of improvement (Cochran, in Nanda and Adler, 1977).

The first three commonalities are straightforward descriptions of the various learning curve forms, but the remaining two require a return to learning theory for discussion. The "s" shaped or sigmoid shaped learning curve has its origins in psychology which states that in the early stages of learning, the gains are positively accelerated as errors, incorrect motions, etc. are eliminated and the subject forms a

learned basis for improvement. It is suggested by many psychologists that improved measurement in the early stages of learning would reveal an "s" shaped form (Bass and Vaughan, 1966). Towill (1976) has not found the "s" shaped form in industrial studies he has reviewed. Another basis for an "s" shaped curve might be negative transfer in the task. If the task stimuli require responses opposite from prior learned responses to the same stimuli, then negative transfer may produce an "s" shaped form. The "s" shaped form has significance for the differences between two learning curves.

The issue of whether to use asymtotic learning models may be discussed from two perspectives: a theoretical perspective on learning and a goodness-of-fit perspective. Fitts and Posner (1971) argue that there are no limits to improvement of performance over time and that limits described in learning curve literature are due to: 1) motivational changes, 2) changes in the subject, e.g. aging, 3) extraneous limits such as machine rates, etc. and 4) arbitrary criteria set by experimenters, e.g. practical time limitations. Evidence from cigar-making, mirror-drawing and key-pressing experiments show continuous improvements over long periods of performance. Arguments that learning does not lead to continuous improvement are based in marginal economics. If learning continued within firms, then marginal cost curves would continue to decline to the delight of the firm -- a situation seldom encountered (Pegels, 1969 in Nanda and Adler).

Other reasons for asymtotic description of learning may be found in the evidence for the occurrence of plateaus. Bass and Vaughan (1966) mention several arguments that support plateaus: first each habit must be mastered before improvement continues; second, new learning is taking place but incorrect learning is being eliminated; and third several parts of a complex task must be mastered before the whole task shows improvement. Another logic-based argument for asymtotic performance may be found

in the ergonomics argument that energy expended is limited by energy intake,
maximum rates of cardiovascular performance, etc. (IUFRO, 1973; Samset, et al, 1969;
Durnin and Passmore, 1967).

From a goodness-of-fit perspective, the oscillation of performance above and
below a particular level may be best described by a horizontal line representing an
asymtotic level. The variance in the task may be great enough to mask the small
improvements due to learning. While users of learning curves may be willing to
acknowledge that theoretical limits to performance improvement may not exist under
specific conditions, the practical description of performance reaching an arbitrary
asymtote conforms to economic reality and experience with gross motor activities.

Current training experiments face the problem of selecting a model form with
certain attributes or developing a form specific to an experimental setting. Each model
form has advantages, but no particular form is universally accepted. A review follows
to illustrate various forms and to examine the advantages and disadvantages (table 1).
The format for this review is structured to make comparisons. Besides the published
form, a standardized form is presented to allow comparisons. The elements of the
standard form are listed below:

| | |
|---|---|
| $Y(t) =$ | Some dependent variable of output, output rate, time per cycle or cost per unit |
| $t =$ | Some independent variable of time or units produced arranged in increasing order. |
| $Y_c =$ | Initial measure of output, output rate, time per cycle, or cost. |
| $Y_f =$ | Amount of output or time per cycle between the initial measure and the ultimate measure at $t = +\text{infinity}$ (Asymtotic learning level = $Y_c + Y_f$). |
| $B_1...B_n =$ | Constants or variables relating changes in output or time per cycle with increasing time or units produced. $B_{(i)}$ may be related to the subject (worker, group, or firm), the particular task, or most likely to both subjects and tasks. |

Table 1. Some Learning Model Forms

| Originator (year) Published Form | Standard form meaning of B | Advantage | Disadvantage |
|---|---|---|---|
| Wright (1936) | $Y(t) = Y_c t^B$ <br> B = constant rate of improvement | original and simple | not asymtotic |
| Carr (1946) tabular lists showing "s" shaped cumulative average man-hour costs | no model presented | recognized that log-linear plots inadequate, "s" shaped curve needed | no model form suggested to accommodate data |
| Stanford Research Institute (1949) $y = a(x+B)^n$ | $Y(t) = B_1 (t + B_2)^{B_3}$ <br> $B_1$ = parameter, equivalent to cost of first unit when $B_2 = 0$ <br> $B_2$ = parameter, i.e. number of units produced prior to first acceptance <br> $B_3$ = parameter (exponent) describing slope of asymtote on a log-log plot | asymtotic and $B_2$ measures design difference or complexity | meaning and rationale of $B_2$ differences unclear |
| DeJong (1957) $mc = a[B+(1-B)x^{-b}]$ | $Y(t) = B_1 \left[ B_2 + (1 - B_2)t^{-B_3} \right]$ <br> $B_1$ = parameter, equivalent to the cost of the first unit produced <br> $B_2$ = parameter, equivalent to minimum level of marginal cost for T, called an "incompressibility factor" <br> $B_3$ = parameter, describing the constant rate of improvement | asymtotic at $B_1 * B_2$ | meaning and rationale of $B_1$ and $B_2$ may be lost in parameter estimation process |

Table 1. Some Learning Model Forms (Continued)

| Originator (year) Published Form | Standard form meaning of B | Advantage | Disadvantage |
|---|---|---|---|
| Levy (1965) $Q(q) = P[1-e^{-(a+uq)}]$ | $Y(t) = Y_c\left[1 - e^{-(B_1 + B_2 t)}\right]$ <br><br> B1 = constant of integration associated with the initial efficiency of the process <br> B2 = f($x_1$ ... $x_n$) exogenous variables w.r.t. time, i.e. training, education, sex, etc. | asymtotic and a modified form addresses training effectiveness | B estimation is a regression that requires subjective choice of $x_i$ measures and actual measurement |
| Glover (1966) $\Sigma y + C = \alpha\, a\, (\Sigma x)^m$ | $\Sigma y(t) + Y_c = B_1(\Sigma_i)^{B_2}$ <br><br> $B_1$ = constant associated with initial performance (intercept) <br> $B_2$ = slope of line on log-log plot of cumulative y and t | visual chart useful, identifies learning plateaus, reduces variability | not asymtotic |
| Pegels (1969) <br><br> $Y_x = \alpha\, a^{x-1} + B$ <br> $0 < a < 1$ <br> $B \geq 0$ | $Y(t) = B_1 * Y_c(t-1) + Y_f$ <br><br> $B_1$ = constant rate of change | asymtotic at $Y = \frac{Y_f}{1 - B_1}$ <br><br> discrete form of Bevis, et. al. below | parameter estimation difficult with <br><br> noisy data |
| Bevis, Finniear, Towill (1970) | equivalent to published form, used as a basis for comparison | | |
| first order: $Y(t) = Y_c + Y_f(1 - e^{-t/B_1})$ | | asymtotic at $Y_c + Y_f$ | parameter estimation possible |
| | $B_1$ = constant rate of change | cumulative difference forms derivable | |

Table 1. Some Learning Model Forms (Continued)

| Originator (year)<br>Published Form | Standard form<br>meaning of B | Advantage | Disadvantage |
|---|---|---|---|
| second order: $Y(t) = Y_c + Y_f\left[1 - \frac{B_1}{B_1 - B_2}e^{-t/B_1} + \frac{B_2}{B_1 - B_2}e^{-t/B_2}\right]$ | | fits "s" shaped data | parameter estimate difficult and meaning of parameters unclear |
| | $B_1, B_2 = $ constant rates of change | | |
| Third and higher order forms available but lack relationship to learning theory and present parameter estimation problems | | | |

Towill's Transfer Functions and Learning Curves

Of the above learning model forms, there is no dominance of one form over others. The experimental dilemma is to select a form, useful as a predictive device, and capable of relating to current learning theory and future directions for theory development. The author has selected the form by Towill and his associates as a starting point for analysis of learning in logging tasks because it has logical parameters and acknowledges the importance of the cumulative difference function.

A Different Use of Transfer Functions

Transfer functions have been used to describe the human operator in a mechanical system where a system stimulus results in a system response through a human operator (Kelley, 1968). The transfer function used by Towill (1976) to describe improvement of performance over time (learning) is only structurally similar to transfer functions describing a human operator in a man-machine system. In the man-machine system, the transfer function describes system response to a stimulus. In the application of transfer functions to learning, the function describes the changes in the system responses over time related to the learning within the system. Where transfer functions are used to describe system response to a single stimulus, the transfer function for the human operator describes operator lag time, responses that are underdamped, overdamped, or critically damped, etc.. Towill's transfer functions for operator improvement over time describe the system (operator plus machines) responses to a series of virtually similar stimuli over time. The resulting function is then a learning curve for a particular task.

Towill (1976) argues that the family of functions described by the transfer functions of increasing order are reasonable descriptors of human behavior for learning.

He points to the common use of the time constant model below to describe learning curve behavior:

$$Y(t) = Y_c + Y_f(1-e^{-t/T})$$

where

$Y(t) =$ model output of time t (usually expressed as a rate of output)
$Y_c =$ model output rate at time t = 0
$Y_c + Y_f =$ model output rate at time t = infinity
$T =$ model time constant
$e =$ 2.7182+, base of Naperian logarithms

Towill's form is structurally consistent with forms of learning curves derived from laboratory learning research. For the simplest model form the stimulus (task presentation) must be nearly identical over time for the learning parameter, T, to have meaning through comparisons and combinations. Thus, Towill's or any form in Table 1 would need to be modified to reflect controlled variation in task presentation, e.g. a change in tree size during learning of felling (Dykstra, 1988). Various combinations of learning curves of the Towill form offer useful insights.

Cumulative Difference Functions

Towill and Bevis (1972) have used the time constant model to measure the effectiveness of training schemes. The vehicle for comparison is the cumulative difference function which is the sum of the differences between two learning curves. Several types of comparisons are possible resulting in different shapes of the cumulative difference function of two learning curves. A different shape also occurs from comparing a learner's performance against a standard or asymtotic performance of a trained person.

Recognizing the shape of these functions leads to insights about the parameters of individual learning curves which form the cumulative difference function. More can be seen from experimental results described later.

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# A THEORY FOR COMPLEX REPETITVE TASKS

Improvement curves or learning curves have been utilized in many situations to describe the decrease in time per unit or the increase in some performance measure as a function of increasing time, number of units, etc. The range of applications extends from cases like a complex, low volume product such as air frames or computers (number of units produced less than 50) to cases like a simple, high volume product such as electrical components (number of units produced in excess of ten million) (Conway and Schultz, 1959, in Nanda and Adler, 1977). The cycle times in these situations may range from months or years to as short as seconds. The tasks may include a multitude of suboperations or a simple combination of two or more body operations (i.e. reach, grasp, position). That improvement curves, manufacturing progress functions, or learning curves of a similar form can describe simple and complex tasks is a testament to the power of these curve forms to describe individual and collective human behavior.

## Not all Tasks Amenable to Straightforward Analysis

However, not all tasks are amenable to straight forward analysis with learning curves. For some tasks, the variation associated with the task may mask the improvement actually taking place as time or the number of units produced increased. Learning theorists have stripped the extraneous variation out of the tasks in the laboratory to get at pure measures of performance. Plots of these data may readily show characteristic learning curve forms. On the other hand, industrial applications of learning curves reflected the characteristic forms because the data were aggregated into larger units, i.e. total time for an air frame assembly, or because the selected task was moderately free of extraneous variation and large sample sizes were available.

Clearly, there are tasks where the data suggest the use of learning curves as descriptors of improvement behavior. However, consider the data plots in Figure 1 below.

**LOGS PER DAY ACTUAL OPERATION**
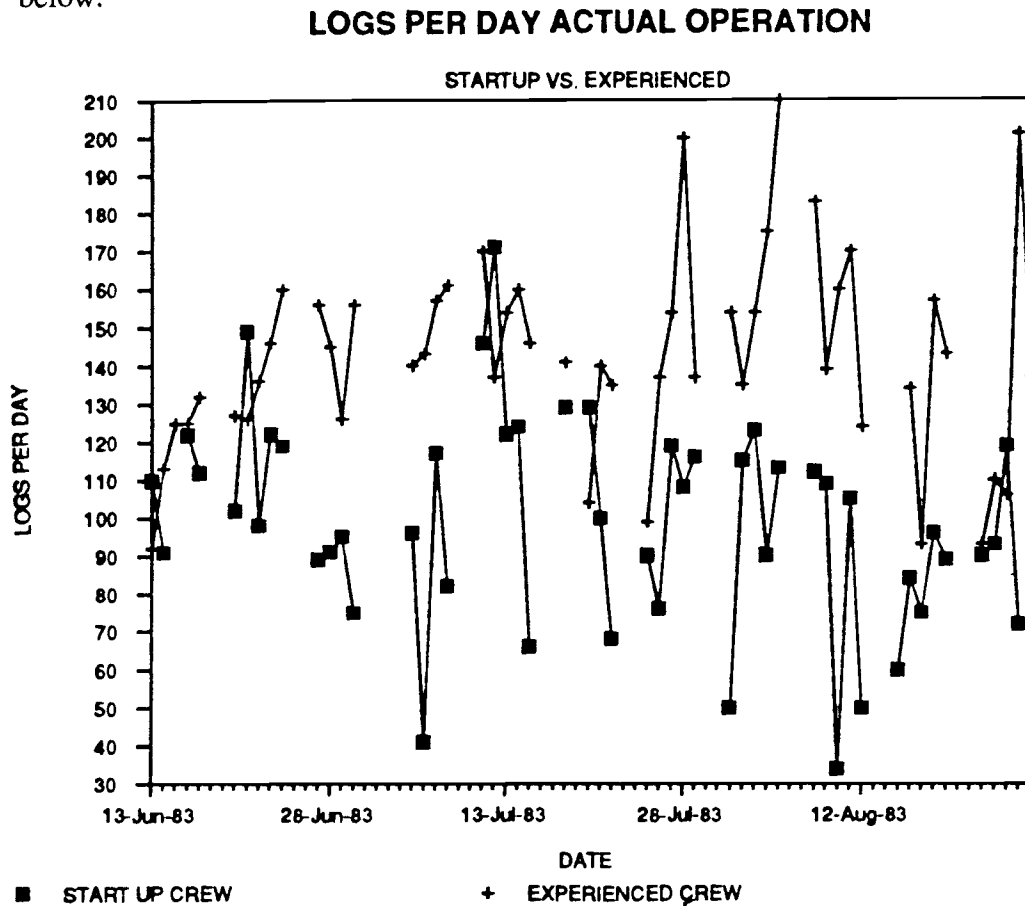


Figure 1. Variability in yarding tasks

These data do not readily suggest the use of learning curves. If these data were from a laboratory experiment on the effects of a particular training scheme, it may be difficult to show statistically that the subjects improved. These data from an industrial situation, indicate the mean of the operations would be used as the estimate of performance rather than a learning curve function. However, the absence of an apparent learning curve form does not indicate that learning is absent. There may be sufficient variation in the task itself to mask the learning effects.

One way to think about the variation exhibited in Figure 1 is to consider the data points as one sample of the possible outcomes on the task in question. Perhaps if the sample were repeated 10, 20, 50, or 100 times, the means of all samples would exhibit the characteristic learning curve form as the large number of samples would reduce the variation in the data. Statistically, this approach would likely demonstrate a learning curve effect because of the central tendencies of large numbers of samples. Practically, the industrial situations would never be repeated to yield the statistical results theoretically described.

## Complex Repetitive Tasks

Between the simple tasks of a few body motions lasting several seconds and project scale tasks lasting several weeks or months are the bulk of the tasks in industrial production. These tasks last longer than a few seconds and are generally shorter than an hour. They are more complex than abstracted learning laboratory tasks but they are repetitive in nature requiring similar activities from task to task. These tasks may or may not be amendable to learning curve analysis depending on the variation associated with the task itself, the environment surrounding the task, what takes place prior to the task, etc. These complex, repetitive tasks can be characterized but exact definition requires a specific description of the task itself. The task procedures must be specified, the conditions surrounding task performance described, the decisions facing the human operator outlined, the relationship to prior tasks defined, etc. before an exact definition of complex repetitive tasks would be useful.

By characterizing complex, repetitive tasks along some of the dimensions that indicate sources of variation, it is possible to see why many complex repetitive tasks have not been described by learning curves. Characteristics of complex repetitive tasks include:

1. The task time is greater than a few seconds and yet shorter than a project duration of several weeks.
2. There are repetitive movements, operations, or sequences that can be described for the task even though variation is present.
3. The human operator is presented with noisy stimulii, e.g. binary decisions or clear alternatives are not always present. Often habits are developed to serve as screens for reducing stimulus noise.
4. The system response is "noisy", e.g. system outcomes are not entirely predictable and not easily related to operator controlling mechanisms.
5. The system is dependent upon a large input of manual operator labor compared to machine dependent systems, e.g. fatigue becomes an important factor.
6. The system rate is controlled by the operator.
7. The production system is arranged in a serial (sequential) fashion where system output depends on a series of tasks or operations, each of which must be completed before the next task can begin.
8. There is a large influence in the system by environmental conditions of the workplace, e.g. work is performed outside a controlled factory environment.
9. There is a large concern for maintaining the "feasibility" of the production system by the operators, e.g. is it safe?, will it break down?, will the current arrangement actually produce?, etc.
10. There is an absence of "technical learning" as defined earlier and a reliance for skill acquisition through "formal" and "informal" learning modes.

These characteristics have been developed by the author's close association with logging tasks that exemplify these characteristics. Readers familiar with construction tasks, certain job-shop manufacturing settings, and like production systems may find commonalities with the above characteristics.

By recognizing that complex repetitive tasks exist such as those found in logging and that these tasks are not easily characterized by learning curves, a number of related questions assume importance. Can learning by "technical" training improve performance? Are analytical techniques available to document training gains? Can the training gains be incorporated into a relevant decision model for assessing the allocation of resources to training? A theory for complex repetitive tasks should address these questions.

Training for Complex Repetitive Tasks

Given the characteristics of complex repetitive tasks, a shift away from "formal"

and "informal" learning modes toward using "technical" training techniques may

improve performance. Technical learning is characterized by the systematic and

structured training leading to skill acquisition. This type of approach is consistent with

planning for humans in complex tasks; McCormick (1970, p. 602) notes:

> ... some systematic procedure may be in order to develop and maintain current
> information regarding the functions and tasks which (at any given stage) are
> tentatively implied. Among the purposes of such analyses are the following:
> identifying the functions or tasks that individually or in combination are
> incompatible with human abilities; the development of training programs for
> personnel who will later be involved with the system, including the development
> of training materials and training aids; and personnel procurement and associated
> manpower planning.
> While there is considerable variation in techniques and forms used for function
> and task analysis, they typically result in an organized presentation of the tasks
> that are to be carried out in the use or maintenance of the system.

A number of training approaches are available to structure training in complex

tasks. The author has used and modified an approach by Mager and Associates (1976)

known as Criterion-Referenced Instruction. An essential element of this approach and

many others is the reduction of the task into a sequence (flow chart) of actions and the

skills required to perform such actions. A task analysis of this form for the

chokersetting task is shown as appendix 1. Once a task analysis has been performed,

the training can proceed to the next crucial steps.

Using the task analysis as a basis, the technical training can be developed by first

identifying the underlying principles associated with the listing of the required skills.

Development of training methods, procedures, aids, practice sessions and so forth can

proceed once the underlying principles are enunciated. For example, in placing the

choker on a log, there is a correct way and an incorrect way. However, the choice is not

a binary one because the procedures are reversed on each side of the skyline corridor,

and furthermore, depend on which end of the log is selected for placement of the

choker. In the absence of an underlying principle, trial and error learning may not yield accurate and consistent performance. However, if an underlying principle is articulated and practice with the principle is provided, accurate and consistent performance may result. For example the principle, Face the short end of the log and place the choker under the log with your right hand, covers the choker placement behavior. Besides the structure of technical training, it is the articulation, adoption and internalization of principles that forms the essential difference between "technical" and "informal" learning. An exhausting time and work study analysis can yield the principles underlying the skills for complex tasks, but alternative methods for revealing principles include close interrogation of experienced workers and observation by trained observers proficient in relating behaviors to results (McCormick, 1979; Latham, 1971; Latham and Wexley, 1981). Once the principles are articulated and internalized through training, they may serve various functions in task performance.

Principles may serve as a "rational" filter for noisy stimuli found in complex tasks; they may characterize or reduce the unpredictability of system output; they may provide interpretation to environmental stimuli beyond the control of the operator; and they may assure feasible system performance. A principle, such as Stop work when winds reach 35 miles per hour, can be a controlling device serving some of the above functions. Other principles can be adaptations of more general principles such as those governing materials handling, e.g. Reduce or eliminate all unnecessary motions. While principles are not the only important element of a task, they function to relate the sequence of movements, operations, and responses to stimuli encountered during training and practice to the work situation.

An Explicit Theory for Complex Tasks

Figure 1 has shown the scatter of performance over time that may mask the notion

of improvement or learning. How then can analysts show that learning was evident?

The author suggests using the cumulative difference functions of two matched groups,

e.g. a control and experimental group or groups trained by two techniques. Much of the

"noise" associated with the subjects, the task, and experimental errors are compensated

for in the cumulative difference equation. The form of the cumulative difference

equation depends on the parameters of the model:

$$Y(t) = K + Y_{c2}t - Y_{c1}t + Y_{f2}t - Y_{f1}t + T_2 Y_{f2} e^{-t/T2} - T_1 Y_{f1} e^{-t/T1} + err(t)$$

(after Towill and Bevis, 1972)

where

$K$ = Constant of integration, generally zero
$Y_{c2}, Y_{c1}$ = Initial performance of groups 1 and 2 at the start of project
$Y_{f2}, Y_{f1}$ = Increment to $Y_{c1}$ that yields the ultimate asymotic level of performance of group
$T_1, T_2$ = Time constant parameter related to the rate of improvement or learning
err $(t)$ = Error term of the model, composed of error contributions from individual learning models, e.g. $err(t) = err_2(t) + err_1(t)$
$t$ = Variable associated with progression of time, number of cycles, units, etc.
$e$ = Base of natural logarithms

The gain in analysis by using the cumulative difference form is that relative rates

of learning by two groups may be inferred by $T_1$ and $T_2$. The rates are suggested by the

form of the cumulative difference model. The source of variation between subjects

within groups is reduced by the cumulative difference form. Conway and Schultz argue

for the use of the unit curve for describing progress functions because ... "the average

curve serves to dampen out variation ..." (1959, in Nanda and Adler, 1977). The

dampening and compensating effect of the cumulative difference function is what

allows insights into learning in complex repetitive tasks.

Consider the data points of Figure 2 showing a cumulative difference function for the differences between a control and experimental group has been added. Figure 2 shows the smooth "s" shaped curve which can be derived from two well-behaved first order learning curve forms or from two data sets as shown for control and experimental groups. Data from complex repetitive tasks can be fitted with a cumulative difference function that allows insights into learning rates (T) and other parameters.
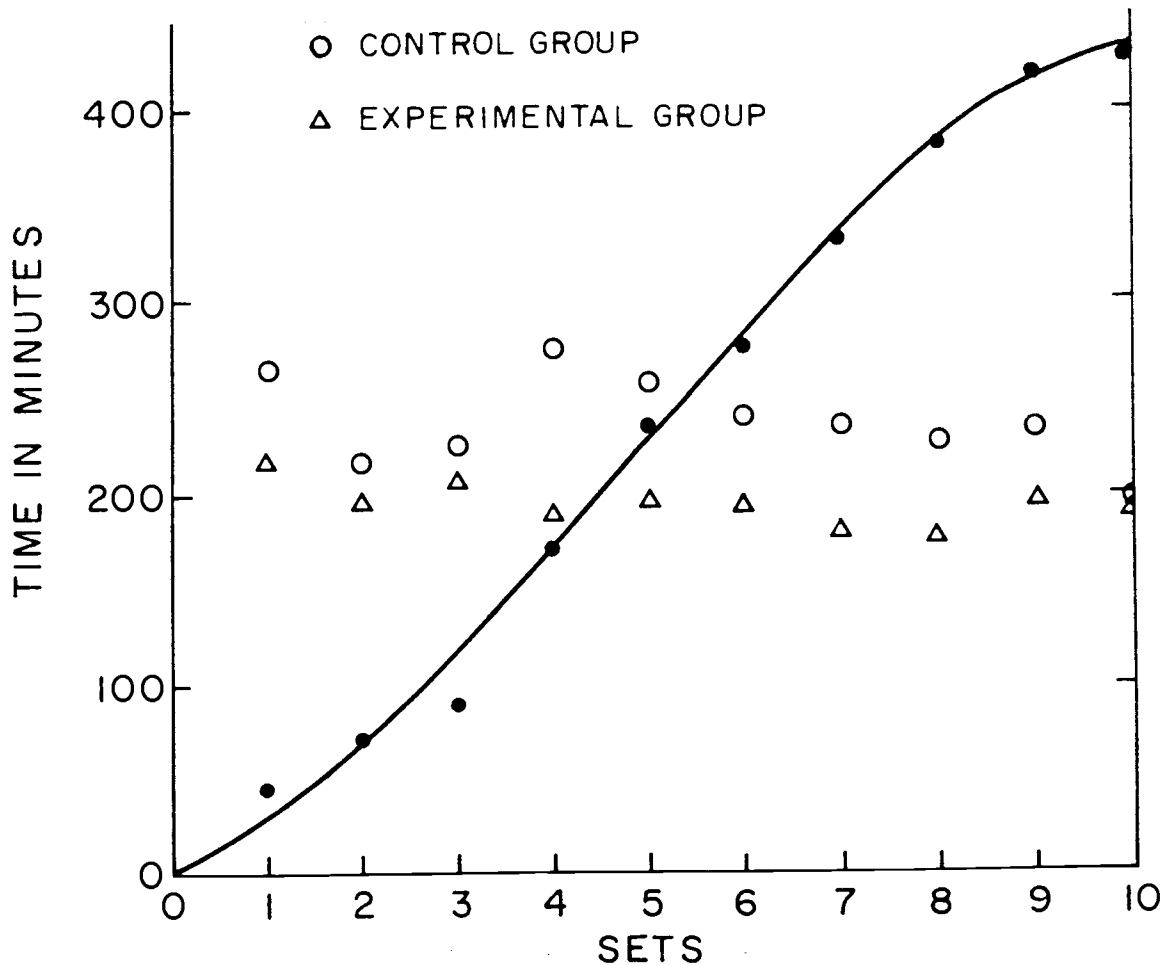


Figure 2. Cumulative Difference Function

Parameter Estimation and Cumulative Difference Functions

While the cumulative difference function described earlier contains the six

parameters ($Y_{c2}$, $Y_{c1}$, $Y_{f2}$, $Y_{f1}$, $T_1$, $T_2$) of two first order learning curve forms, there is no

guarantee that rational parameter estimates can be obtained from common parameter

estimation procedures. The nonlinear nature of the model contributes to the parameter

estimation problem. Depending on the parameter estimation procedure used, the

following dilemmas may occur in finding the six parameters of the cumulative

difference form.

1. Noisy data may give erroneous parameters or fail to provide parameters that reduce the residual sum-of-squares effectively.
2. Parameters of the form (A*B - C*D) may give problems of reflection, i.e. A = 2, D = 2, B = 4, C = 4 is equivalent to B = 2, A = 4, C = 2, D = 4. There is reflection plane in parameter space that yields equivalent results with parameters reversed.
3. Parameters of the form (A*B - C*D) may be found so that one pair of parameters forms a straight line and the other pair deviates from a straight line to form the cumulative function that minimizes residual sums-of-squares.

A description of parameter estimation techniques for Towill's first order learning

curve models and similar nonlinear forms is inculded in various sources (Bevis,

Finnear, and Towill, 1970; Sriyanda and Towill, 1973; Towill, 1973; Nie, et al, 1970;

and Buck, Tanchoco and Sweet, 1976). Several strategies can be employed to obtain

rational parameter estimates. Strategies include:

1. Reduce the number of parameters in the model by some rational means.
2. Start iterative models with good initial guesses.
3. Drop noisy data, i.e. outliers or the early noisy performances in the series, or those outliers with assignable causes.
4. Bound parameters to reasonable values, i.e. no negative values
5. Iterate on some parameter estimates, i.e. the increase to asymtotic performance level, $Y_c + Y_f$. Try values of $Y_f$ that reduce residual sum-of-squares.
6. Employ some direct estimation procedures such as those described by Towill (1973).
7. Be cognizant of time delays in cumulative difference forms, i.e. vacillation of values near zero for the first few cycles may indicate a cumulative lagged model form might be appropriate.

Considerable care must be employed when using the above strategies to obtain parameter estimates because the strategies require dropping information, losing degrees of freedom, overemphasizing one parameter to account for variation, or combinations of these. Used rationally, the strategies provide insight into parameters of the cumulative difference function which is the combination of two learning curves.

A rational approach to parameter estimation for the cumulative difference function of the form:

$$Qd = [Y_{c2} + Y_{f2} - (Y_{c1} + Y_{f1})]t + T_1 Y_{f1}\left(1 - e^{-t/T_1}\right) - T_2 Y_{f2}\left(1 - e^{-t_1/T_2}\right)$$

might be as follows:

1. Determine if number of parameters can be reduced, i.e. $Y_{c2} = Y_{c1}$ eliminates two parameters. Or use actual $Y_{c2}$ and $Y_{c1}$ values if available.
2. Use the data from the individual learning data to determine if $Y_{f2} = Y_{f1} = Y_f$; thus, two parameters are eliminated if possible.
3. Iterate on the $Y_f$ parameter from the individual learning data at best perfromance level, add one standard error, two standard errors, etc. until a lower sum-of-squares is located. Iterative search techniques may then be applied as desired to improve the sum-of-squares value.
4. Compare the values of two fitted first order learning curve forms using their parameters in a cumulative difference form with the parameters in a cumulative difference form with the parameters found for the cumulative difference form outright. A lower sum-of-squares for the parameters from the cumulative difference form over the parameters from the individual learning forms would provide some confidence in the parameter estimation using the cumulative difference form.

## A Proposed Model for the Economic Evaluation of Logging Training

Once the magnitude of training gains are quantified, an economic model is required to assess the value and tradeoffs for the firm associated with training alternatives. The model should incorporate training gains, training costs, a set of constraints applicable to the model and the impact of time as an important dimension. Specifically, the job survivor concern of whether workers will be with the firm after training. The model shown in Figure 3 includes these considerations.
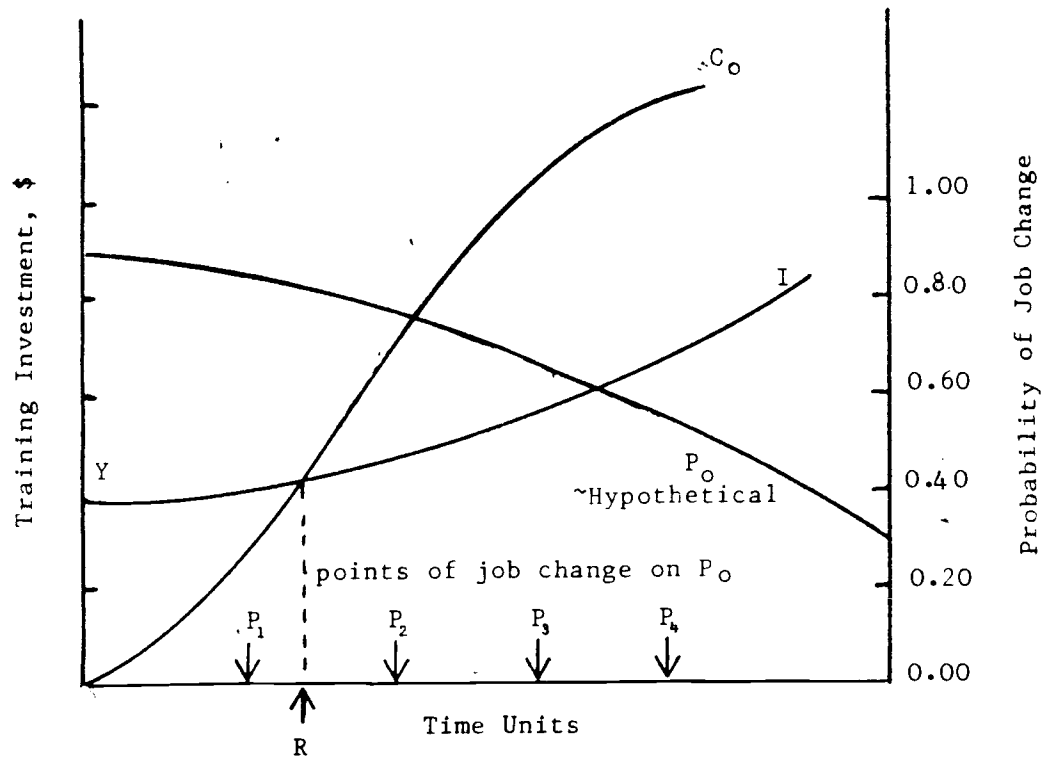
Figure 3. Proposed Model for the Economic Evaluation of Logging Training

The curve I is formed by the compounding of the initial training investment, Y, forward in time at a specified interest rate, i.e. i = 15%, 20%, to reflect the firm's alternative investment opportunities. $P_o$ is the firm's cumulative density function of job surviving for a particular occupation, i.e. for a given worker in the interval

t = 0 to t + $\Delta$t (just after training) chances are 91 out of 100 that the worker will stay with the firm, while at end of the interval there is a chance of 30 out of 100 that the worker will stay with the firm.

The cumulative cost savings curve, $C_o$, is derived from the cumulative difference function between two workers or groups of workers. Possible forms of the cumulative difference function have been earlier described. The sigmoid shape is a common form of the $C_o$ curve.

$$C_o = (systems\,rate)*[Y_{c2} + Y_{f2} - (Y_{c1} + Y_{f2})]t + T_1 Y_{f1}\left(1 - e^{-t/T_1}\right) - T_2 Y_{f2}\left(1 - e^{-t/T_2}\right)$$

It is sufficient to note at this point that the $C_o$ curve is developed by applying some economic dimensions to the cumulative difference function to describe training gains. For some firms, if the recovery point, R, occurs while the probability of the worker remaining with the firm is still high, the firms would undertake training. However, the model becomes more complex as the recovery point occurs later. An expected value function incorporating the curves of Figure 3 can provide useful information for managerial decisions. A full explanation of the model is offered in a later chapter.

The axis of the curves require some explanation. The ordinate has two scales. One scale is a standard dollar scale running from zero upwards; the other scale is a probability scale running from zero to one. The abscissa is a time scale starting at first production after training running forward in time. If the scale terminates at the end of one year, the costs and benefits are treated from an analytical standpoint as current income and expenses without much influence from the time value of money. If the scale extends beyond one year to several years, the time value of money could have significant effects and must be explicitly treated in the analysis. However from a tax standpoint, the cost of training is still treated as an expense in the year it occurred, and the benefits that increase income are taxed in a given year when they occur (Work in America Institute, Inc., 1978). The timing of training costs and benefits provides a basis for arguments over how to properly account for them in terms useful to managers and others.

Completeness of the Model

The model above does not reflect the full costs or benefits associated with implementing a logging training program. The listing below identifies some of the costs and benefits not explicitly treated.

| Possible Benefits from Training | Costs |
|---|---|
| Improved safety performance | Training start-up costs i.e. fixed costs attributable to training |
| Improved motivation Reduction in turnover | Retention costs to keep trained workers |
| Reduction in absenteeism | Lost production costs from not retaining experienced worker |
| Less down time | |
| Less system delays Improved maintenance, less wear and damage of capital resources | |
| Improved quality of output Less environmental damages Improved coordination between interacting activities, i.e. improved flow | |

A number of benefit-cost scenarios may be appropriate for various logging firms. Furthermore, some of the above benefits and costs are probabilistic in nature and the underlying probability distributions are unkown at present. Safety performance improvement is an example of this probabilistic dilemma. Other benefits and costs may be anticipated but may not be realized, such as retention costs to keep trained workers. The model is developed to treat the dominant costs and benefits associated with the decision to implement logging training within the firm.

Dominant Cost-Benefits in the Model

It is likely that some combination of benefit-cost tradeoffs dominate the training decision. Domination may occur because of the magnitude of benefits and costs, or

because that particular combination reflects the dominant concern of the firm. Once an analysis has been completed, additional sensitivity analysis on the magnitude of costs and benefits provides reference points for the combination of benefits and costs not included in the model. Refer to the obstacles to structured training for logging skills articulated by logging firms in the Oregon survey. The order of obstacles was noted as follows:

1. firm lacks time to train

2. structured training is too expensive

3. size of firm restricts training

4. firm prefers the informal "on-the-job" training

5. firm lacks personnel to train

6. firm predicts union difficulties with structured training

7. firm forsees difficulty getting workers interested in training

8. firm is concerned with trained workers leaving the firm

   (after Garland, 1979)

The economic model contains the dominant benefits and cost from the standpoint of the expected absolute magnitudes, and the model partially addresses the list of obstacles above. A large difference between benefits and costs should interest logging firms to: allocate time and dollar resources to structured training; reassess the effectiveness of informal training; seek union cooperation; and consider mechanisms to interest workers in training activities. The size of the firm and the lack of training personnel inhibiting structured training might suggest cooperative or association activities. Finally, the model explicitly accounts for worker turnover.

Optimality with Training Models

In the absence of a link between the design of a training effort and the plan for evaluating the results of training, the evaluation of training effectiveness is often an afterthought. Bass and Baughan (1966) identify four evaluation schemes to determine training effectiveness: opinion surveys, objective measurements of performance, i.e. production measures, staff evaluation, and an overall appraisal of aggregrate growth. In some firms the training may be undertaken simply because the management "feels" good about the activity. Murphy (1979) has identified some economic criteria important to training decisions within firms:

1. The magnitude and timing of the training investment (one time expenditure)

2. The magnitude and timing of expenses (annual or serial expenditures)

3. The source, magnitude and timing of returns to training

4. The taxation impacts of training decisions

5. The effects of the method of comparison
   a. minimum acceptable return-on-investment (ROI)
   b. payback and breakeven approaches
   c. net present value approaches

These criteria are useful in evaluating training alternatives and in the initial decision to undertake training within the firm.

One approach to optimality of training decisions is the traditional minimum cost analysis for two opposing costs that will be incurred. Consider the case described earlier by Bevis and Towill (1972) which identifies the lost production cost for training a worker up to an asymtotic level of performance. While training costs will be incurred in any event, a function for the training cost may be developed which includes T, the learning rate parameter. It may be assumed that it will cost more to train for the lower values of T; to shorten the time to full production, a more intensive and costly training program will be required. At a point where the total cost is a minimum (where the

marginal cost of lost production is equal to the marginal training cost), the preferred

value of T is indicated and the training effort associated with that T should be

undertaken (Figure 4). A similar approach has been described by Levy (1965 in Nanda

and Adler, 1977) for the firm's required rate of learning for adopting a new process

involving learning versus expanding an existing proven process.
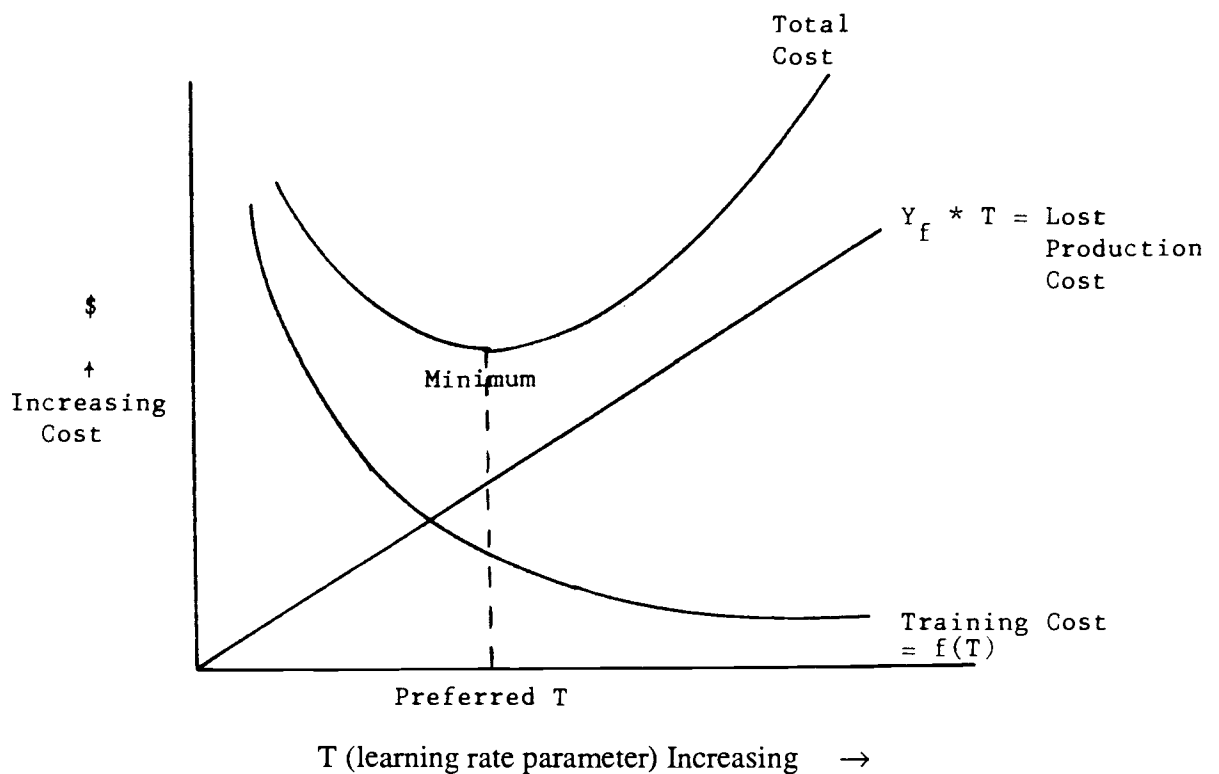


Figure 4. Training Cost Minimization

White (1980) has suggested that training in the forest products industry should be

undertaken provided that successive increments of expenditures yield the firm's internal

rate of return (IRR) or the opportunity cost of borrowing capital to finance the training

effort. Figure 5 below shows where the cutoff point would be for training expenditures.
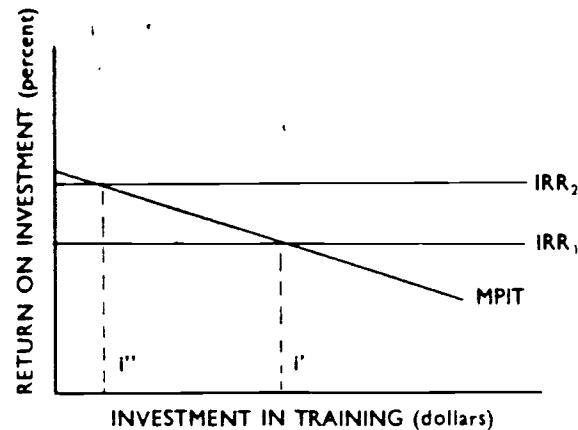
IRR$_1$, IRR$_2$ = Constant Interval Rate of Return of the firm

MPIT = Marginal Productivity of Investment in Training

i', i" = Highest level of attractive investments in training

(after White, 1980)

Figure 5. Comparison of Investment in Training with Alternative Investment
Within the Firm

As logical and valid as White's approach may seem, it may not be useful because of the
assumptions underlying the model and because it does not fully express the firm's
experience with training. Also, the timing of the expenditures and returns are not fully
treated in White's model.

Model Assumptions

Two crucial assumptions of various techniques are: that training comes in
measurable quantities or "lumps" and that increasing resources applied to training leads
to diminishing returns from the training effort. For the first assumption, time is usually
selected as the proxy measure for "lumps" of training; training may consist of one day,
one week, one month, and so forth. Costs for these proxy measures may be in direct

proportion to the time spent; however, the pattern of expenditures may not be at all proportional to time for training efforts. Furthermore, the "lumps" of training depend on the training method itself. Are two weeks of classroom training equivalent to two weeks of simulator training?

The second assumption probably does hold for various points along the spectrum of training expenditures; however, there may be steps or thresholds in the spectrum of training expenditures beyond which substantial gains may accrue for small expenditures of resources. Consider the development of a simulator device to be used in training. Initial costs may be high but training effectiveness may be substantially enhanced.

Timing Impacts

Riggs (1977) has acknowledged the various patterns of costs and returns associated with improvement programs such as training (Figure 6).
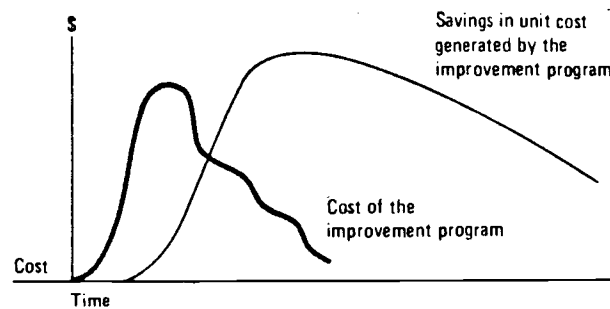


Figure 6. General Trend of Costs and Savings Caused by an Improvement Program
(after Riggs, 1977)

The timing impacts of costs and returns has two important dimensions related to training for logging tasks: The effects of job changing among workers after training and the appropriate compounding or discounting of expenditures and returns related to the time value of money. Both of these dimensions will be addressed later in specific terms of the author's proposed methodology.

The Firm's Experience with Training

An essential element of several decision methodologies is either prior experience with training expenditures and returns or sound estimates of expected expenditures and returns. For many logging firms this element will be extremely difficult to incorporate into decision methodologies because of their limited or nonexistent experience with technical training. What is needed for logging firms is a decision methodology that provides information for a specified amount of training at an estimated cost and expected pattern of returns. Information on the costs and returns of various "lumps" of training may accumulate over time, but the decision to undertake training initially will be dependent on the magnitude and timing of training expenditures and returns. The firm's first question is whether to undertake training or not, and then to learn from its experiences with logging training. The value of a decision approach may be in the way firms can learn from their trials with logging training not in the demands for precise and specific information or estimates on training expenditures, returns, and the magnitude and timing of these.

Summary of the Theory for Complex Repetitive Tasks

It has been shown that the variation in some tasks makes it difficult to analyze learning effects. These tasks are termed complex repetitive tasks and have been characterized but not specifically defined. Logging tasks are some common examples of complex repetitive tasks. Technical training can be designed for complex repetitive tasks that begins with a task analysis and the articulation of principles that govern behavior in the task. The cumulative difference function has been suggested to measure the learning effects bewteen two groups trained by different techniques.

A model for the economic evaluation of complex repetitive tasks has been introduced and will be more fully explored in a later chapter. A brief discussion of optimality criteria in some training models has been initiated. However, it is first important to document the gains due to designed training in the chokersetting task through a careful experiment.

## Transition from Theory to Application

Three views of the logging training decision are possible. The first view, at one end of the spectrum, assumes an environment of <u>perfect information</u> where theory exists to make decisions with full information. Worker behavior is known or the probability distributions governing behavior are known. There is no variance associated with the logging task, and there is no variation between workers. Learning follows curves predicted by theory. At the other end of the spectrum is the third view of the logging training decision. The decision environment is full of <u>variation and imperfect information</u>. The firm wants to know if training is a worthwhile expenditure from a productivity standpoint. Workers come and go for unexplained reasons. Every day's logging and nearly every choker set appears a little different. Some workers appear to be learning while others appear to be making no progress. What can logging training do for the firm?

The second view of the logging training decision is between the two above. <u>Experimentation provides information and develops and confirms theory</u>. A theory is developed to treat the training decision and an abstraction of the complex logging environment is the basis for an experiment. Statistical procedures and experimental design treat variation to uncover underlying patterns and meaning. Experimental and economic results have to be scaled from the experiment to the environment of the logging firm. Theory developed for continuous functions may be applied in discrete

forms or may be applied with curves fitted from data containing variation. This treatise intends to find rational compromises between perfect information assumed in theory and the logging environment where variation in the tasks and workers masks the patterns associated with training.

# EXPERIMENTAL PROCEDURES

The problem of variation associated with logging tasks has made it difficult for researchers to specify the expected gains occurring from logging training. A designed experiment has been conducted to understand the variation. Experimental procedures are described in this chapter while the results of the experiment are presented in the following chapter.

## Overview of the Experiment

Thirty trainees were retained for six weeks at a half-time rate. They were selected to match the characteristics of new entrants to the logging industry.

Subjects were split into two groups based on an initial performance on a chokersetting task and randomly assigned to a control or experimental group. The control group received training as the industry currently provides it. The experimental group received a designed training program emphasizing principles and techniques of chokersetting.

The dependent measures in the experiment were time per cycle and error counts. Performance times were measured and error counts were noted for resets (repositioning the choker to clear an obstacle), whistle signaling and carriage spotting mistakes.

Subjects performed 3,000 cycles. Each of the thirty trainees did ten repetitions on ten work stations. The stations were arranged to simulate the estimated frequency of occurrence of particular chokersetting techniques in logging. Additional cycles (180 in number) were measured on the free path chokersetting station. A variety of statistical analyses were performed in the data from the experiment.

## The Experimental Subjects

Thirty woodsworkers-in-training were retained for six weeks at a half-time rate. They were selected to match the characteristics of new entrants to the logging industry. These characteristics are outlined in prior research (Sorenson, Bible and Garland, 1979). Basically, new entrants and job seekers in the logging industry are young males (less than 45 years of age), with a high school education, and no previous logging experience. Of the above characteristics, only age and prior experience were variables for screening. Trainees must be above eighteen years of age to work in logging occupations to comply with U.S. Department of Labor regulations for hazardous occupations. Interviews with subjects determined whether they had prior logging experience; prior logging experience of any kind disqualified applicants from participation. Table 2 summarizes some relevant characteristics of the subjects.

Approximately 40% of the subjects were obtained from a job order placed with the Oregon Employment Division in Corvallis, Oregon. However an administrative delay due to the all male restriction caused a delay in recruitment, even though prior clearance was obtained to meet Affirmative Action requirements of Oregon State University. Subsequently, newspaper advertisements were placed in the Albany Democrat Herald and Corvallis Gazette Times newspapers. Interviews were held until thirty suitable applicants were identified. Trainees were initially paid $4.75 per hour, which later rose to $4.89 per hour. The project began on June 18, 1979 and terminated July 28, 1979. Subjects worked half days for five days each week.

Table 2.  Characteristics of Job Seekers and New Entrants to the Logging Labor
Force Compared to Subjects

| Age | Education | Sex | Ethnic |
|---|---|---|---|
| < 22 =  9% | < 12 = 25-36% | 90+% | 93-99% |
| 22-44 = 72% | 12 = 55-59% | Male | Majority |
| > 45 = 19% | > 12 =  9-16% | | |

(composite from Sorenson, Bible, Garland, 1979)

SUBJECTS IN THE EXPERIMENT



AGE

MEANS

CONTROL        = 23.6 Yrs.

EXPERIMENTAL = 23.8 Yrs.

▨ = EXPERIMENTAL

◩ = CONTROL



EDUCATION

MEANS

CONTROL        = 13.4 Yrs.

EXPERIMENTAL = 13.3 Yrs.

▨  = EXPERIMENTAL
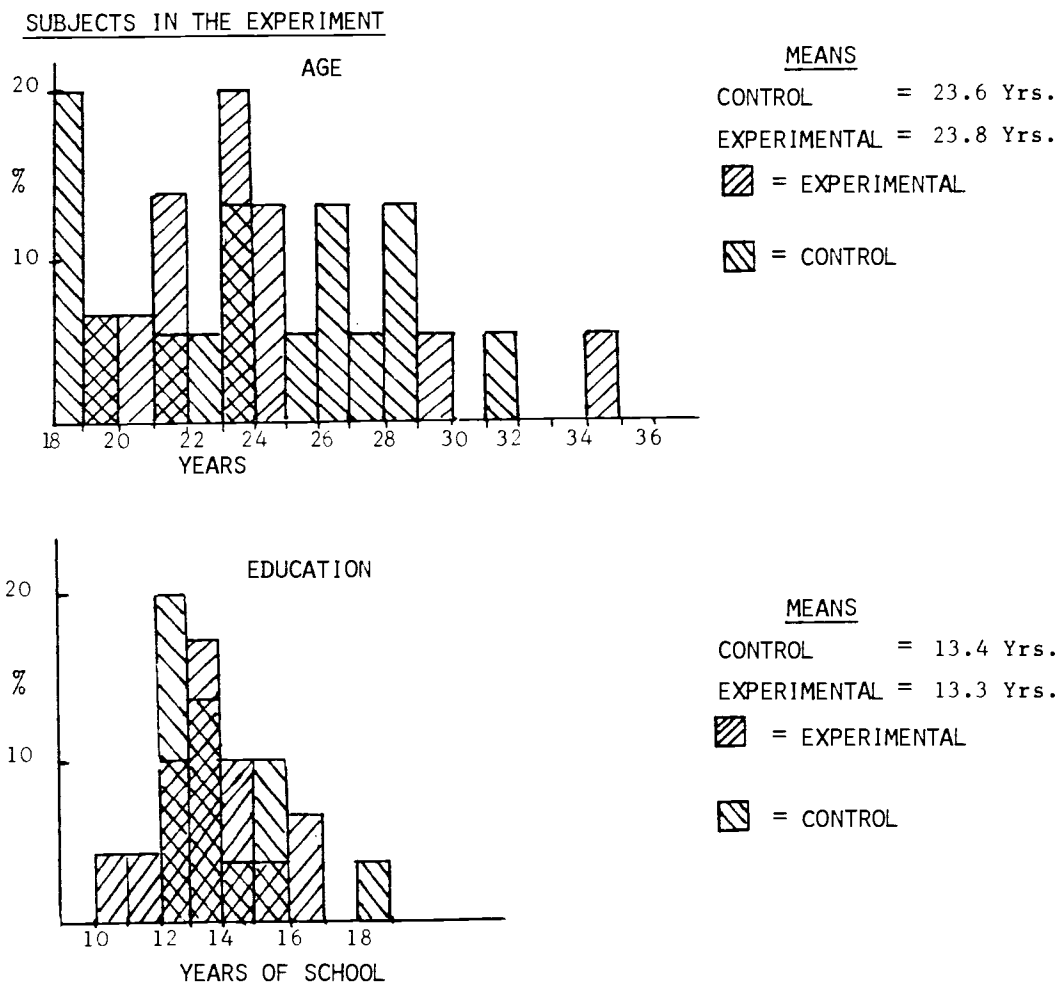
◩ = CONTROL

Assignment to Control or Experimental Groups

The entire group of successful applicants was assembled at the start of the experiment and provided an initial orientation and training in safe lifting and line pulling procedures. Following this exposure, the subjects (on an individual basis) were given a demonstration of chokersetting on the free path task on station five. Each subject then walked through the task at a slow rate, then performed the task at a normal pace, and was finally timed on the third performance of the task. The recorded times were used as the basis for splitting the trainees into a control and experimental group. The subjects performance times were paired from fastest to slowest. The subjects in each of the fifteen pairs were assigned to the control or experimental group on a random basis.

Replacement of Subjects

As expected, within the first few days of the experiment, four subjects were replaced in the experiment. Two subjects each were replaced within the control and experimental groups. Essentially the same procedure was followed for each replacement as the original group, except the replacements were given individual instruction. Replacements were automatically assigned to the control or experimental group to replace the individual who left the project. The initial times by subject number are shown in Table 5 for each group after the final groups were stabilized. Replacements performed the tasks necessary to catch up with their respective groups as part of the ongoing experiment. A few absences that occurred during the experiment were handled in the same fashion.

The Yarder Operator and Chokersetter Trainer

Two other people besides the project leader were involved in the experiment. A 1979 Forest Management graduate from Oregon State University was retained to operate the yarder during the experiment. This individual was trained by the project leader to operate the yarder and use the whistle signals. Approximately one week of intermittent practice was available to gain experience on the yarder. A junior level student in Forest Engineering who had prior experience in setting chokers was retained to serve as a chokersetter trainer for the control group. Approximately one week of intermittent practice was available to work with the yarder operator.

Provisions for Protection of Human Subjects

While some tasks in logging are inherently dangerous, i.e. using a chainsaw, the chokersetting task selected for this project was designed to minimize exposure to unsafe conditions. Special precautions are required when human subjects participate in research projects. For this experiment supervision was far greater than in typical logging operations. Frequent rest cycles minimized fatigue and subjects were trained in proper lifting and pulling techniques. All participants in the project were given the opportunity to take a first aid course with pay. Gloves and protective headgear were provided for the experiment. First aid supplies, a phone, and transportation were always available at the site. Furthermore, the Timber Harvesting Systems Laboratory is ten minutes drive from Good Samaritan Hospital in Corvallis.

A statement of informed consent was signed by each subject prior to the experiment. Performance data on each subject was kept according to the number

assigned rather than by name. Subjects were not allowed to view or discuss the performance of other subjects. Group averages only were reported to subjects at the end of the project.

One minor injury was reported during the project. One subject had a log fall adjacent to his foot which presumably broke his little toe. A doctor prescribed a minor remedy, and the subject returned to work the following day. Returning the logs to their original positions by hand was the most strenuous and dangerous activity.

## Variables in the Study

Dependent Variables

Chapanis (1959) identifies several common dependent measures or variables in human factors experiments: time per task, errors, output per unit time, time or trials to a level (i.e. training time required to operate a machine), and psychophysical criteria (i.e. sensory thresholds). This study used time per cycle and error counts as dependent measures.

The chokersetting cycle was measured as the time per cycle beginning when the whistle signal was given to position the carriage until the log reached the skyline corridor. The visual signal to end timing was the observed vertical position of the mainline with the log in the skyline corridor. Time per cycle was the primary dependent variable in the experiment.

Three other dependent measures of performance were noted as errors. Error counts are defined below:

Whistle errors: a count was made if an obvious error occurred or if the yarder engineer had to signal that he had not received or understood the signal.

Carriage spotting error: a count was made if the subject had to reposition the carriage or if the carriage was outside a stopping zone of approximately eight feet and the resulting cycle had a reset due to carriage placement.

Resets: If a cycle included at least two separate chokersetting activities and the cycle was not a rub-tree station, the number of chokersetting tasks (rehooking the choker on the log to clear an obstacle or free a hang-up) beyond the initial task were counted as resets.

## Independent Variable

The only independent variable for the experiment was the cycle number or set number (order of task performance). Thus, cycle number ranges from one to ten in the overall experiment and from one to sixteen for free path chokersetting.

## Qualitative Measures

Two qualitative measures were also obtained during the experiment by the project leader and the chokersetter trainer. The subjects in the control or experimental groups were ranked from highest to lowest performers within that group. Ratings for the work pace were also ascribed to each subject. A normal work pace would be rated as 1.0 while a rating of 0.7 would indicate 70% of normal and 1.3 would indicate 30% faster than normal. Rankings and ratings were made at the end of the experiment before experimental data were summarized.

## Cycles, Stations, and Sets

The chokersetting cycle has been defined above as a time measure on a chokersetting task. Two additional terms need definition and explanation.

Stations: Ten chokersetting stations were arranged at the Timber Harvesting Systems Laboratory to approximate typical conditions found in commercial thinning operations. Four of the stations were related to specific techniques required to move the log beyond obstacles; one station was a free path station; and the remaining five locations were termed random log location stations.

Sets: The specific positioning of logs on the stations was termed the log set. The log set was the particular position of the log on a station. For example, if the task on station 1 was to require the "roll" technique to clear an obstacle, the log set would be the position of the log that required a "roll" technique to clear the obstacle. The

log sets changed on nine stations while the log set for station five was constant for the entire experiment. Ten combinations of log sets were yarded during the experiment.

The Schematic diagram below is meant to clarify the terms, cycle, station and set:

Set 1 . . . . . . . . . . . . . . . . . . . . . Set 10

RANDOM ⊗ TECHNIQUES          RANDOM ⊗ TECHNIQUES

[i] = stations
      1.....10
/ = logs
•, = trees as
    obstacles
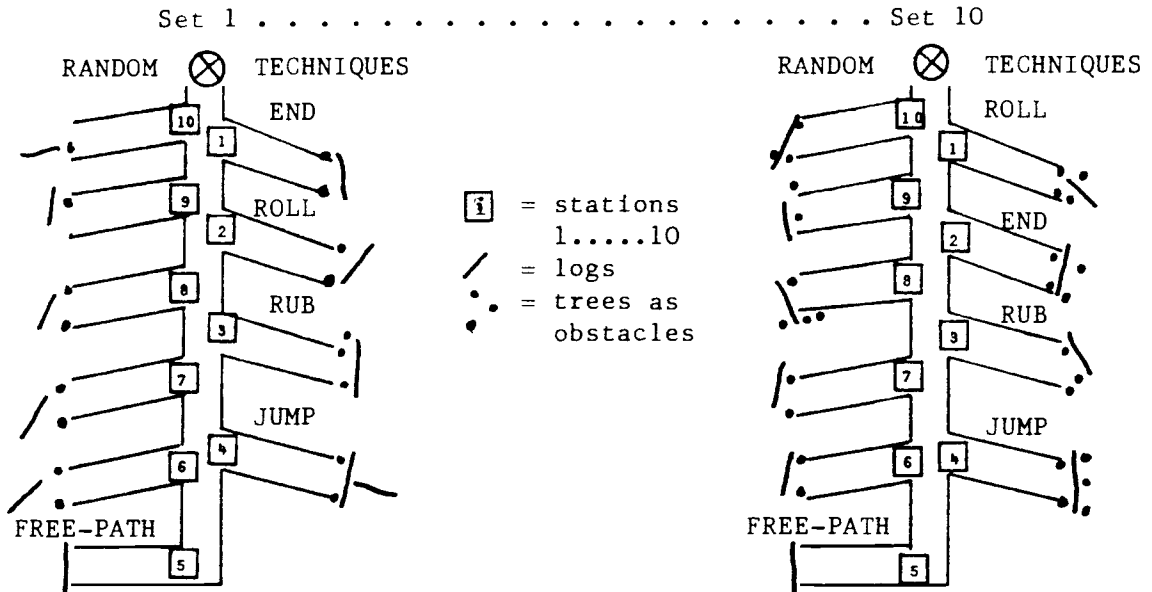
Figure 7. Stations and Sets Diagram

Number of Observations on Cycles

The sums of cycles by sets by subjects are listed below.

| Cycles on Stations | X | Sets | X | Subjects | = Number of observations in the main experiment |
|---|---|---|---|---|---|
| $\sum\limits_{1}^{10}$ | X | $\sum\limits_{1}^{10}$ | X | $\sum\limits_{1}^{30}$ | = 3,000 |

An additional six cycles were recorded on station 5 for each subject to develop the

learning curve on that station; thus with the set for station 5 held constant an additional

180 observations were recorded.

$$\begin{array}{ccc} \text{Cycles} \\ \text{on} & X & \text{Subject} & = \text{Additional observation on Station 5} \\ \text{Station 5} \end{array}$$

$$\begin{array}{c} 16 \\ \Sigma \\ 11 \end{array} \quad X \quad \begin{array}{c} 30 \\ \Sigma \\ 1 \end{array} \quad = 180$$

A total of 3,180 observations were taken over the six week course of the experiment.

## Techniques, Task Complexity and Free Path Chokersetting

In actual practice, to successfully move logs from the location where they were felled and bucked requires the use of certain techniques. Four techniques can be identified and related to principles which can be transmitted through training. The use of the techniques described below can be observed in actual field operations but the frequency of use has not been evaluated. For this experiment, an estimated frequency of occurrence of techniques was imposed, plus; random log locations, comprising 50% of the cycles, were part of the total frequency of occurrence. The pattern of log sets presented to the subjects included four technique stations (1-4), five random log location stations (6-10), and a free-path choker setting station (5). The techniques, random log location procedures, and the free-path chokersetting activity are described in Table 3.

## Task Complexity

The task complexity is not equal for the techniques, random log locations, or free-path chokersetting. Free-path chokersetting has had the noise of the system stimulus and response removed. There were no obstacles; the choker position was pre-selected; a choker hole was available; and if system errors not attributable to the

Table 3. Chokersetting Techniques

| Stations | Description | Frequency of Occurrence | Abbreviation |
|---|---|---|---|
| 1-4 | Positioning the choker: proper selection of the choker position along the length of the log can aid clearing obstacles. Generally it is the selection of which end of the log offers the best extraction path. | *10% | END |
| 1-4 | Rolling the log: the choker is placed on the log such that the initial log movement is a rolling movement rather than a dragging motion. Technique is useful for moving the log parallel to the long axis to clear an obstacle. | *10% | ROLL |
| 1-4 | Using a rub tree: the line is redirected around a tree or stump to obtain the proper direction of pull to clear an obstacle. The choker must be reset once the original obstacle is cleared and the line removed from around the tree or stump. | *10% | RUB |
| 1-4 | Jumping a log: the choker is placed on the log so that the line is between the log and the obstacle. The line tension lifts or directs the log past the obstacle. The "jump" description comes from the quick movement of the log as the line tension increases rapidly. | *10% | JUMP |
| 6-10 | Random log locations: should be termed "quasi" random log locations. An attempt was made to position logs differently for each of 10 sets without specifically incorporating the techniques listed above. An attempt was made to orient the logs throughout the angular arcs of a circle so that a particular station was not associated with a particular log placement. | 50% | RAND |
| 5 | Free path chokersetting: was the "constant" task of the experiment in that an attempt was made to first remove the sources of variation in the task and perform the task precisely the same each time for each subject. | 10% | FREE-PATH |

\* The frequency of occurrence for those techniques noted by an asterisk is only approximate in that a specific technique was not always present once and only once in a particular cycle. It may have been presented twice in the same cycle.

subject's performance were detected, the cycle was restarted. The random log locations do not have specific complexity associated with them; their complexity ranges from extremely simple to rather complex. A priori, it would seem that the END technique would be less complex than others. In contrast, the RUB technique requires two chokersetting tasks; selection of a rub tree and a more complex whistle signaling sequence. The two techniques, JUMP and ROLL may fall between the two above in complexity, but it is not possible to distinguish between these two techniques. Other than the FREE-PATH station, the simplest task may be a random log location not requiring any technique, whereas the most complex task may involve a combination of techniques in the random log locations.

Comparison of the Experimental Tasks to Actual Chokersetting

Taken individually, the experimental chokersetting tasks are not directly similar to the daily activities of chokersetters. However, when the total log positions are considered on sets one through ten, the allocation of techniques to stations one through ten may approximate the skill level required in chokersetting tasks in a commercial thinning operation. About 40% of the logs may require specific techniques of RUB, END, ROLL, or JUMP, while about 10% would be like the FREE-PATH station, and the remaining 50% may or may not require techniques as did the RAND stations. The subjects were not provided a lengthy time period to assess the log location before beginning the task and they were under time pressures similar to the logging environment. Collectively, the log positions on the ten stations for one set would be typical of the range of difficulty encountered in chokersetting. The subjects encountered the logs at each station without anticipating the type of technique to use on the task, i.e. the techniques were not associated with a particular station. The attempt to

maintain the fidelity of the experiment to actual logging conditions required that the various techniques be encountered at varying stations. It would be quite a departure from actual logging conditions to encounter all RUB, END, ROLL, or JUMP techniques in sequence (from set one to set ten) or at a particular station. While the experiment may have been more efficiently conducted by performing all techniques in sequence or at fixed stations, the actual logging environment presents a variety of techniques at any chokersetting task.

Major differences between the experiment and actual chokersetting include: the removal of terrain and timber influences, the scale of the operation, and that the subjects only set one choker whereas multiple chokers would be set in an operational setting. Furthermore, after a subject completed the chokersetting task on a station, the log was returned to the precisely located position by two other subjects for the next subject. This laborious, but necessary, repositioning consumed a substantial portion of the time on a set of logs and thus, there was much more time between chokersetting tasks than in actual operations. Subjects were not allowed to view the performance of other subjects as might be the case in an actual logging situation.

## Experimental Apparatus

The Timber Harvesting Systems Laboratory consists of a laboratory building, a scaled skyline logging system, and a small timber stand located at Peavy Arboretum adjacent to McDonald Forest. The site is located approximately ten miles north of Corvallis on Oregon Highway 99. The site exists in nearly the same form of the experiment as of 1989. The laboratory building houses a two-drum yarder salvaged from original use on a well drilling apparatus. The fixed skyline system uses 5/8 inch skyline and 3/8 inch main line and haulback lines. A standing skyline using one double

tree intermediate support runs approximately 550 feet to the tail tree. The corridor width was approximately 15 feet and the measured lateral yarding distance to logs was 25 feet. The ground was flat. Because trees of sufficient size were not available for the necessary height or for use as anchors, a local power company was retained to set power poles in place of trees and to set artificial anchors in place of the stumps commonly used in logging. An "A" frame was constructed to support the skyline near the yarder and provide clearance for the system.

The carriage used on the skyline system is patterned after the carriage supplied with the Igland-Jones Trailer Alp Yarder. Slack is pulled through the carriage manually from the mainline drum on the yarder. Because the yarder transmission could not be disengaged for each cycle to allow free spooling for slackpulling, the yarder operator was required to pull slack from the yarder on signal from the chokersetter. While this procedure is cumbersome and time consuming, it is analogous to some skyline systems which have mechanical slackpullers. A commonly used radio/voice signalling system was available for the experiment.

The timber stand was originally an experiment to determine weather influences on flowering in Douglas-fir (Pseudotsuga menziesii, Mirb.-Franco). The stand was eighteen years old and approximately 4" - 5" diameter at breast height (4.5 feet above the ground). The stand area was approximately 275 feet in length by 150 wide. Sufficient area was available to accommodate the ten chokersetting stations. Logs for the experiment were supplied by contractors operating on McDonald Forest. They were cut to a length that simulated the log movement in commercial thinning operations. While logs from commercial operations may range in size from 15 cm (6 inches) to 75 cm (30 inches) in diameter and from 4 m (12 feet) to 20 m (60 feet) in length, the logs in the experiment ranged from 15 cm (6 inches) to 30 cm (12 inches) in diameter and

from 3.3 m (10 feet) to 5.6 m (17 feet) in length. The weight of the experimental logs had to be controlled so that they might be returned by hand [maximum approximately 182 kg (400 pounds)].

The yarder was operated at half-throttle to match the yarder power with log movement. Trees were removed to assure that a feasible extraction path was available for the nine stations within the timber stand. A few damaged trees were removed during the experiment. Log locations for each set were marked with ribbon, paint, and long bolts driven into the ground. Much of the apparatus for the experiment was donated by the logging industry.

<div align="center">Experimental Controls and Sources of Variation</div>

Measuring performance in logging tasks required coping with many sources of variation. In field logging operations the sources include timber size; topography; machine variations; brush conditions; weather conditions; environmental, safety, and other regulations; and crew changes to name a few. From an experimental viewpoint with the objective of measuring the influence of training on task performance, effective strategies to minimize unwanted variation are required in designed experiments. Strategies include: 1) eliminating the variation entirely 2) fixing the variation by sources 3) randomizing the variation to the degree possible, and 4) measuring the variation through experimental design (McDowell, 1975; Chapanis, 1959). Variation not removed by these strategies is included in the error terms of the experiment.

To the degree that potential sources of variation were identified in advance of the experiment, the strategies above were employed for the following sources of variation.

| Source of Variation | Strategy |
| --- | --- |
| Trained experimental group versus trained control | Measure through experimental design group |

| | |
|---|---|
| Task variation (i.e. differences between types of techniques, log sets, etc.) | Measure through experimental design |
| Learning effects over time curves | Measure through learning |
| Variation between subjects | Measure through design incorporating as many subjects as possible |
| Subject's actual skills | Pairing subjects in initial performance and then splitting into control and experimental groups |
| Fatigue | Frequent rest periods |
| Subject motivation | At attempt was made to hold motivation constant by instructing subjects to "Do your best". A questionnaire and interview after the experiment attempted to discern any large differences between groups |
| Trainer of the control group | The trainer's training techniques were fixed to the degree possible through instructions by the project leader |
| Yarder operator | The yarder operator's behavior was monitored by the project leader and corrective instructions were given as needed |
| Field and system conditions | As many sources of variation that could be identified were fixed, and when system influences were aberrant, the cycle would be terminated and restarted |
| Measurement errors | Time study errors tend to be normally distributed and randomly occurring |
| Subjects learning from other subjects | Eliminate such learning by not allowing subjects to view the performance of other subjects and by instructing them not to discuss any aspect of the station or their performance. No feedback on performance times was given until the experiment was concluded |

## The Treatment: Documentation of Training

The overall objective of this project is to assess the gains from woodsworker training on the chokersetting task. To be useful to the logging industry, the training

alternatives for the control and experimental groups must reflect the existing practices and potential practices of logging firms. The training program for the control group was designed to mirror current practices of logging firms. The training program for the experimental group might have been as intensive as a two week course on chokersetting, but that intensity is beyond the means of most logging firms. The training for the experimental group was scaled to be within reach of most logging firms in Oregon. At present it is not possible to quantify a training effort in logging in any measurable way that is uniform across the populations and training situations. The following description of the training is meant to provide the reader with information about the treatment in the absence of "units" of training.

The fundamental distinction between the control and experimental groups in the research project was the training effort provided the experimental group. The difference in training was between a casual on-the-job training effort (common now in the logging industry) and a designed training effort. The major element of the designed training was the identification of chokersetting principles to be transferred to the trainees. Where possible, a criteria was established to indicate by observable performance when training had been accomplished.

Training for the Control Group

The control group was provided on-the-job directions and observed the chokersetter trainer using skills and principles of setting chokers. The trainer did not explain the principles in the procedures to the control group unless questioned by the trainee. The control group was expected to "pick up the techniques" on their own. Simply seeing a particular procedure may or may not allow subjects to internalize and

transfer that technique or procedure to new situations. Initially, the control group was given a description and followed instructions of the chokersetter trainer for 150 cycles (15 ss by 10 observations each on set 1). At the end of eight days of chokersetting, the control group was expected to use the whistle signaling system and spot the carriage. They had been told at the beginning of the experiment that they would be expected to learn the whistle signals and learn to spot the carriage by the end of the second week of the project. See Figure 8 for a sequence and comparison of the training provided both groups. By the end of set 3, all specific training had stopped for both the control and experimental groups.

Training for the Experimental Group

The basis for training the experimental group is the task analysis format (after Mager, 1976, Appendix I). The task analysis identifies the activities and required skills for the chokersetting task in the experiment. The skills are taught through lecture, demonstration, and feedback during the training period. The training focused on the four techniques of chokersetting mentioned earlier and on the principles to be used as behavioral guides. The principles of chokersetting that were made explicit to the experimental group are listed in Appendix I.

The experimental group was provided a designed training program that emphasized the principles of setting chokers, and where feasible, a previously identified criteria was met prior to the termination of the training effort. By describing the designed training program it is possible to identify the amount of effort required for a designed training program. The experimental group received a four hour lecture/demonstration training effort that identified the principles of setting chokers and some of the techniques associated with setting chokers. At the first of the program, the

1/2 day training for experimental group emphasizing principles

carriage spotting and whistle use demonstration

began using whistles on Set 3

began using whistle on Station 5

received instruc-tions | received feed-back

verbalized selection

Set 1 | Set 2 | Set 3 | Set 4 | Set 5 | Set 6 | Set 7 | Set 8 | Set 9 | Set 10

EXPERIMENTAL

FREE-PATH
CHOKERSETTING
CYCLES

1  2    3    4    5    6  7  8   9 10 11  12  13 14  15 16

1  2    3    4    5    6 7 8   9 10   11 12 13 14 15 16

whistle signaling and
carriage spotting tests

Set 1 | Set 2 | Set 3 | Set 4 | Set 5 | Set 6 | Set 7 | Set 8 | Set 9 | Set 10

CONTROL

received instruc-tions

began using whistles on Set 3

began using whistles on Station 5

DAY  18  19 20 23 24 25 26 27 30  1  2  3  4  7  8  9 10 11 14 15 16 17 18 21 22 23 24 25 28 29

TOTAL LOGS
YARDED

330    650    930    1230 1560    1890 2220    2550 2880    3180

LOGS YARDED
PER
SUBJECT

11    10    10    10    11   11    11   11    11   10

11    21    31    41   52    63   74    85   96    106

Subjects split into control and experimental groups

July 4th Holiday

Figure 8. Chokersetting Training Diagram

experimental group was given a card that identified the whistle signals to be used in the course of the experiment. They were asked to commit these to memory. These cue cards provided a learning device for the experimental subjects. For the first 150 cycles, the experimental group was given feedback on how to set the choker in a particular way to move the log to the corridor. Following the first 150 cycles, the experimental group received a one hour demonstration of how to spot the carriage and were given instructions that allowed them to spot the carriage within six feet of a designated point. Also during this same hour they were provided instructions on how to use the whistle signaling system.

Training Criteria. Criteria were established for assessing whether the training effort had been successful was appropriate for two skills: whistle signaling and spotting the carriage. The whistle signaling skills were fundamental to the chokersetting task as defined for this project. It was essential that the subjects be able to correctly signal the yarder engineer to provide the appropriate function 95% of the time. During the initial training effort, the subjects were given an opportunity to practice with the whistle signals. They were subsequently tested until they all were able to signal the yarder engineer correctly 95% of the time during 15 whistling situations. For the carriage spotting exercise, the experimental group was given a demonstration in how to spot the carriage and the principles of spotting the carriage were identified, but there was not an opportunity to provide each subject with an individual test of carriage spotting ability. At the end of the experiment, both the control and experimental groups were given tests of whistle signaling and carriage spotting. Errors for these two functions were noted throughout the course of the project for both groups.

Feedback and Verbalization. The experimental group was given approximately two weeks of feedback by the chokersetter trainer on their performance after the chokersetting task was completed. The control group was not provided this same feedback. At the end of two weeks the experimental group was asked to perform without feedback for the next three weeks. During the final week of performance which constituted approximately 300 cycles, the experimental group was required to describe in advance of starting the timed cycle their selected technique for moving a log to the skyline corridor. They were not provided feedback as to the correctness of their techniques, but they were asked to verbalize their thought processes. The objective was to provide the researcher with an understanding of the way in which the training had transferred to the experimental group.

Training Within Reach of Most Logging Firms

The requirements for the designed training effort of the experimental group were such that the training effort would be within reach of many of the logging firms within Oregon that are in the size classification of approximately ten employees. From the above description it can be seen that the training effort was not extraordinary and not beyond the capabilities of the firms who might have had some exposure to chokersetter training techniques. Thus, it seems feasible that many firms within the state could provide the incremental difference between a casual on-the-job training effort and a designed training effort during the course of their normal operations. The logging firms may initially need some assistance to implement training programs of the type described above. Larger firms with greater resources may be quite capable of providing training substantially beyond the process described above.

Order of Task Performance

The order of task performance must be clearly understood for the experiment. Questions may arise on how and why the experiment was performed as it was. For example, why not measure the number of chokers set in a specified time period as opposed to the time to set chokers on a specified arrangement of logs (log sets)? Why not run one subject at a time rather than rotate them? Did the time between cycles result in forgetting? Did the intervening cycles on technique stations influence performance on the FREE-PATH station? Should the subjects have performed each RUB, ROLL, END ... stations in consecutive order? These are valid questions that can be addressed through a description of the order of task performance.

Each Log Set Constitutes a Whole

Each of the ten log sets constitutes a group of experiences that the chokersetter might face on a daily basis on actual operations. The chokersetter would face a variety of log positions that require using the techniques of RUB, ROLL, END and JUMP in a mixed order. Thus, taken as a whole, each set of log positions encompasses the range of techniques encountered by chokersetters. It would be a real abstraction from actual operations for subjects in the experiment to run each technique consecutively, i.e. all RUB, ROLL, etc. techniques. An essential part of the task is to select the proper technique to use on a particular log position.

From the above description, it can be seen why it is not feasible to measure the number of chokers set in a time period (this is the measurement practice used by Towill and others for learning curves). Each log set contained ten stations with logs at positions that were arranged to require RUB, ROLL, END, JUMP or some random techniques as well as a FREE-PATH station. These ten measures represent samples of the techniques used by chokersetters in actual operations. If it were possible to control

the field environment and the inherent sources of variation for a field experiment, the

measure of the number of chokers set for a specified time period would be appropriate.

However, an experiment on actual operations would be difficult to conduct due to the

variability of operations, and there would be no assurances that the cycles measured

from day to day would be comparable as to the level of skill required.

By defining a "set" of logs to encompass the mixed order of log positions

requiring certain techniques and then replacing the logs precisely for each subject, the

comparability between control and experimental groups is maintained.

The Order of Performance on FREE-PATH

The free path chokersetting task on station five was used initially to pair the

subjects into control or experimental groups. For the next four sets of log positions, the

FREE-PATH station was performed in the middle of the respective sets of logs. Then

at the beginning of set six, the FREE-PATH task was performed, as shown in figure 9

below, both at the beginning and the middle of a set.

```
Sets 1 to 10
        1       2       3       4       5       6       7       8       9       10
   *-------*-------*-------*-------*-------*-------*-------*-------*-------*-------*
   ↑     ↑       ↑       ↑       ↑   ↑   ↑   ↑   ↑   ↑   ↑   ↑   ↑   ↑   ↑
   1     2       3       4       5   6   7   8   9   10  11  12  13  14  15  16
Performance Order of the FREE-PATH tasks 1 to 16
```
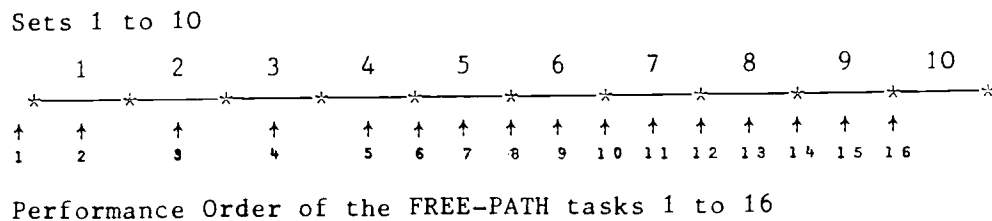
Figure 9  Sets and FREE-PATH Order

For the last five sets, the FREE-PATH task was performed at the beginning and

middle of the sets to obtain more frequent views of subject performance on the

FREE-PATH task. As for the contribution of intervening performance on technique

stations to the FREE-PATH performance, it is clear that, indeed, the station five

(FREE-PATH) performance is sandwiched between the performances on log sets. It is more appropriate to think of FREE-PATH performances as indicators of the learning taking place on the more complicated technique or RAND stations. What is important is that the control and experimental groups remained comparable on the number of intervening task performances whenever the FREE-PATH station was measured. Because the basic task of setting chokers remains similar across all techniques, it is unlikely that forgetting occurred between task performances.

Rotation of Subjects to Stations other than FREE-PATH

Initially, a prescribed order of station performance for each subject was attempted, but the replacement of logs required two subjects and the timing made it impossible to schedule the subjects to a particular order of stations. During the experiment, subjects rotated through the stations in an apparent random fashion as observed by the project leader. The project leader would begin a log set at station 1, 4, 6, 10 and have one subject perform the chokersetting task. The subject would then reposition the log after the cycle while the project leader would move to another station and perform a cycle there. After repositioning the log, the subject would rotate to a station of his choice to await an opening. This procedure eliminated fixing an order of rotation and provided a "nearly random" order for performance on stations within a log set. Subjects were not allowed to perform two consecutive cycles without a rest interval.

Experimental Design

Goldstein (1974) notes the scarcity of experimental designs that limit threats to internal and external validity. Examples of typical designs are contrasted with the design of this experiment in Table 4. The current project sought to minimize the threats

# Table 4. Comparison of Experimental Design

X = Treatment
R = Randomization used
$T_i$ = Testing

Sources of Invalidity

| | History | Maturation | Testing | Instrumentality | Regression | Selection | Mortality | Interaction of Selection Maturation | Interaction of Testing & X | Interaction of Selection & X | Reactive Arrangements | Multiple X Interference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Internal | | | | | | | | External | | | |
| 1. Case study $X\,T_2$ | - | - | | | | - | - | | | - | | |
| 2. One Group Pre/Post Test $T_1\,X\,T_2$ | - | - | - | - | ? | + | + | - | | | | |
| 3. Pre/Post test control group $R\,T_1\,X\,T_2$ / $R\,T_1\ \ T_2$ | + | + | + | + | + | + | + | + | - | ? | ? | |
| 4. Solomon 4 group $R\,T_1\,X\,T_2$ / $R\,T_1\ \ T_2$ / $R\ \ X\,T_2$ / $R\ \ T_2$ | + | + | + | + | + | + | + | + | + | ? | ? | |
| 5. Time series $T_1\,T_2\,T_3\,T_4\,X\,T_1\,T_2\,T_3\,T_4$ | - | + | + | + | ? | + | + | + | - | ? | ? | |
| 6. Non equivalent group $T_1\,X\,T_2$ / $T_2$ | + | + | + | + | ? | + | + | - | - | ? | ? | |
| **. Combination design for chokersetting experiment $R\,T_0\,X\,T_1 \cdots T_N$ / $R\,T_0\,X\,T_1 \cdots T_N$ | + | + | | + | + | + | + | + | + | + | ? | + |

+ = factor controlled
- = weakness
? = possible source of concern
blank = factor not relevant

(after Campbell and Stanley in Goldstein, 1974)

to internal and external validity for the chokersetting training effort. The fact of sensitization to the testing instrument does not appear applicable to the current project, and the reactive arrangements between subjects and experimenters remains a source of concern.

The use of pre-test, post-test, a control group, and random allocation to control or experimental groups, aids in reducing threats to validity. Other threats to validity have been described earlier as sources of variation.

The statistical design to analyze the current experiment rests on five testing procedures: an overall analysis of variance; a pattern of t-tests for the log sets, a t-test of the parameters of some learning curve forms; difference between the learning curve models for control and experiment groups; and some non parametric tests of the errors and indicators noted during the experiment. Ratings and rankings were also analyzed.

Analysis of Variance

The analysis of variance for the data in the overall experiment (log sets 1-10) uses a variant of the randomized block design -- a split-plot design. Montgomery (1976) outlines the linear statistical model form similar to what follows:

$$Y_{ijkhm} = M + T_i + B_j + \varepsilon^*_{ijm} + S_k + (TS)_{ik} + \varepsilon_{ijkhm}$$

where

$Yi_{jkhm}$ = response variable (performance times)

M = Grand mean

T = Treatment      i = 1,2

B = Block      j = 1, top 5 ss on initial performance, station

S = Sets      5; 2, middle 5 ss; 3, bottom 5 ss

k = 1, ... 10

$\varepsilon_{ijm}$ = Whole plot error    h = stations nested in sets index, (1 ... 10)

$\varepsilon^*_{ijkhm}$ = Split plot error    m = individuals nested in treatments,

$$(1,2,3,4,5)$$

A weakness of the split-plot analysis of variance is that an estimate of mean square error ($\sigma^2$) is not available but rather is combined with other sources of variation. In addition, no explicit tests of block effects are available. The blocking to reduce the variation between subjects within groups was an attempt to cope with the high variation between subjects earlier shown by Cottell and others (1976). In a study of 34 logging machine operators over 757 shifts nearly 2/3 of the variation was between operators within firms. The hypothesis tested in the analysis of variance is that for the effects listed in the model above (with the exception of B and I) there is a significant effect, i.e.:

$H_o$: Effect equals 0

against

$H_A$: Effect does not equal 0

The minimum alpha level for significance is set at $\alpha = .05$ for the F-test of significance in the analysis of variance.

Pattern of t-tests

Another statistical procedure is suggested by the sigmoid shape of the cumulative difference function. If the sigmoid shape is present, a pattern of the significance of t-tests between control and experimental groups should emerge. For the ten log sets in the experiment, using each set as the basis for a t-test between control and experimental groups, one would expect the pattern of significance to be initially low (i.e. small t values), then increase in significance for the middle sets, and then decrease in

significance at the end of the sets. Normally, it is the magnitude of the t-statistics that is of interest to researchers, but for learning analysis, it is both the magnitude and pattern of t-statistics that provides information.

T-test of Parameters

A t-test may also be used with the parameter estimates of the individual learning curves of the 30 subjects. That is, an unpaired t-test for the learning parameters for the control and experimental groups would suggest differences between the groups. Concern is raised whether this test can be significant if the confidence intervals on the individual parameters are large. In this event, a nonparametric distribution-free test, i.e. Kruskal-Wallis, may be useful for the learning parameters (see description below).

Differences Between Learning Curve Models

Using the means of performance on each set (1-16) for the freepath chokersetting station provides group parameter estimates for the learning curves of the control and experimental groups. The confidence intervals for the learning parameters would not be expected to overlap if a significant difference were present. The 95% confidence interval is selected for the experiment.

Nonparametric Tests of Errors

The error counts associated with the carriage spotting, whistle signaling, and resets as well as the indicators associated with learning a technique present statistical problems for t-tests. A distribution-free, nonparametric test such as Kruskal-Wallis is preferred for these types of measures. The hypotheses is similar for the above measures and is shown below for the training treatments.

$$H_o: T_c = T_E$$

vs

$$H_A: T_c \neq T_E$$

reject $H_o$ if calculated statistic $\geq X^2(k-1, \alpha)$

accept $H_o$ if calculated statistic $\leq X^2(k-1, \alpha)$

T = treatment effect          k = number of treatments

Other nonparametric tests are used to compare rankings of the control and experimental groups with actual ranks and initial and final ranks. Spearman's rank correlation coefficient is utilized for these comparisons.

## Summary of Experimental Procedures

The foregoing description of experimental procedures should help readers understand the conduct of the experiment. The following chapter provides the results of the experiment and reports the significant findings and statistical tests.

EXPERIMENTAL RESULTS

Strategy for Reporting

It may be helpful to the reader to generally outline the strategy for reporting the outcomes of the training experiment. First, it will be shown that the control and experimental groups initially started the experiment at the same level but were not at the same level at the end of the experiment. Second, it will be shown that the groups' performances differed by expected patterns resulting from training. Third, the experimental design will be explored through the analysis of variance results. Fourth, the learning models will be fitted for the control and experimental groups where possible. Fifth, the cumulative difference models will be developed. Sixth, overall comparisons are made for the techniques of chokersetting identified. Finally, the use of ratings and rankings will be discussed.

Initial and Final Performances

The purpose in initially matching and splitting the control and experimental groups was to assure that both groups started at the same point in learning the chokersetting task. Table 5 shows the initial performance (cycle 1) on station five, FREE-PATH chokersetting, to be essentially the same for control and experimental groups as measured by an unpaired t-test. While pairing was used to match and split the groups there is no justification for maintaining the pairing throughout the experiment. Initial rankings are also supplied in table 5. Two measures of final performance are similarly presented in table 5 to show that the two groups were not performing at the same level at the end of the experiment. On station five there is a significant difference between the final performance of the control and experimental groups as measured by

an unpaired t-test. In addition, the sum of all performance times over the experiment is significantly different as similarly measured by an unpaired t-test. The experimental group improved by 18% in time over the control group.

The t-test comparisons are made using the unpaired t-test which showed initially there was no difference between control and experimental groups. However, at the end of the experiment there was a significant difference between control and experimental groups at the last cycle (trial 16). Finally, the difference between control and experimental groups over the entire experiment (sets one through ten, all stations) is shown to be significant using a t-test and the .05 level of significance. Ranks are provided in parentheses next to performance levels in table 5.

## Pattern of Differences Due to Training

It has already been mentioned that a particular pattern of differences between control and experimental groups might be evident in the statistical tests at points in time, i.e. after the completion of sets 1, ... 10. The pattern would be one showing less significance early in the project, a large significance in the middle of the project, and less significance at the end of the project. Each set is considered separately, and the level of significance from a particular test is associated with the set of log positions for all stations.

### All Sets, All Stations

Table 6 shows the pattern of significant t-tests for the times on sets one through ten (all stations). The pattern follows the expected pattern, illustrating that initially there is less difference between control and experimental groups; then, in the middle of the

Table 5.  Some Summary Statistics by Group (within group rankings, times in seconds)

| SS | Initial Performance at Station 5 | Final Performance at Station 5 | Total Performance all sets, all stations | SS | Initial Performance at Station 5 | Final Performance at Station 5 | Total Performance all sets, all stations |
|---|---|---|---|---|---|---|---|
| 30 | 41.60( 1) | 35.7( 3) | 9,846(11) | 15 | 39.08( 1) | 32.5( 4) | 7,595( 7) |
| 29 | 41.70( 2) | 36.3( 5) | 9,603( 9) | 14 | 41.69( 2) | 31.3( 1) | 7,770(10) |
| 28 | 45.74( 3) | 38.9( 9) | 10,504(13) | 13 | 43.91( 3) | 34.3( 9) | 7,560( 6) |
| 27 | 46.53( 4) | 36.0( 4) | 8,649( 4) | 12 | 46.84( 4) | 32.3( 3) | 6,730( 1) |
| 26 | 47.32( 5) | 49.3(14) | 9,044( 7) | 11 | 48.98( 7) | 41.8(15) | 8,577(14) |
| 25 | 48.71( 7) | 31.8( 1) | 8,594( 3) | 10 | 49.32( 8) | 36.4(10) | 7,481( 4) |
| 24 | 53.55(12) | 39.4(10) | 10,447(12) | 9 | 52.08( 9) | 33.0( 8) | 7,985(11) |
| 23 | 50.81( 9) | 36.4( 7) | 8,733( 5) | 8 | 52.46(10) | 36.1(12) | 7,240( 2) |
| 22 | 52.59(11) | 40.9(11) | 9,740(10) | 7 | 55.44(12) | 32.5( 5) | 7,529( 5) |
| 21 | 54.41(14) | 46.4(13) | 7,926( 1) | 6 | 56.76(13) | 36.4(11) | 7,317( 3) |
| 20 | 55.53(15) | 53.2(15) | 12,602(15) | 5 | 54.83(11) | 40.6(14) | 8,415(12) |
| 19 | 51.30(10) | 37.6( 8) | 11,071(14) | 4 | 48.62( 5) | 40.0(13) | 8,506(13) |
| 18 | 48.99( 8) | 42.3(12) | 8,770( 6) | 3 | 61.82(15) | 33.0( 7) | 9,171(15) |
| 17 | 48.67( 6) | 34.2( 2) | 8,158( 2) | 2 | 60.94(14) | 32.8( 6) | 7,647( 9) |
| 16 | 53.76(13) | 36.1( 5) | 9,227( 8) | 1 | 48.86( 6) | 31.8( 2) | 7,640( 8) |
| Mean Value | 49.41 | 39.63 | 9,528 | | 50.77 | 34.99 | 7,811 |

## T-Test Comparisons

Initial performance on Station 5

$$t_{calc} = .6708 < t_{critical} \quad \text{no difference}$$
$$.05, 28 \text{ df}$$

Final performance on Station 5

$$t = 2.63 > t_{critical} \quad \text{significant difference}$$
$$.05, 28$$

Total performance on all sets, all stations

$$t = 4.80 > t_{critical} \quad \text{significant difference}$$
$$.05, 28$$

Table 6. T-Tests of Performance Times on Total Stations on Log Sets
One Through Ten

| Set | T value | *Two-tail probability |
|-----|---------|----------------------|
| 1 | 1.91 | .066 |
| 2 | 1.50 | .144 |
| 3 | 1.52 | .139 |
| 4 | 4.69 | .000 |
| 5 | 3.20 | .003 |
| 6 | 2.69 | .012 |
| 7 | 3.37 | .002 |
| 8 | 2.65 | .013 |
| 9 | 2.09 | .045 |
| 10 | .45 | .658 |

* Test is of the hypothesis

$$H_o: M_{control} = M_{experimental}$$

versus

$$H_A: M_{control} \neq M_{experimental}$$

A low probability rejects $H_o$ and accepts $H_A$ if two-tail probability is less than .05.

experiment the training gains are evident; and finally, the control group is catching up with the experimental group as shown by the lack of significant difference in the test of performance on the last set.

Pattern for Error Counts

The pattern of test significance might be somewhat different for the error counts of resets, whistle signaling errors, and carriage spotting errors. Figures 10 through 12 show the total errors on the log sets one through ten and the pattern of significance for a Kurskal-Wallis distribution-free, non-parametric test of the training treatments. The whistle signaling errors show a pattern in Figure 10 that begins with initially large differences between the control and experimental groups that generally diminishes over time to the point where the last three log sets show no statistically different measures. The carriage spotting errors follow a general pattern of initially little significance followed by statistically significant differences in the middle of the experiment and no differences at the end (see figure 11). The pattern of resets follows the pattern of carriage spotting errors generally with the exception that at the end of the experiment the actual number of resets by the experimental group exceeds that of the control although the difference is not statistically significant (see figure 12).

The fact that these error counts come together near the end of the experiment suggests that matching the groups was nearly equal, allowing the two groups to practically achieve the same performance on these measures by the end of the experiment. The difference due to training is that the experimental group reached a level of performance sooner than the control group.

Figure 10. Whistle Signaling Errors
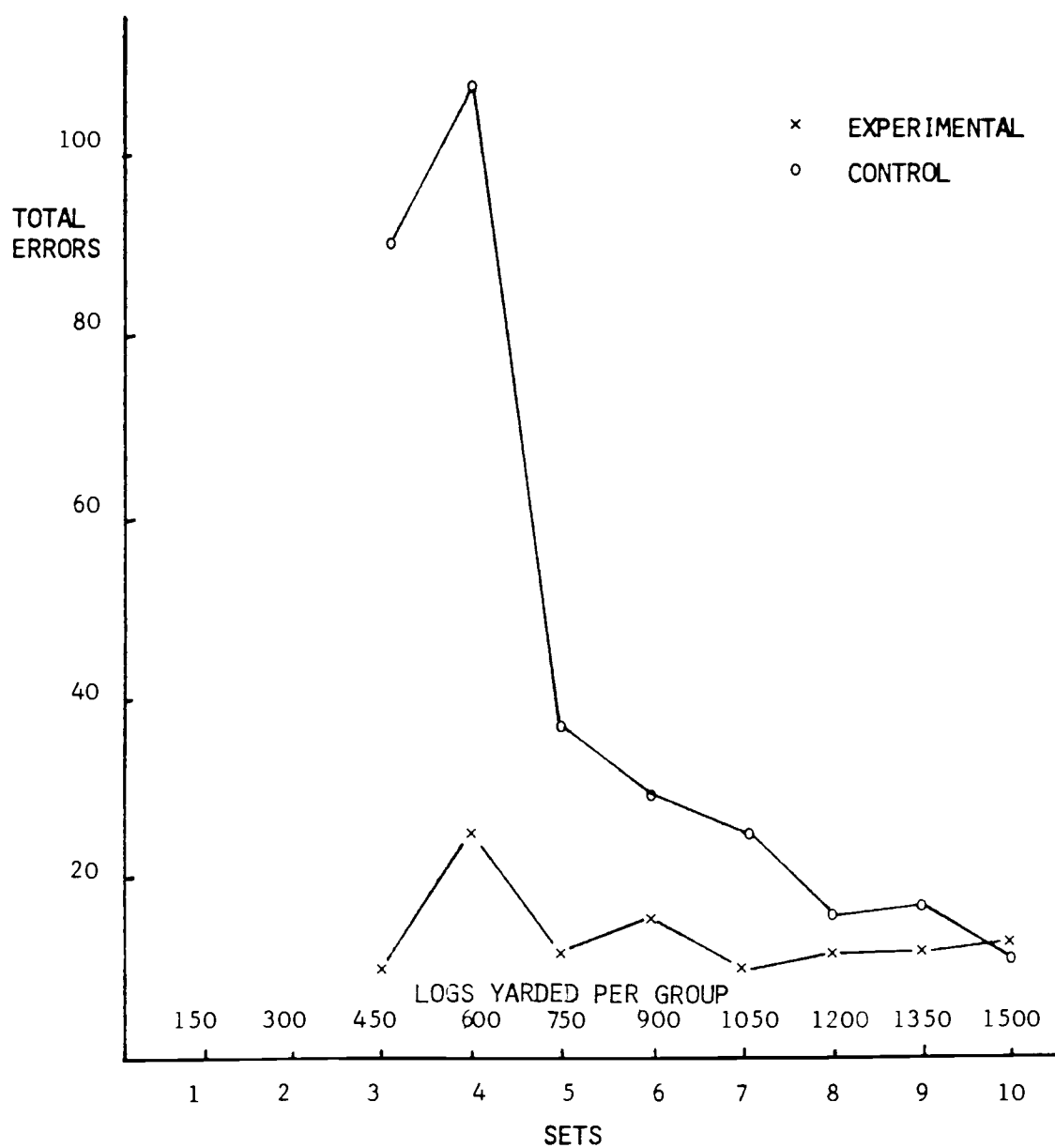
| SETS | $\chi^2$ Value of Significance | SETS | $\chi^2$ Value of Significance |
|------|------------------------------|------|------------------------------|
| 3 | .0000 | 7 | .0093 |
| 4 | .0028 | 8 | .5940 |
| 5 | .0132 | 9 | .4314 |
| 6 | .2126 | 10 | .1461 |

× EXPERIMENTAL

○ CONTROL

TOTAL ERRORS

20

10

LOGS YARDED PER GROUP

| 150 | 300 | 450 | 600 | 750 | 900 | 1050 | 1200 | 1350 | 1500 |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
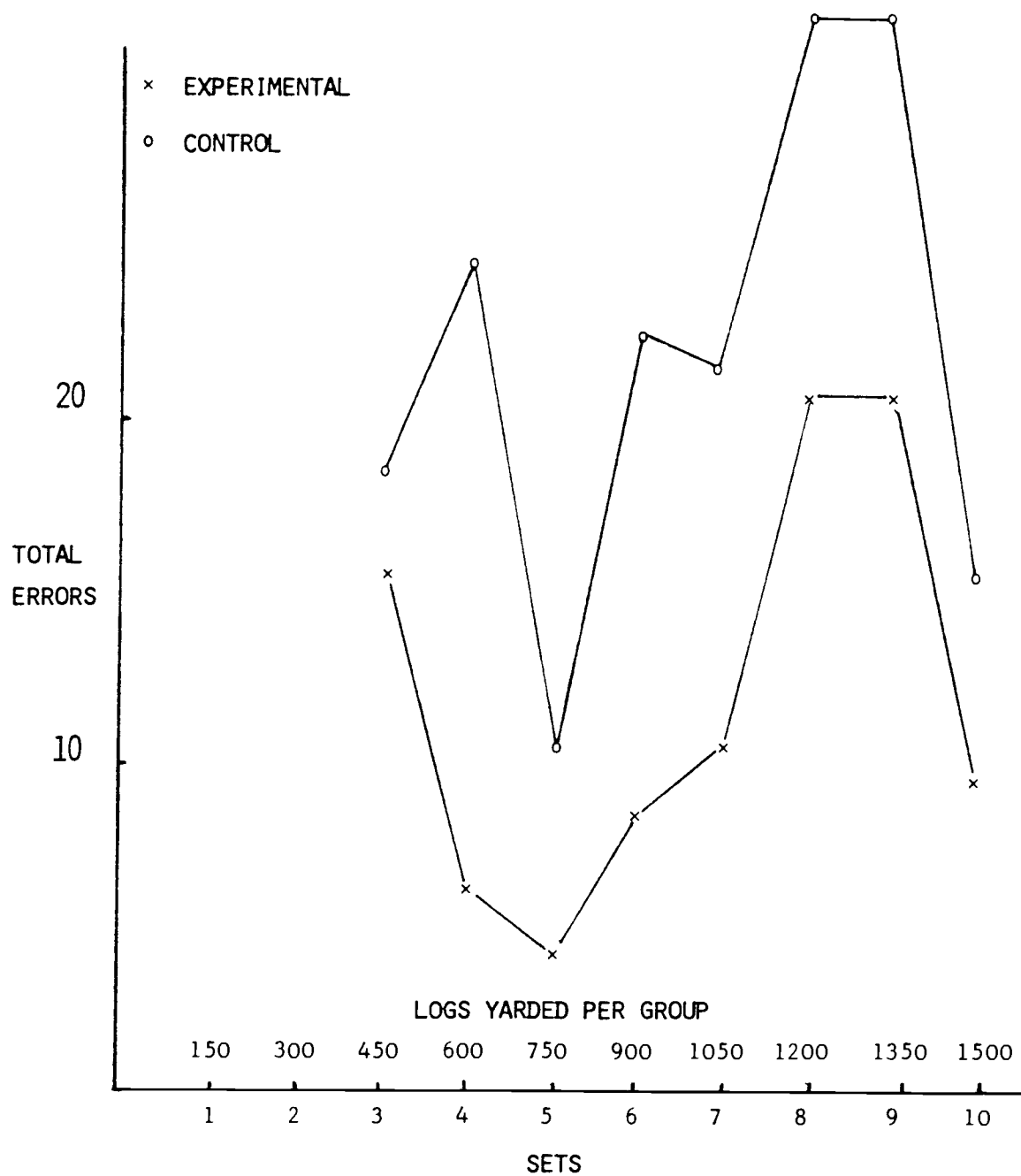
SETS

| SETS | $\chi^2$ Value of Significance | SETS | $\chi^2$ Value of Significance |
|---|---|---|---|
| 3 | .5087 | 7 | .0574 |
| 4 | .0036 | 8 | .5502 |
| 5 | .1656 | 9 | .5360 |
| 6 | .0220 | 10 | .1841 |

Figure 11. Carriage Spotting Errors

Figure 12. Total Resets Over 10 Sets
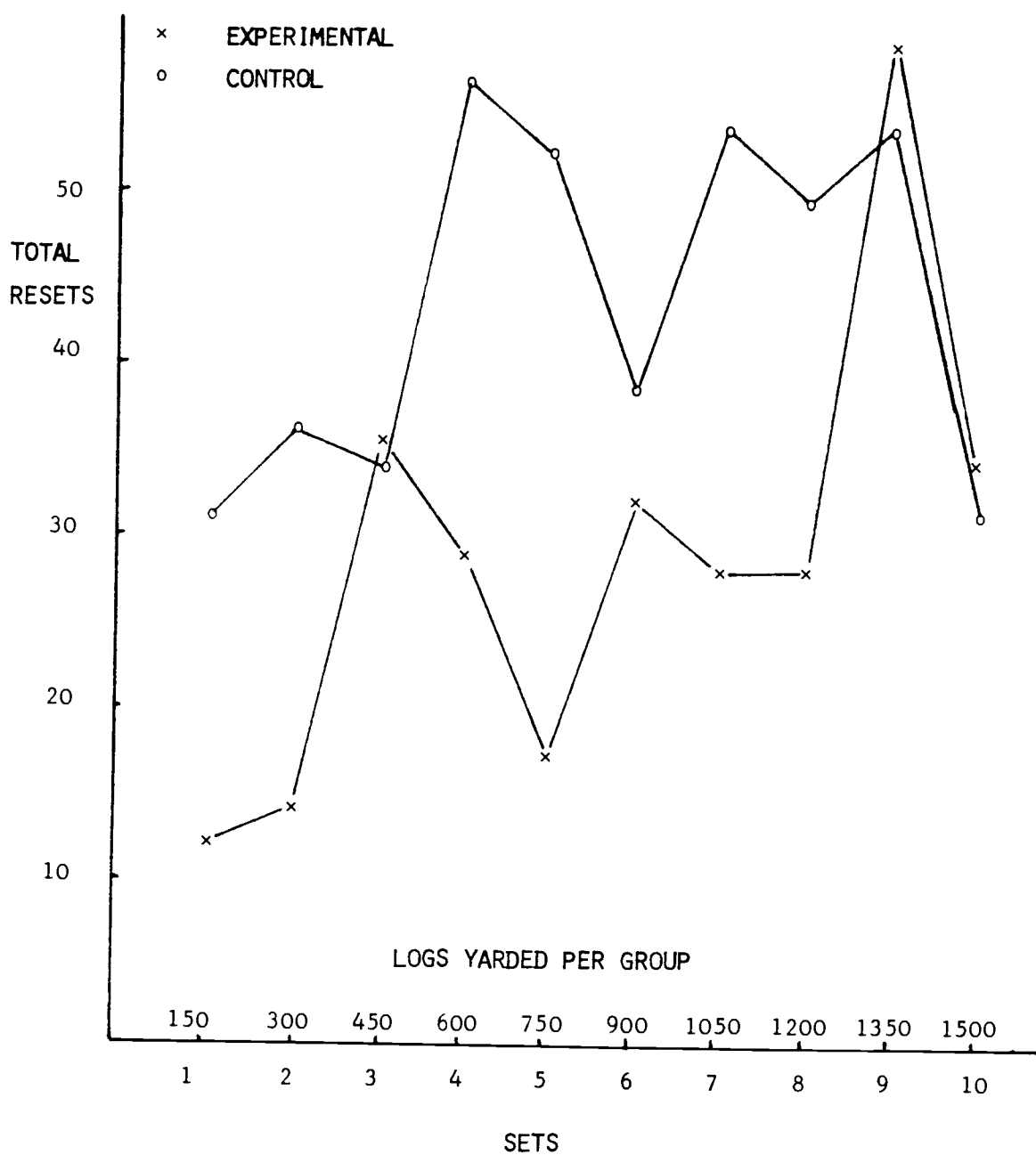
| SETS | $X^2$ Value of Significance | SETS | $X^2$ Value of Significance |
|------|---------------------------|------|----------------------------|
| 1 | .0657 | 6 | .3743 |
| 2 | .0144 | 7 | .0611 |
| 3 | .7071 | 8 | .0923 |
| 4 | .0190 | 9 | .6443 |
| 5 | .0020 | 10 | .4712 |
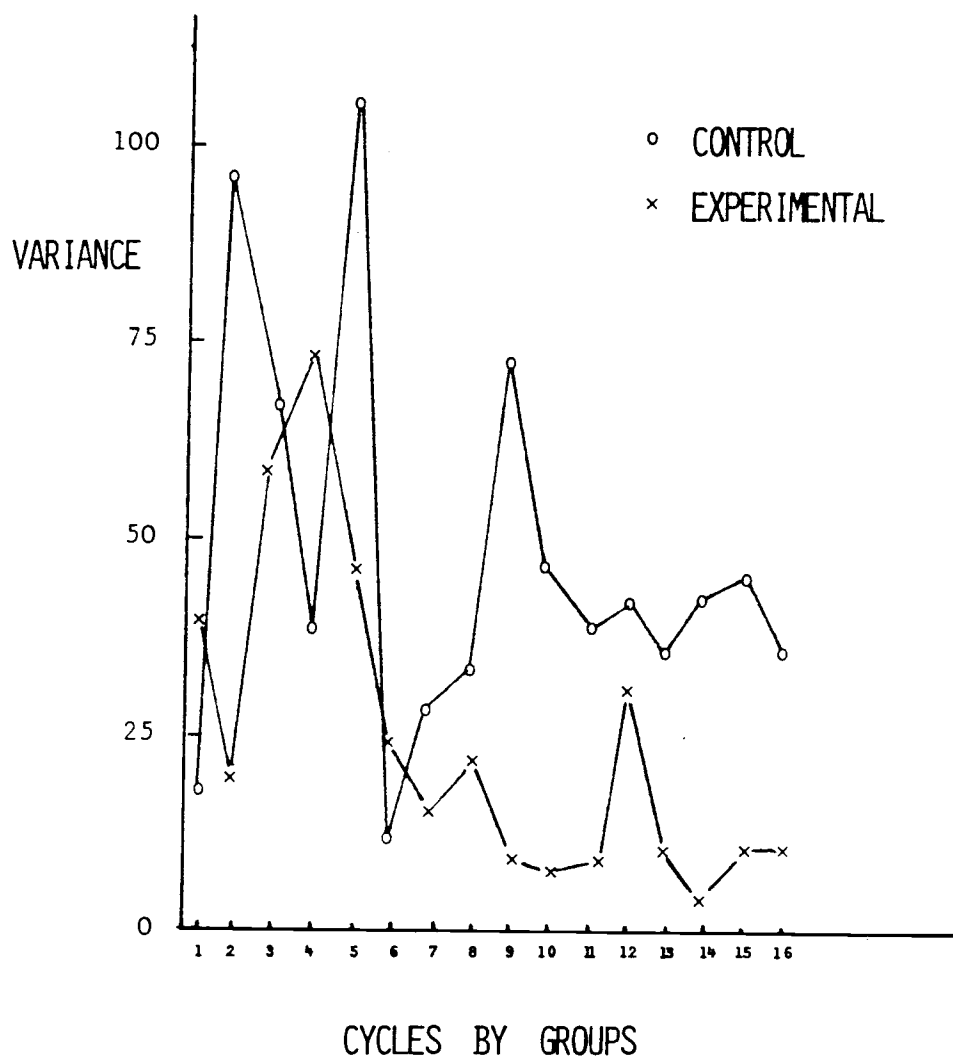
Figure 13. Variance at STATION 5

Pattern of Variances on FREE-PATH Cycles

Another statistic that indicates learning is the variance of the control and experimental groups on station five, FREE-PATH chokersetting. Towill and Bevis (1972) describe cycle time distributions of operators doing training which suggest a reduction in variance by the end of training. It may be further postulated that the variance of a group trained by an effective training program should be less than a control group. Figure 13 shows this reduction in variance on station five for both control and experimental groups. Note that there are initially large fluctuations in the variances of both groups but by the middle of the experiment the variances are stabilizing. An F-test for the equality of two variances shows that for $\alpha = .05$, and a one-sided test of the ratio of the variances at 14 degrees of freedom, the ratio, $\sigma_c^2/\sigma_e^2$, must exceed about 2.15 (Duncan, 1952). From cycle nine to cycle sixteen this is generally true with the exception of cycle twelve for the experimental group. No explanation is offered for this singular jump in the variance.

Along with the other patterns suggesting the influence of training, the variance associated with the performance of a simplified task may be an indicator of improvement.

## Analysis of Variance

Table 7 reports on the analysis of variance (ANOVA) for the split-plot experimental design. The linear statistical model has been outlined earlier in the experimental design section with the various subscripts. Overall conclusions only are listed below:

1. The treatment effect, $T_i$, is significant at the level, $P < .0005$; training effects are significant averaged over the entire experiment.

88

Table 7. Analysis of Variance (ANOVA) Split-Plot Design

| Source | Degrees of Freedom | Mean Square | F Calculated | Level of Significance | Remarks |
|---|---|---|---|---|---|
| B (block) | 2 | 8924 | - | - | |
| T (treatment) | 1 | 221045 | 58.3 | $p < .0001$ | $F_{2,10}$ used by pooling T X B & I/T terms |
| T X B | 2 | 3602 ┐ | | | |
| | | ├─ 3791 | | | |
| I/T (individual in treatment) | 8 | 3839 ┘ | | | |
| I/T X B | 16 | 13273 | - | - | |
| S (set) | 9 | 9591 | 3.44 | $p = .005$ | |
| T X S | 9 | 5717 | 2.05 | $.05 < p < .1$ | |
| S X B | 18 | 2600 ┐ | | | $F_{9,36}$ used by |
| | | ├─ 2791 | | | |
| S X T X B | 18 | 2982 ┘ | | | pooling C X B & C X B X T terms |
| I/T X S | 72 | 3297 | | | |
| I/T X S X B | 144 | 3339 | | | The remaining sources of variation due to the station interaction effects are not detailed here because they are not involved in tests. |
| Total | 2999 | | | | |

2. The set effect, S, is significant at the level, p = 0.005; the performance is different at different sets (time).

3. The treatment by set effect, T X S, is marginally significant, .05<p<.1; the treatment effects are not consistent over the sets. Recall that at the beginning and end of the experiment there is little difference between groups, while in the middle of the experiment, there is a large difference. The ANOVA does not provide this information but reflects it.

The divisor for the F-tests are the pooled interaction terms for whole plot and sub-plot interaction (Montgomery, 1976). It is a logical procedure given that the blocks are not interacting with the treatments and were formed in advance of applying treatments. While a direct test of the efficiency of blocking is not available in the split-plot design, the difference between the I/T x B mean square and the block mean square might be due to somewhat different variances within blocks, but this is a matter of speculation only from the ANOVA.

In summary, the ANOVA tells us that the training was effective for the experimental group. Also, the ANOVA suggests that, averaged over all sources of variation, the performances change over the ten sets of logs. The manner in which it changes is not suggested by the ANOVA. Raw data suggests both groups improved. Finally, while both groups improved, the treatment by set effects suggests that the rates of improvements were not the same.

<center>Fitting the Learning Models</center>

The general form of the learning model selected for this experiment is from Bevis, Finnear and Towill (1970). The model has been transformed somewhat to describe the experiment and the data has been transformed to fit the model. The model form and transformations are described below:

$$Y(t) = Y_c + Y_f(1-e^{-t/T})$$

where,

t = normally a time measure, i.e. day 10. For the experiment, t is defined to be the cycle number (for FREE-PATH Chokersetting) or set number (for 10 sets of 10 stations) of the data.

Y(t) = normally output rate at time, t. Data from the experiment collected as time per cycle. Y(t)is the time per cycle after t cycles or sets.

$Y_c$ = cycle time at t = 0

$Y_c$ - $Y_f$ = asymtotic cycle time at t = infinity

e = base of Naperian logarithms, 2.71828+

T = learning rate associated with the experiment, i.e. at t = T approximately 63% of the increment to the ultimate output rate has been reached.

While the data has been collected in discrete points, the learning models are smoothed for simplification of mathematical manipulations. Equivalency of the discrete and continuous forms is described in Buck, et. al. (1976) and Goldberg (1958).

## Parameter Estimation

The fitting of the model form and parameter estimation depend on the data and the model fitting procedure. The procedure selected for this experiment for parameter estimation is based on SPSS-NONLINEAR (Statistical Package for the Social Sciences, Robinson, 1979). SPSS-NONLINEAR allows the use of Gauss' or Marquardt's method of minimizing a sum-of-squares expression with initial parameters selected by the user. Marquardt's method is sensitive to the scaling of parameters, and thus Gauss' method was selected.

## Gauss' Method

Given an explicit regression model to be fit to a data set, the sum-of-squares expression can be written to include the model parameters as the only unknown

quantities. Initial "guesses" of the parameters are supplied and the first partial derivatives of the sum-of-squares function are evaluated through a Taylor series expansion of the function near the initial values. When the higher order terms of the Taylor series are ignored, the model may be rewritten in a standard form of a linear regression model. The linear regression model form is an approximate sum-of-squares function which can be iteratively solved for successive sets of best estimates of the parameters in the model. The iterations continue until the stopping criteria listed below are satisfied.

Stopping Criteria

The nonlinear regression is an iterative minimization procedure for the model parameters that stops when the following predetermined criteria are reached:

1.  the parameters change very little on two successive iterations (tolerance predetermined)

2.  there is little change in the sum-of-squares function (tolerance predetermined)

3.  the ratio of the current sum-of-squares to the initial sum-of-squares is less than a predetermined tolerance

4.  a user-set iteration count has been reached

For the parameter estimation procedure, the default stopping criteria were utilized with an iteration count set at 50 or 100 iterations which were seldom reached.

Arithmetic Overflow

With many parameter estimation procedures such as SPSS-NONLINEAR problems may be encountered when using "e" raised to large or small powers in the SPSS-NONLINEAR package. Unless "good" initial guesses of the parameters start the iterations, irrational exponents of "e" may cause arithmetic overflow.

"Good" Initial Estimates and the Data

The particular form of the data may yield parameter estimation difficulties as well. "Noisy" data may influence parameter estimation by "sidetracking" the iteration procedure at a local minima of the sum-of- squares expression. Illogical parameter estimates may result even after many iterations. "Good" initial guesses for the parameters help avoid this dilemma. Good initial estimates of parameters may be achieved by several strategies. Sources outside the data set may be utilized if available. For example, the asymtotic value, $Y_c + Y_f$, may be known for certain tasks from historical data (Towill, 1973) or as a consequence of machine rates limiting human performance. An approach using data only contained within the experiment may also yield adequate results. For example, the first few cycles of performance may be extremely noisy in a learning experiment. Fitting a model of a limited number of data points may yield the asymtotic level, $Y_c + Y_f$, with sufficient accuracy to serve as a starting point for parameter estimation with the full data set. This procedure was used to obtain parameter estimates for the FREE-PATH chokersetting activity.

Learning Curves for the Group Means on FREE-PATH Chokersetting

For the FREE-PATH chokersetting task on station five, the means of performances of the 15 control and experimental subjects can be plotted for the 16 cycles then performed. This task has had as many sources of variation removed as feasible, and thus, it is the beginning point for fitting learning curves. Table 8 shows the results of all curve fitting.

The model forms show the relationships for the group means on cycles 1 to 16. The ordinal base for the time variable is used here for comparability purposes, but the
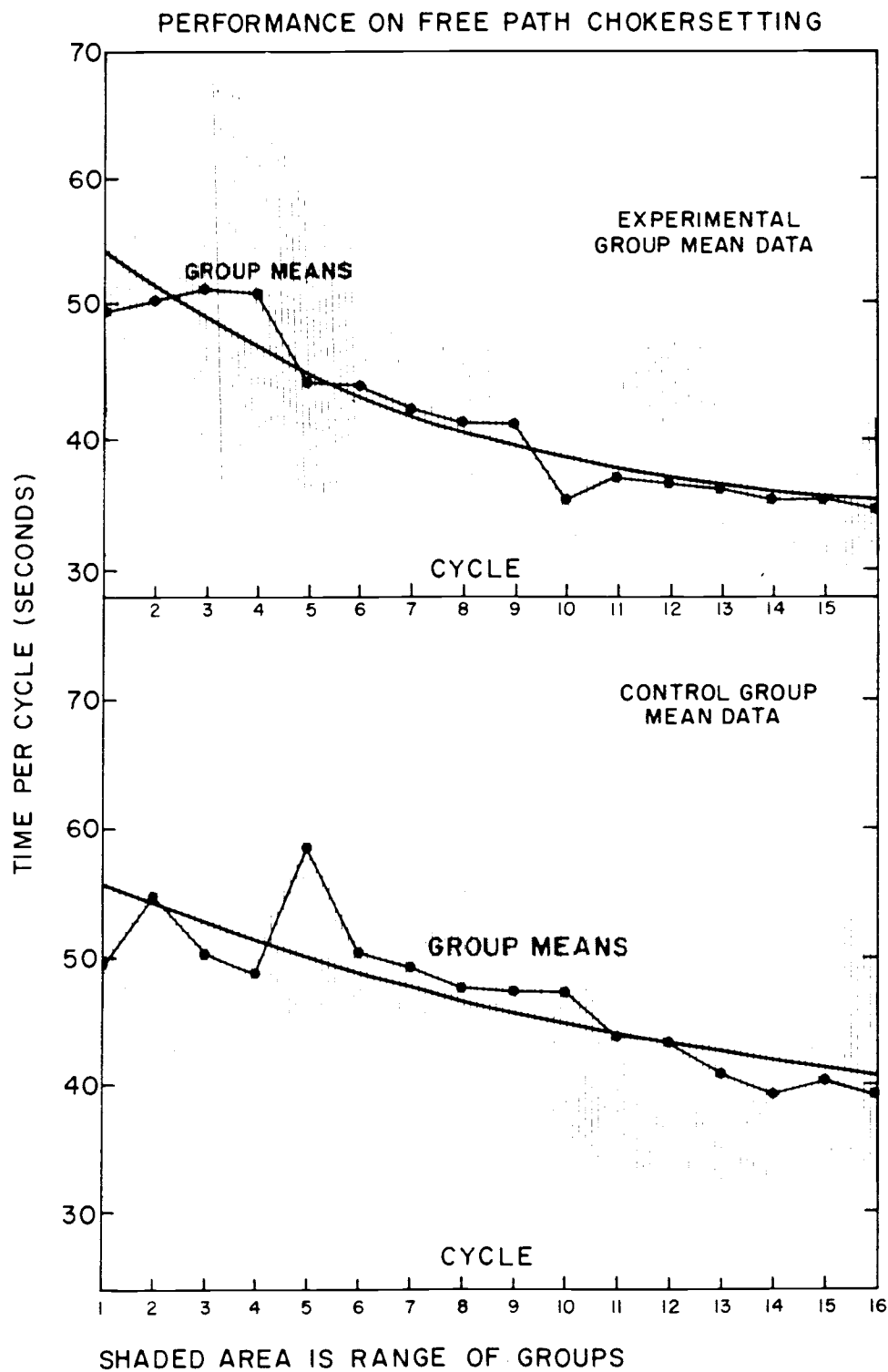
Figure 14. Performance on FREE-PATH Chokersetting

Table 8. Learning Curve Models and Cumulative Difference Functions

Model forms:

Learning curve: $Y_{(t)} = Y_c - Y_f(1 - e^{-t/T})$

Cumulative difference:

$$Q_{d(t)} = ((Y_{ce} - Y_{fe}) - (Y_{cc} - Y_{fc}))t + T_c Y_{fc}\left(1 - e^{t/T_c}\right) - T_e Y_{fe}\left(1 - e^{-t/T_e}\right)$$

Learning curves fitted to free-path chokersetting.

| | Control Group | | | | | Experimental Group | | | |
|---|---|---|---|---|---|---|---|---|---|
| SS | $Y_{cc}$ | $Y_{fc}$ | $T_c$ | $R^2$ | SS | $Yc_e$ | $Y_{fe}$ | $T_e$ | $R^2$ |
| 16 | 56.22 | 53.76 | 49.33 | .441 | 1 | 59.29 | 48.86 | 20.99 | .745 |
| 17 | 55.79 | 48.67 | 33.09 | .603 | 2 | 71.52 | 38.28 | 2.92 | .816 |
| 18 | 52.67 | 48.99 | 62.38 | .524 | 3 | 72.53 | 36.93 | 2.41 | .708 |
| 19 | 61.82 | 51.30 | 30.36 | .338 | 4 | 57.11 | 48.62 | 27.08 | .731 |
| 20 | 61.17 | 5.49 | 4.73 | .055 | 5 | 63.07 | 54.83 | 26.48 | .645 |
| 21 | 63.28 | 54.41 | 32.39 | .522 | 6 | 66.17 | 29.52 | 3.66 | .831 |
| 22 | 53.20 | 27.27 | 31.81 | .189 | 7 | 53.11 | 33.45 | 15.43 | .792 |
| 23 | 57.71 | 50.81 | 36.01 | .431 | 8 | 56.41 | 23.13 | 5.20 | .795 |
| 24 | 56.25 | 53.55 | 33.34 | .556 | 9 | 54.89 | 40.54 | 19.74 | .798 |
| 25 | 47.53 | 48.71 | 49.96 | .510 | 10 | 51.97 | 49.32 | 39.60 | .912 |
| 26 | 54.36 | 47.32 | 65.49 | .321 | 11 | 54.72 | 15.21 | 5.32 | .600 |
| 27 | 54.51 | 46.53 | 35.34 | .760 | 12 | 53.63 | 26.12 | 8.66 | .792 |
| 28 | 66.96 | 45.74 | 20.82 | .463 | 13 | 58.72 | 43.91 | 18.11 | .508 |
| 29 | 46.21 | 41.70 | 46.50 | .434 | 14 | 52.22 | 41.69 | 29.25 | .481 |
| 30 | 47.40 | 41.60 | 58.29 | .564 | 15 | 51.03 | 29.87 | 16.53 | .588 |

| $\overline{Y}_{cc}$ | $\overline{Y}_{fc}$ | $\overline{T}_c$ | | $\overline{Y}_{ce}$ | $\overline{Y}_{fe}$ | $\overline{T}_e$ |
|---|---|---|---|---|---|---|
| 55.67 | 44.36 | 39.32 | | 58.43 | 30.33 | 16.09 |

Model forms based on means of group performances on free path chokersetting (cycles 1 to 16)

| SS | $Y_{cc}$ | $Y_{fc}$ | $T_c$ | $R^2$ | SS | $Y_{ce}$ | $Y_{fe}$ | $T_e$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| All | 55.52 | 55.0 | 48.77 | .743 | All | 55.54 | 30.47 | 13.07 | .926 |

Model forms based on means of group performances on all sets (one through ten).

| SS | $Y_{cc}$ | $Y_{fc}$ | $T_c$ | $R^2$ | SS | $Y_{ce}$ | $Y_{fe}$ | $T_e$ | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| All | 102.25 | 40.0 | 25.85 | .25 | All | 92.21 | 15.82 | 1.97 | .54 |

transformation to performance by days or cumulative numbers of cycles produce similar model forms with marginally lower r-squared values.

The model forms are illustrated as Figure 14 along with the range of individual performances on each cycle. If the chokersetting task were similar to the FREE-PATH chokersetting task, these models of group means would be reasonable descriptors of the mean group performance of a control and experimental group. Controlled factories or electronic assembly plants with short cycle tasks exhibit these features as do experiments with learning in laboratories. Interpretation of the models shows the groups started at virtually the same point which is consistent with the design of the experiment. The groups learn at different rates as indicated by the T variables. The amount of gain for each group at the asymtotic performance level is less clear for interpretation. Based on model parameters, the experimental group would be expected to reach a reasonable asymtotic performance level of around 25 seconds for the task if the experiment were to be run for a long time. The control group has parameters established by bounding the maximum level of performance improvement ($Y_c$-$Y_f$) such that the improvement cannot produce negative (or very small performance times) inconsistent with reality. This is interpreted as a parameter used to produce the best fit for the observations of interest in the experiment. If the experiment were run for a very long time, it is likely that the parameter for the amount to be improved would change to some level consistent with that of the experimental group or to some limiting level of the physical environment. It is also true the learning parameter would change somewhat, but for the range of interest, not significantly.

The r-squared values for the fitted models also indicate higher variation for the control versus the experimental group. This is consistent with other measures shown above as well.

Individual Learning Curves for Subjects

Learning curves have been fitted to individual subjects for the control and experimental groups. Table 8 shows the values of the parameters with their associated r-squared values. In general, the experimental group has higher r-squared values than the control. For both groups the maximum amount of improvement was not allowed to produce negative performance times and the parameter $Y_f$ was bounded at the level of the initial performance time of the individual. Two of the control group and nine of the experimental did not need such bounding procedures for the modeling of individual subjects' parameters. For both groups models were fit without bounding and the parameters (if consistent with signs) were similar to those shown in table 8. The bounding procedure slightly changes the r-squared values but generally in the third decimal place.

Only one subject in the control group, subject 20, shows such little improvement and has such a low r-squared value as to question whether a learning effect is present. This result with this subject is consistent with data and observations described later (ratings and rankings). It is not inconceivable that one subject would learn either very slowly or not at all.

The parameters from individual subjects are used later to compare various pairings of subjects to answer the questions of whether proper selection of subjects could have been as effective as the training gains documented.

Means of Individual Performance Parameters

The mean values of the parameters of the individual subjects are listed in table 8. By way of comparison with the model forms based on the means of group performances, these mean parameters are of the correct magnitude and relation. The

implication in this is that the data sets are relatively consistent and it would not be unreasonable to compare future parameters for the same experiment with those of these groups.

Unpaired t-tests of the mean parameters of both groups show the starting points or initial performances to be statistically the same. The learning parameters are statistically different (and set at .05). Because of the bounding procedures, it is not reasonable to compare the $Y_f$ parameters. Were the experimental procedures a standardized task, parameters from future individual performances could be compared to those of the groups or individuals in the study.

## Model Forms Based on Means of Group Performances on All Sets by All Subjects

The model forms fitted to the entire data of ten sets are shown on the bottom of table 8. The variability in experimental yarding operations changes the r-squared values to substantially lower values. Also, the parameters are unique to the experimental conditions. Under actual yarding conditions, it is unlikely that data variability would reveal the extent of learning shown in Figure 15.

## Performance of Individual Subjects on Sets One through Ten

It is not possible to find learning curve forms for the individual subjects on the experiment. Data variability is too great as shown by the two example subjects in Figure 15 . Even when like chokersetting techniques are isolated in the data, it is not possible to discern learning effects of the type shown for FREE- PATH chokersetting or the means of group performances on sets one through ten. The smoothing response of averaging or removing variability is necessary to show the effects of learning unless the raw cumulative difference function is taken as evidence of learning gains. See figure 3 for a cumulative difference function.
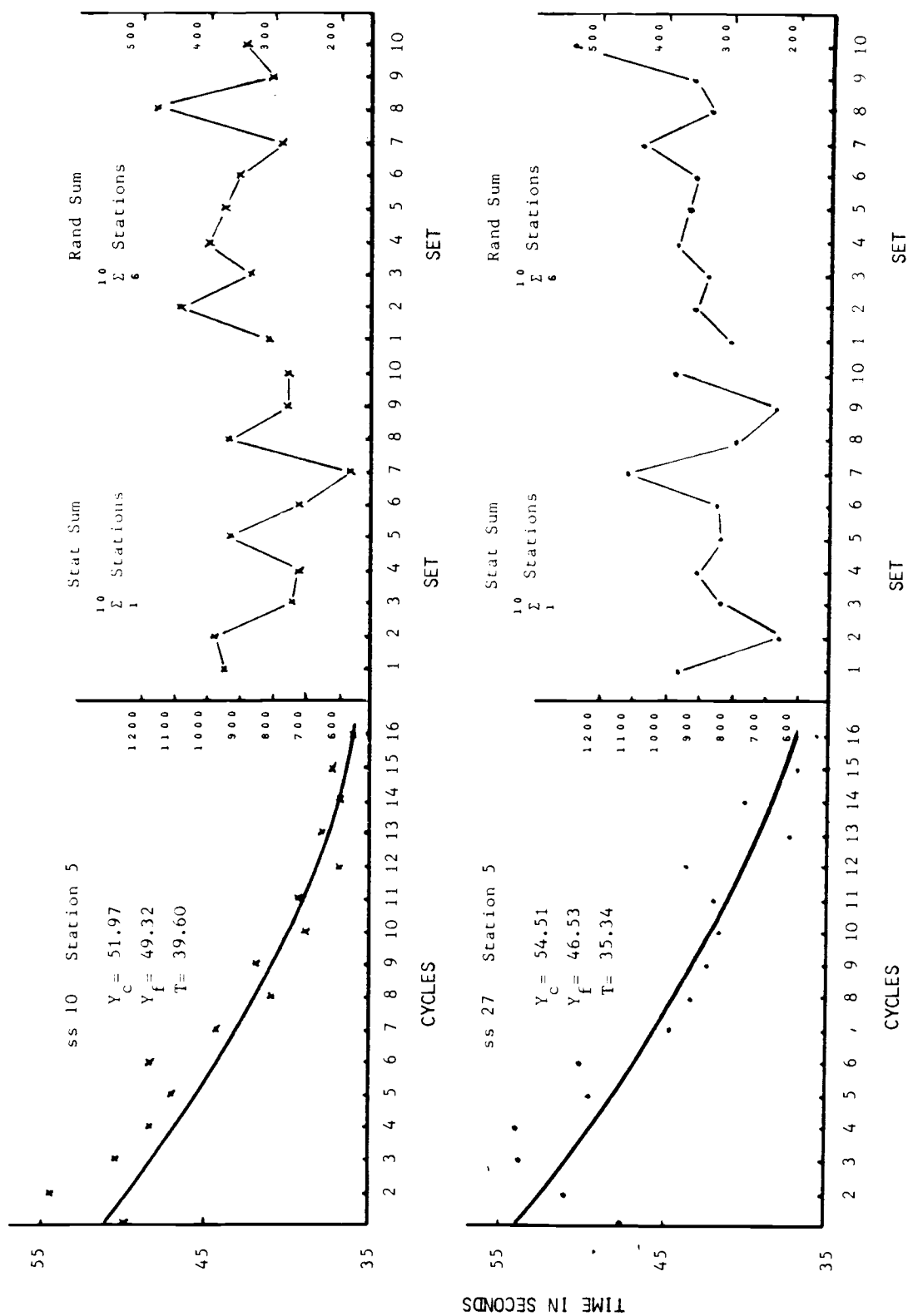
Figure 15. Example Performances on FREE-PATH, All Stations and Random Station Chokersetting
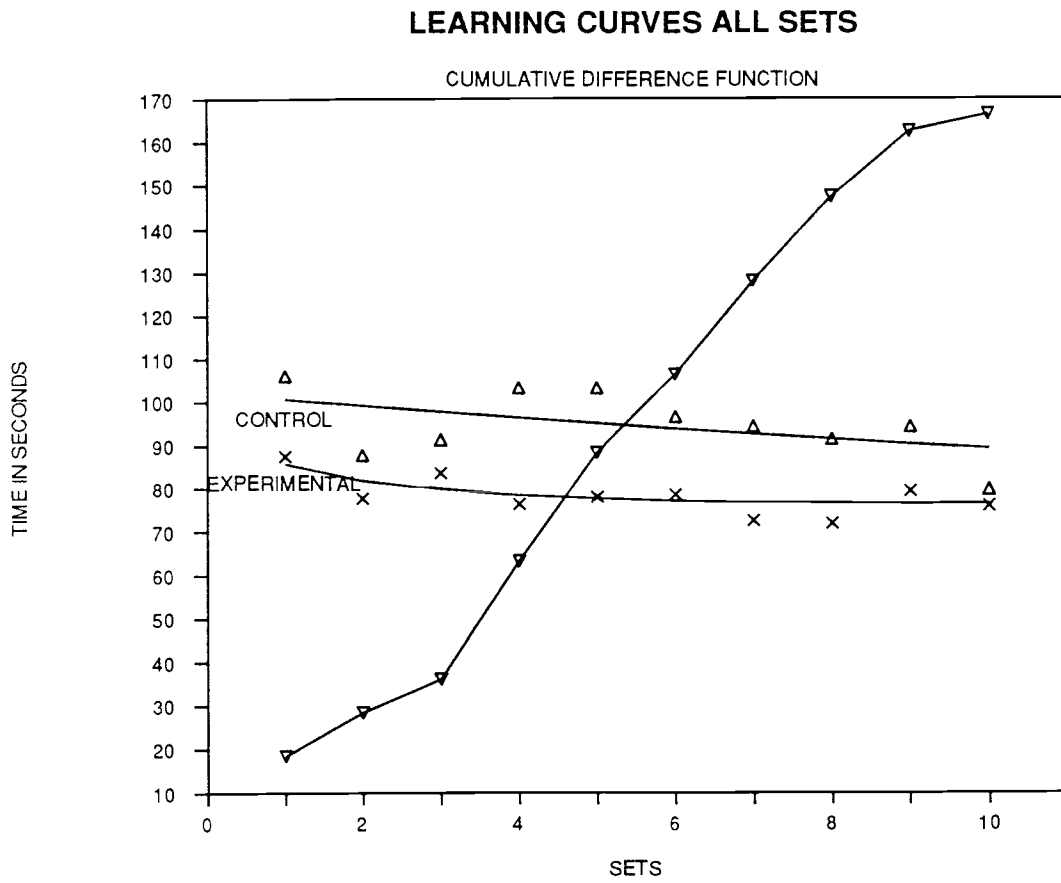
Figure 16. Learning Curves and Cumulative Differences

Cumulative Difference Forms

The cumulative difference form is obtained by subtracting two learning curves. The general form is shown in table 8 and using the parameters of the model for the group performances on the entire experiment, an estimate of the value of training can be derived after Towill and Bevis (1972). For the experiment above, the cumulative difference function is reduced by removing the $Y_c$ terms because the two groups started at virtually the same starting point in the individual model forms.

The cumulative difference function is complex to model directly because of the interaction of variables e.g. $T*Y$ terms make it difficult to isolate the contributions of each variable. Unless prior information is used to restrict the model development process or eliminate variables, the number of variables and their reflexive properties make it difficult to fit a cumulative difference model directly.

From a practical standpoint, the actual gains from training as reflected in the cumulative differences are what logging firms want to see. For the experiment, the cumulative difference data are shown in figure 16. The next chapter assigns economic value to the gains from the experiment.

The cumulative difference function has various forms that illustrate different learning outcomes. For this experiment, the cumulative difference functions for the learning curves of individual subjects gives these possibilities:

1. Control and experimental start at the same level and end at the same level -- learning is reflected in the T values which shape the cumulative difference curve.

2. Control and experimental start at different levels which could make the cumulative difference negative for a time depending on the rate of learning, T, to become positive.

3. Control and experimental end at different levels which could make a cumulative difference function start positive and go negative.

4. Various combinations of starting levels and ending levels, combined with different learning rates make unique forms of the cumulative difference function.

The above forms are shown in a later chapter to illustrate the sensitivity analysis of training gains.

## Comparisons of Chokersetting Techniques

There are basically six categories of chokersetting performance covered in the experiment. The magnitude and timing gains for FREE-PATH chokersetting and the entire experiment have already been discussed. Also, t-tests were performed to show the pattern of training gains for the total time on all tasks for the entire experiment. Listed in table 9 are the separate, unpaired t-tests for the categories of performance in the experiment over all performances in that category of chokersetting. The t-tests treat the entire experiment as a sample broken into the six categories. Table 9 shows significant differences in all categories except in the simplest technique of selecting which end of the log for setting the choker. These differences show the experimental group outperformed the control but they do not show the rates of learning.

Table 9. Training Gains by Chokersetting Category

| Category | Mean Values (secs.) | | T-Value | Significance (2-tail prob.) |
|---|---|---|---|---|
| | Control | Experimental | | |
| TOTAL TIME | 9528 | 7811 | 4.80 | .000 |
| RUB | 1597 | 1171 | 3.13 | .004 |
| ROLL | 849 | 599 | 3.52 | .001 |
| JUMP | 1312 | 1020 | 4.12 | .000 |
| END | 909 | 822 | 1.52 | .139 |
| RAND | 4385 | 3822 | 2.95 | .006 |
| FREE-PATH | 497 | 442 | 3.47 | .002 |

## Ratings and Rankings

The use of a rating to assess a worker's rate of performance is a cornerstone of time and motion analysis. Elaborate schemes have been developed for factory work to

develop the validity of ratings. Some similar prior work is available for logging tasks in

the rating area (Appelroth, 1988). For this project, both the chokersetter trainer and the

project leader rated the subjects within groups to check on the potential for the

relationship of rating to actual performance. The groups were also ranked in the same

fashion to determine if the commonly heard logger's boast, "I can tell a good

chokersetter by watching them work," has any basis. Ratings are given as values in the

range 0.7 to 1.3, meaning a rating of 0.7 indicates a work pace 30% slower than normal,

etc.

Rankings were between subjects within groups in the range 1 to 15, best to worst.

While raters conducted the time study of the project, summary statistics were not

reviewed prior to the rating activity.

Table 10 shows these ratings and rankings compared to the rankings based on

time, learning parameters, etc. Spearman's Rank Correlation Coefficient is used to test

whether rankings are substantially in agreement (Anonymous, Hewlett-Packard, 1976).

A $r_s$ value of -1 would indicate that rankings are in complete disagreement while a +1

would be complete agreement. The following interpretations may be extracted from

Table 10:

1.  Ratings by the project leader and the chokersetter trainer are reasonably
    consistent, but there is not an absolute relationship between ratings and total time
    on all stations.

2.  For the control group there is reasonable agreement between initial time on station
    five and total time on station five, $r_s = .444$. For the experimental group there is
    disagreement between these same rankings; those who did well on the initial time
    were not those who did well on the total time, $r_s = -.414$.

3.  There is relatively strong agreement between the project leader's ranking and the
    total time in the experiment for the control group, $r_s = .793$, and weak agreement
    for the chokersetter trainer's rankings and the total time rankings there is a weak
    agreement, $r_s < .22$.

4.  There is very weak agreement between the ranking learning parameters obtained
    on station five and the rankings for total time on the experiment.

Table 10. Ratings and Rankings

| SS | Ratings by | | | | Ranks | | | |
|---|---|---|---|---|---|---|---|---|
| | Trainer | Project Leader | Total Time | Initial Time on Station 5 | Total Time on Station 5 | Project Leader | Trainer | T on Station 5 |
| 30 | 1.2 | 1.0 | 11 | 1 | 3 | 10 | 1 | 12 |
| 29 | 1.0 | 1.1 | 9 | 2 | 1 | 7 | 10 | 7 |
| 28 | 1.0 | 0.9 | 13 | 3 | 14 | 12 | 8 | 5 |
| 27 | 1.0 | 1.1 | 4 | 4 | 6 | 8 | 7 | 4 |
| 26 | 0.9 | 0.9 | 7 | 5 | 11 | 13 | 9 | 14 |
| 25 | 1.0 | 1.2 | 3 | 7 | 2 | 2 | 11 | 8 |
| 24 | 1.1 | 1.1 | 12 | 12 | 4 | 6 | 3 | 2 |
| 23 | 0.9 | 1.0 | 5 | 9 | 10 | 5 | 5 | 9 |
| 22 | 0.9 | 1.0 | 10 | 11 | 5 | 11 | 12 | 1 |
| 21 | 0.9 | 0.9 | 1 | 14 | 13 | 4 | 13 | 10 |
| 20 | 0.7 | 0.7 | 15 | 15 | 15 | 15 | 14 | 15 |
| 19 | 0.7 | 0.8 | 14 | 10 | 12 | 14 | 15 | 6 |
| 18 | 1.1 | 1.0 | 6 | 8 | 7 | 3 | 4 | 13 |
| 17 | 1.2 | 1.0 | 2 | 6 | 8 | 1 | 2 | 3 |
| 16 | 1.1 | 1.1 | 8 | 12 | 9 | 9 | 6 | 11 |

+.444
.0946
.793
.2107
.029

Spearman's $r_s$

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 15 | 1.2 | 1.3 | 7 | 1 | 6 | 2 | 4 | 13 |
| 14 | 1.1 | 1.1 | 10 | 2 | 11 | 9 | 2 | 14 |
| 13 | 1.2 | 1.0 | 6 | 3 | 12 | 8 | 1 | 7 |
| 12 | 1.0 | 1.2 | 1 | 4 | 3 | 1 | 11 | 6 |
| 11 | 1.2 | 1.1 | 14 | 7 | 9 | 3 | 3 | 5 |
| 10 | 1.0 | 1.1 | 4 | 8 | 10 | 12 | 7 | 15 |
| 9 | 1.1 | 1.0 | 11 | 9 | 7 | 7 | 10 | 10 |
| 8 | 0.9 | 1.0 | 2 | 10 | 4 | 10 | 13 | 1 |
| 7 | 1.0 | 1.1 | 5 | 12 | 5 | 5 | 8 | 9 |
| 6 | 1.0 | 0.9 | 3 | 13 | 8 | 13 | 6 | 3 |
| 5 | 1.1 | 0.9 | 12 | 11 | 15 | 14 | 9 | 12 |
| 4 | 0.8 | 0.8 | 13 | 5 | 13 | 15 | 15 | 11 |
| 3 | 1.1 | 1.3 | 15 | 15 | 2 | 6 | 12 | 2 |
| 2 | 0.9 | 1.0 | 9 | 4 | 1 | 11 | 14 | 4 |
| 1 | 1.0 | 1.2 | 8 | 6 | 14 | 4 | 5 | 8 |

-.414
.118
.100
.064
.114

Spearman's $r_s$

The above relationships between rankings and ratings are incompletely developed and further development is suggested, such as a check list (Latham, 1971) for specific behaviors. Ratings and ranking were useful in assessing the performance of subject 20 in the control group. Data and models suggested slow performances and little, if any, learning. Subjective measures confirmed this prior to a review of the data or building the models.

## Summary of Results

A variety of statistical tests and data have been presented to show the results of the chokersetting training experiment. These results can best be summarized by a series of short statements.

1. The control and experimental groups started equally. The training caused some patterns of differences during the middle of the experiment, and at the end of the experiment, the two groups were coming together on various performances.

2. While learning curves cannot be fitted for the individuals on the entire experiment, learning curves can be fitted for free path chokersetting.

3. Learning curves and the cumulative difference function can be found for the entire experiment.

4. The ANOVA shows compelling evidence that the training effects are significant for the experiment.

5. Various data give insights on the training of chokersetters and performance on tasks.

6. Ratings and rankings provide weak information compared to objective measures of performance.

The statements above will be extended in the following chapter by incorporating the training gains of the experiment into the decision model for use by logging firms.

ECONOMIC IMPLICATIONS

The productivity gains by a designed training effort for chokersetters have been documented with a scientific experiment. An 18% time difference between the experimental and control groups was found for the experiment. The differences between groups must be incorporated into a model for the economic evaluation of training alternatives. The model should have meaning when viewed from the decisionmaker's perspective. The model should also reflect economic criteria such as the time value of money and marginal analysis. Finally, the model should treat probabilistic phenomenon and be capable of sensitivity analysis.

## The Model Revisited

The basic structure of the model has been introduced earlier and is now revisited for more explanation and elaboration starting with the basic model in figure 3. A full explanation of the curves shown in the model and the development of some others is offered later in this chapter. Three curves are of interest: $C_o$, the cumulative cost savings curve of training gains; I, the training investment curve; and $P_o$, the curve describing the probability that the worker will still be with the firm at time t. Two vertical axis are used on the graphical display: the scale of dollar resources refers to the $C_o$ curve while the scale of probabilities running from zero to one refers to the $P_o$ curve. The horizontal axis has a time dimension that covers the relevant period of costs and returns due to training.

Point R on the time scale is a point of interest because it describes where the cost of training has been recovered by the training gains. Riggs (1977, p. 122) notes the practical meaning of the recovery point, R: "Variations in the cost savings pattern ...

make economic analysis difficult because measurements taken at different periods
exhibit different savings-to-cost ratios of total savings to total costs over different time
intervals. "A yardstick of effectiveness for programs to improve personnel practices is
how long it takes for the savings resulting from a program to equal its cost. This
payback rating can be used to compare trials of different programs to determine which
areas deserve continuation" (see figure 6 for a graphical look at Riggs' statement).

While the payback criteria is widely used it is generally inadequate for economic
analyses because it often fails to account for the time value of money invested and does
not take into consideration the economic life of the assets (DeGarmo, Canada, and
Sullivan, 1979). The only criteria a payback measure addresses is the speed of
recovering investments or costs. That of course is a fundamental question in the
author's decision model. Do training gains accrue fast enough to recover the training
cost before the worker leaves the firm or changes jobs within the firm? By explicitly
considering the time value of money and the "economic" life of training through the
cumulative cost savings curve, the recovery point, R, becomes much more meaningful
than a conventional payback point. In addition, the probability of the worker remaining
with the firm is a central question. While decisionmakers may view the recovery point,
R, in relation to the curve $P_o$, the probability curve needs to be explicitly treated in the
decision. The reader can see that if the worker leaves the firm at $P_1$, the training
investment has not been recouped; whereas, at $P_2$ and beyond, the training investment
has been recovered. The difference between the $C_o$ curve and I curve represents a gain
to the firm in excess of the cost of training plus interest on the resources used for
training.

The decision to incorporate compounding in the model is largely a matter of whether the gains accrue at a sufficiently fast pace or not. For the chokersetting experiment, gains accrue so rapidly that compounding of costs or gains is not relevant. This is not the general case for the model. For some types of logging jobs, such as machine operation or complex manual tasks (timber felling), the time for gains from training may be years. Also, firms may devise various schedules of payments and these schemes may extend over such periods as to make interest concerns of importance. Finally, the level of training costs may be such that the source of funding may be borrowed funds or at least, funds which should earn interest from alternative investments.

## Development of the Curves in the Model

Three viewpoints are adopted to explain the curves in the logging training decision model: the first viewpoint is from a world of perfect information; the second viewpoint is from the experiment; and the third viewpoint is from logging firms facing a world of variation and imperfect information. Compromises on the certainty of information provided by the decision methodology are necessary at each viewpoint, and modification of the decision methodology itself is necessary as imperfect information is utilized.

Theoretical Development: Perfect Information, No Variation

It is assumed that learning curves exist for logging tasks with only the variation associated with training present. The cumulative difference function is formed and gains are associated with the cumulative difference function through differentiable functions. The job leaving probability density function is known and can be integrated.

The time dimension is uniform across all curves brought together; no scaling problems exist. The expected value function of the training decision is the criteria for designed training in the logging firm.

Gains Due to Logging Training. The gains due to training are reflected in the cumulative difference function of two learning curves (after Towill, 1972). For a curve using time saved over the cycles performed, the transformation is a straightforward multiplication of system cost per unit time. This assumes that the system could effectively use the time saved on productive activities. Total system cost is an appropriate multiplier for yarding systems where the pace of the entire operation is dependent on the slowest chokersetter.

Training Investment Curve, I. The training investment curve, I, is found by accumulating the amount of money invested in training to the start of operations. In the absence of compound interest, the curve would be a straight line across figure 3. Continuous compounding would form the shape of a monotonically increasing, concave function. The shape of the training investment curve is a management decision by the firm.

For the analysis of the experiment a single "lump" of training costs are incurred just at the start of the trainees performance. Other patterns of training investment could be incorporated into the model including various step functions to coincide with decisions to remain with the firm by the trainee as shown in later discussions of sensitivity analysis.

Job Leaving and Survivor Curves. It would be ideal if firms had data on job change experience for occupations that allowed probability estimates to be made for individual

firms. Life analysis of the type by Barta (1976) would describe the "retirement" (job

leaving) frequency curve of an occupation and the "survivor curve" to be used in the

author's decision model. "Retirement" would be defined to be any movement out of a

particular occupation. Figure 17 below describes the retirement frequency curve and

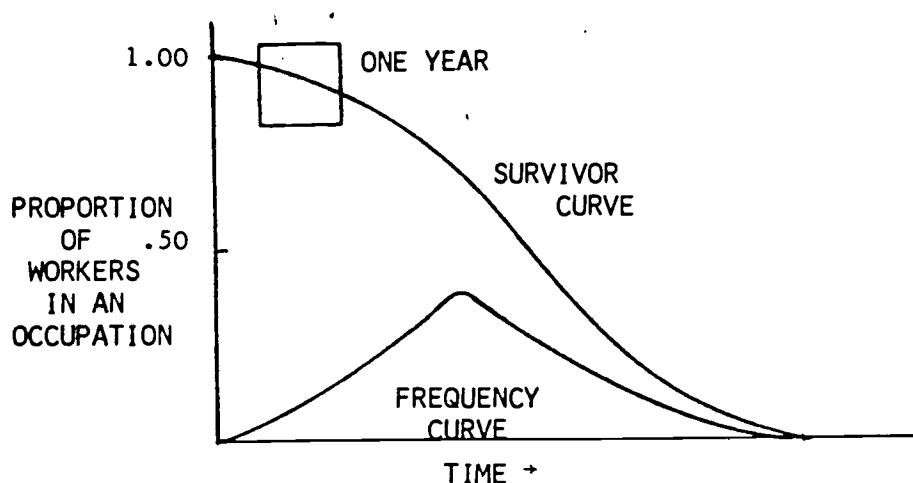the survivor curve for the entire life of an occupation.



Figure 17. Retirement Frequency Curve and Survivor Curve (after Barta, 1976)

The probability density function described by the frequency curve above is given for

job leaving to be f(t) while the survivor curve is a complementary cumulative density

function given by $P_o(t) = 1.0 - \int_o^t f(x)dx$. The period of interest on t is not the entire

time starting at t = 0 until t' where $P_o(t') = 0$. The period of time is related to the

decisionmaker's time horizon, i.e. one year as in Figure 17.

Expected Value of the Training Decision. From a theoretical viewpoint, the decisionmaker in a logging firm would invest in logging training if the expected value of training were positive in the interval of interest. The decision model is shown below in the continuous form where:

$$E_{v(t)} = C_{o(t)}P_{o(t)} - I_{(t)} - W(1 - P_{o(t)})$$

where,

$t$ = Interval of interest
$E_v$ = Expected value of the training decision
$C_o$ = Cumulative difference function for two learning curves appropriately valued for the firms logging conditions
$I$ = Training investment, an initial sum compounded (if appropriate at a specified interest rate) or a schedule of training investments
$P_o$ = Job staying probability from survivor curve
$W$ = Penalty cost for replacing workers; assumed to be small for this example
$R$ = Recovery point where a deterministic view of the decision has training gains equal costs (no job changing)
$R'$ = Recovery point where $E_v$ becomes positive for probabilistic view of the decision (includes expected job changing)

The expected value function is formed by perfect knowledge of workers decisions to leave the firm. With some early probability that the worker might leave the firm, the small gains accruing are reduced by the fact that there is some probability of not receiving them. Thus, the expected value function starts negatively and rises as the gains accrue modified by the probability of the worker learning. The expected value function shown in figure 18 is a series of expected value computations at various points in time.

The recovery point $R$ is the point where cumulative cost savings exceed the cost of training where the worker is certain to stay with the firm at least in the interval of interest. The $R'$ recovery point with risk is the point where the expected gain function becomes positive for the long run probabilistic outcomes of workers receiving training,

returning expected gains and leaving the firm according to the probabilistic function
underlying the survivor curve. The general form of the expected gain is illustrated in
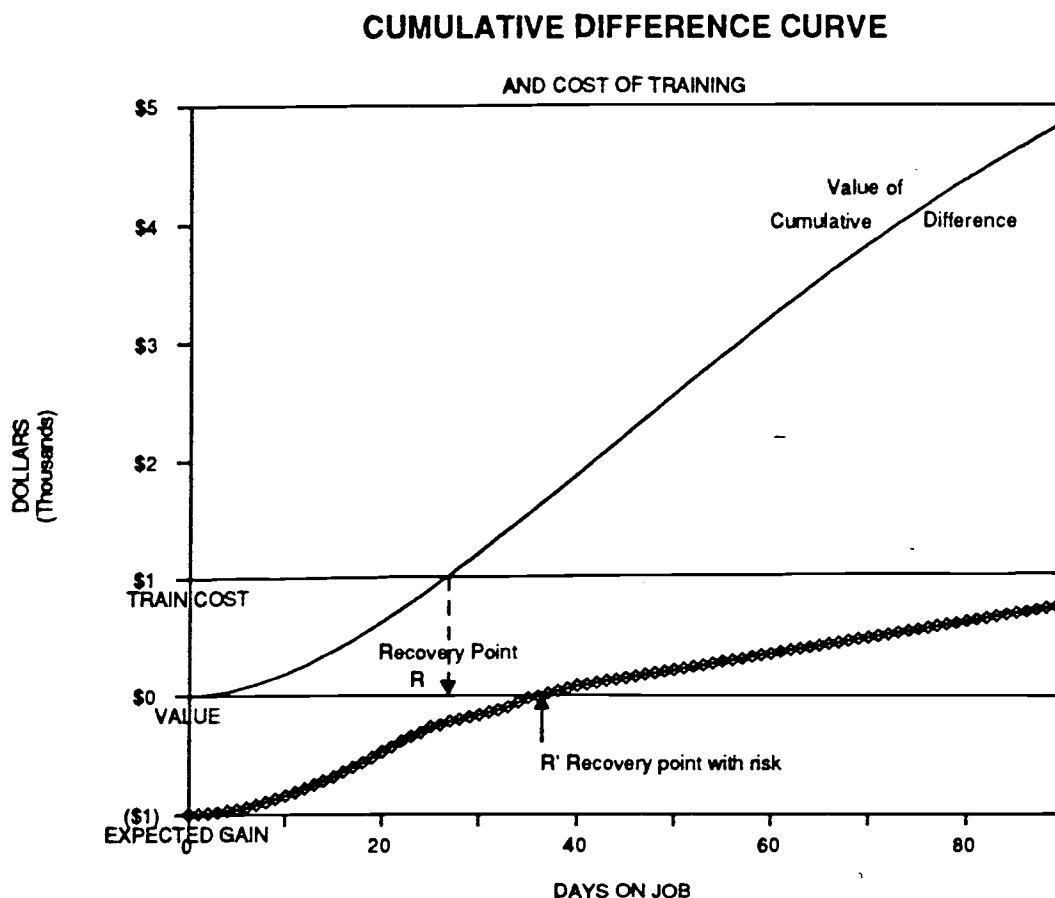Figure 18.

## CUMULATIVE DIFFERENCE CURVE

**AND COST OF TRAINING**



Figure 18. Decision Framework.

The Penalty Cost for Workers Leaving the Firm, W. In the model above, logging firms
might consider the costs of replacing workers who leave the firm. Such costs include
recruiting, selection, costs to train up to point of the leaving worker, delays from
working below full staffing, etc. However, these costs have been assumed to be low for
the logging industry at present, and are therefore, excluded from the analysis further in
this assessment.

Gains from the Experiment

Moving away from a world of perfect information and known functional forms we examine the experiment and attempt to decision model. Just as the decision model is an abstraction, the experiment has been abstracted from actual yarding operations to the experimental setting in order to document training gains. The problem is to translate experimental results that are appropriately scaled to actual yarding operations into data for application of the model.

Scaling the Experimental Gains

The training experiment measures the training gains from fifteen chokersetters in a control or experimental group setting chokers on 1500 cycles each. An alternative experiment would have been to look at two chokersetters, one receiving the training of the experimental group, the other receiving the standard training of industry. Certainly, during the six weeks of the experiment, more cycles could have been completed by each of the subjects, perhaps as much as fifteen times as many cycles. However, the results would be strictly limited to two subjects alone and there would be no way to match the control or experimental subjects as was done in the current experimental design. Earlier research indicated variation among subjects to be especially important as well (Cottell, et. al., 1974).

How then can the experimental results be scaled to actual yarding operations from which the experiment was abstracted? Two views are possible. First, the experiment can be viewed as a firm hiring fifteen chokersetters and giving them the dose of training described for the experiment and hiring an additional fifteen chokersetters and training them in the usual fashion. With this unusual work arrangement, each subject worker

would alternatively work in the yarding operation for the number of cycles each subject performed in the experiment. Differences in performance between groups would be summarized after various numbers of cycles corresponding to the log sets of the experiment. The time saved would be plotted on a cumulative difference function for each measurement point. A cumulative difference function similar to the one of Figure 18 would result.

A second view is also possible. The gains of fifteen control and experimental subjects are representative, when averaged, of what a firm might expect from picking any two "average" workers. The difference in performance resulting from the difference in training given. At the measurement points in the experiment corresponding to log sets, the performance of the control "average" and the experimental "average" would yield some differences. Taken as a cumulative difference function, the result would be the same values as in viewpoint one above.

The major difference between the experimental setting and actual chokersetting experience is the number of cycles performed by subjects during the experiment and what an actual beginning chokersetter would face in an operation. Certainly under some actual conditions, new chokersetters could perform many more cycles but not vastly more cycles than those performed by the control or experimental groups per day (Mahon, 1985). It is the author's judgement that the experimental chokersetting conditions and the learning differences associated with them are representative of the magnitude of gains with similar training operating in controlled field situations.

The chokersetting tasks selected for the experiment contained difficulties related to skill acquisition rather than repeated cycles of free path chokersetting. Experience

leading to behavioral changes in subjects is likely gained from performing tasks and seeing their results rather than repeating empty learning tasks. Loggers who have seen the experimental apparatus and procedures have not challenged the outcomes.

It is doubtful that additional cycles in chokersetting beyond those performed by the subjects in the experiment would have substantially changed the outcome of the experiment. The chokersetting task was selected for its reasonable simplicity and because it is the entry level task for new woodsworkers. It can be mentioned that when the experienced chokersetter trainer performed the experimental tasks, his performance was similar to those of subjects during the latter stages of the experiment. The experimental procedures are not claimed to hold for complex tasks of machine operation or other complex manual tasks, e.g. tree felling.

The fundamental question is whether the magnitude and timing of gains due to training are represented by the cumulative difference function. As a starting point in research on assessing gains from chokersetter training, the cumulative difference function of time from the experiment can be matched by a hypothetical logging operation using chokersetters similarly to those of the experimental conditions. If the hypothetical operation using a control and experimental (trained) chokersetter yields the same cumulative difference function, a match is obtained and results of the experiment are scaled to the hypothetical operation.

Given the same operating conditions of the hypothetical logging firm, a match can be found for the cumulative difference function of the experiment. Ranging functions of many common spreadsheet programs can help find such a match if certain model parameters or conditions are supplied. In the experiment, the starting points are the same for both control and experimental groups, and it may be assumed, the control group might eventually reach the same performance level in chokersetting tasks.

Finding a match from among trial parameters can be an iterative procedure that minimizes a sum of squares value between the experimental cumulative difference function and that of the hypothetical logging firm. Sufficient accuracy may even by obtained from visual inspection of graphical plots of the two functions. This procedure has been used to find a matching operation to the experimental results below.

Gains due to Training Chokersetters

Using the cumulative difference function of the experiment and making assumptions about the hypothetical operation, a match between the two cumulative difference functions has been found using the visual inspection procedure of matching the graphical results of the cumulative time savings.

The distribution of time on chokersetting tasks is presumed to be 50% of yarding time and the number of cycles per day is based on the chokersetting time available. The starting point for the chokersetting task is 7.0 minutes for both control and experimental groups. Both groups are assumed capable of eventually reaching an asymtotic performance level of 4.0 minutes. The learning parameters found for the control and experimental subjects were 45 days and 30 days respectively. The resulting smoother learning curves for these parameters are shown as Figure 19. The resulting cumulative difference function that matches experimental results is given in Figure 18. Cost of the operation is assumed to be $200 per hour. Time-per-cycle saved between control and experimental is multiplied by the time cost and accumulated as the cumulative difference function.

Training Cost Curve I

The training cost curve for the experiment is difficult to specify for the training provided to the experimental group. Certainly, the half day of training would cost less than $1,000. Thus, the amount is arbitrarily set as that figure. Various cost schedules for training may be conceived, but for low levels of training such as for the chokersetting task, a single lump cost at the beginning of the trainee's work operation is easiest to consider.

The most glaring deficiency of logging training is that it is currently impossible to specify what gains might accrue from a level of training cost inputs. Equivalent results from training may be obtained from low dollar inputs as well as from high cost training schemes. The effectiveness of training depends more on the design of the training rather than the cost of the training itself.

Job Change (Survivor) Curve, $P_o(t)$

The development of the job change probability curve, $P_o$, for a firm requires data collection and analysis which identifies the proportion of workers changing jobs (leaving the firm) at various points in time. The job leaving probability density function is often difficult to analyze because of problems with integration (Barta, 1976). However, the discrete forms may be identified as in Figure 20. The classes of time associated with the job leaving proportions may be added to form the cumulative frequency distribution of job leaving for each $\Delta t$ or class equivalent to $t = 1, 2, \ldots$ etc. A smooth curve may be fitted to the midpoints of the classes to form the cumulative frequency distribution of job leaving. The survivor curve or probability of staying on the job is given by the complementary cumulative frequency curve of job leaving.
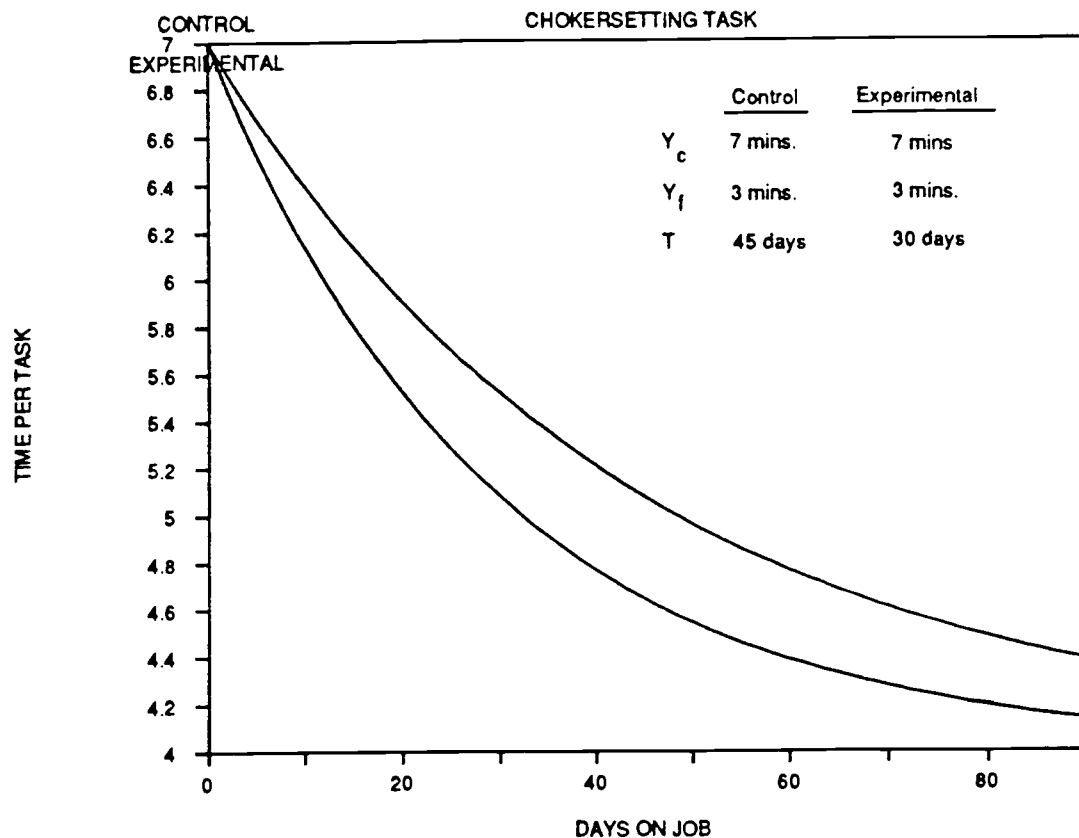
## SAMPLE LEARNING CURVES



Figure 19. Example Application of Chokersetting Training

The actual discrete complementary cumulative frequency distribution would be utilized by the firm if available, but small firms may lack the sample size to develop the survivor curve. For this reason, industry wide survivor curves for various logging occupations have been developed by the author.

Industry Job Leaving. The magnitude of job leaving in the logging industry has been documented by Sorenson, et. al. (1979). Listed in Table 11 are the percentages of peak employment levels that left the average Oregon logging firm in the year 1978 for the various logging occupations. These are average rates of job leaving activity for the

firms in the survey; however, some firms had little job leaving activity, while others had

rates in excess of 500%. Workers in that occupation for that firm turned over five times

during the year.

Table 11. Job Leaving Percentages

| | | | |
|---|---|---|---|
| Rigging Crew (inc. chokersetters) | 38% | Landing Crew | 24% |
| Skidding Machine Operator | 23% | Log Truck Drivers | 33% |
| Loader Operator | 7% | Logging Supervisors | 7% |
| Fallers and Buckers | 19% | Total--all occupations | 24% |
| Yarder Operator | 21% | | |
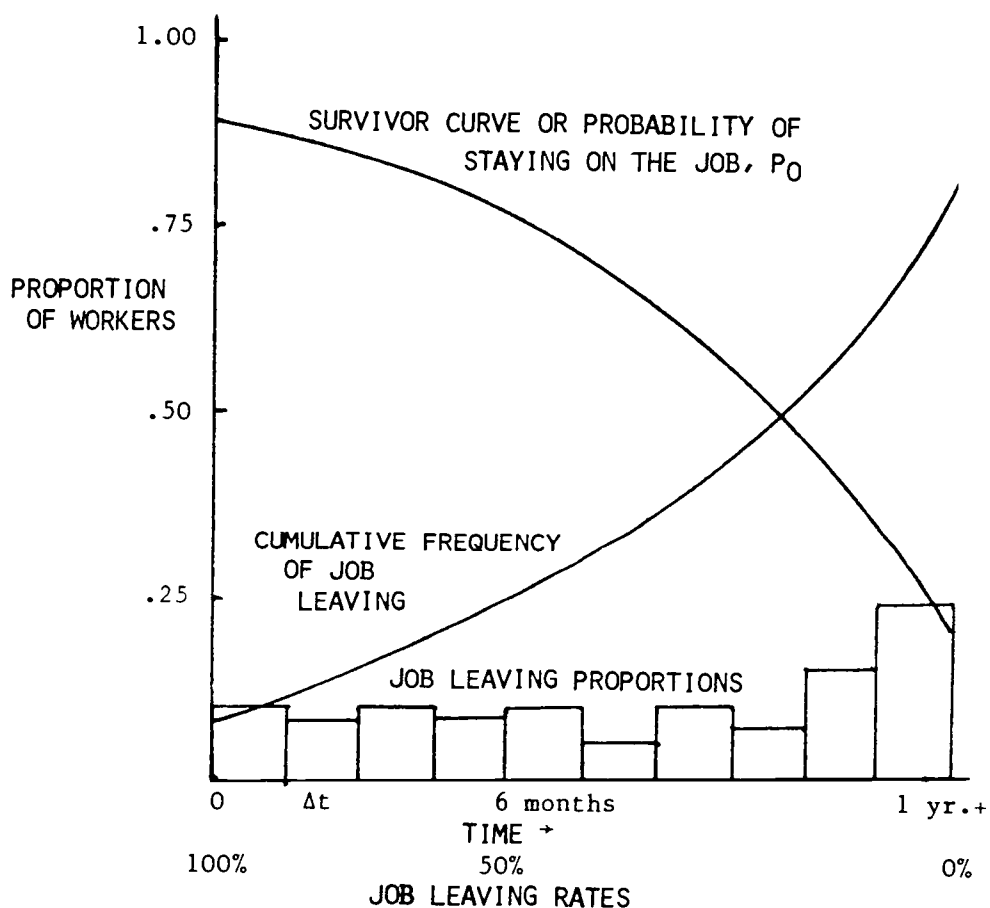
Figure 20. Development of the job change probabilities.

The job leaving rates for firms in the industry wide survey by Sorenson, et. al. (1979) can provide data for development of a job leaving distribution and the survivor curve. For various occupations the author has found curves using the data of Sorenson, et. al. (1979). The $P_o$ curves were formed by fitting an exponential model of the form, $P_o(t) = 1. -Le^{tc}$, where t is the time variable and c is the parameter fitting the distribution. The value, L, is the percentage of firms that have very high job leaving rates (in excess of 100%) which corresponds to a propensity to change employers at any time. Thus, when L = .11, 11% of the firms experienced job leaving rates where the entire workforce in an occupation turned over. The probability of a worker staying with the firm immediately after training is around .89. Conversely, an L value of .02 would indicate very little early job leaving in a particular occupation for the industry.

Table 12 shows the job changing distributions for the various occupations in logging. They are the complementary cumulative distributions of job leaving by firms for 1978, and fitted to the model of the form, $P_o(t) - 1.-Le^{tc}$ (t = 1,2, ... 12). The model parameters have been described above. The curves fitted below are only valid for t less than 12 months.

Table 12. Job Changing Distributions

| Job or Occupation | L, Probability of Leaving firm immediately after training | C, Change Parameter |
|---|---|---|
| Rigging Crew | .110 | .175267 |
| Skidding Machine Operator | .029 | .238621 |
| Loader Operator | .000001 | .889290 |
| Fallers and Buckers | .020 | .274835 |
| Yarder Operator | .020 | .024358 |
| Landing Crew | .085 | .143970 |
| Log Truck Drivers | .048 | .189902 |
| Logging Supervisors | .021 | .195492 |
| Total All Occupations | .022 | .316575 |

The measures in Table 12 reflect industry-wide job leaving in a particular occupation and may not reflect the job leaving within a firm. Logging firms should use their own job leaving experience in a $P_o$ curve.

Job Leaving of the Firm. For the experiment, data in table 13 have been used from data of a firm which experienced thirty-two chokersetters leaving the firm. Data are the proportion of the thirty-two job leavers who stayed at least one month, two months, etc. It is presumed that woodsworkers will not remain chokersetters forever and the only concern of the firm are those chokersetters who leave prematurely, e.g. less than about 10 months in the sample data. These are the data used for the expected gains in Figure 18.

Expected Gains from the Experiment

The decision methodology can be visualized as an interpretation of Figure 18. The training cost I is taken as a flat line which indicates current operating funds are used without interest considerations. The value of the $C_o$ curve is obtained from matching the experimental results with data from a typical firm. It also does not reflect interest considerations. In a certain world, where there was no chance of a trained worker leaving the firm, the point of recovery, R, is reached after 26 days.

The true situation is that a worker has some probability of leaving the firm. Using the data from job staying of chokersetters above (table 13), the expected value function can be formed to show the expected gains. The expected gains start out negative because there is some risk the worker will leave after small cumulative difference values have accrued. At the point where expected gains become positive, R' about 37

days, the firm's expectation is to recoup its training investment. The form of the

expected value function represents a series of decisions about training effects and the

likelihood the trained worker will remain with the firm.

Table 13. Chokersetter Job Staying (Survivor Curve).

| t = months | Proportion of workers |
|---|---|
| 1 | .844 |
| 2 | .625 |
| 3 | .344 |
| 4 | .286 |
| 5 | .282 |
| 6 | .219 |
| 7 | .219 |
| 8 | .219 |
| 9 | .219 |
| 10 | .156 |
| 11 | .156 |
| 12+ | .156 |

n = 32 chokersetters who left the sample firm

If the expected gains never become positive, the series of decisions would indicate

that there is little likelihood the training investment would be recouped. Thus, the

decisionmaker might conclude the cumulative difference values are insufficient, the

cost of training was too much, the risk of a trained worker leaving too great, or some

combination of these outcomes.

If the expected gains become positive, the firm would likely recoup its training

investment in the time frame of interest. Expected gains do not continue upwards

rapidly much beyond 60 days because there is an increase in job leaving in the

probability data used. This effect mirrors reality in that after 60 days, chokersetters may

leave the firm or shift to a different job within the firm at about this point in time.

If the penalty cost function, W, were some component of the firm's decision methodology, the recovery point, R', would occur somewhat earlier. As present penalty costs for workers leaving the firm are now thought small compared to training costs, they are not included here. This perception of low penalty costs may not be accurate now or especially in the future.

## Development of the Training Decision from the Perspective of the Logging Firm

The individual logging firm faced with the economic decision whether to invest resources in training chokersetters or other woodsworkers operates in a complex environment. A firm faces much variation and lacks information. In contrast to the decision model developed from a theoretical perspective and from the designed experiment, the following salient differences are noted:

1. Operating conditions with variation in firms may mask differences attributable to training.
2. Firms lack control or comparative group or individuals to assess training gains.
3. Firms have not developed job change distributions.
4. Firms face small sample sizes from which to project results.
5. Firms have limited understanding of the concept of expected values or the time horizon effects of the training decision.

These differences require sound judgements and extrapolations to use the decision model.

## The Gains Due to Training: Percent Difference

Cumulative cost savings curves of the type developed earlier are difficult to develop from resources available to a typical logging firm. First, the firm size is likely to be too small to make a comparison between a control and experimental group. Second, the logging conditions will be extremely variable from day-to-day, and

managers may have difficulty assessing the training gains amid large variations in production. Logging managers may be able to estimate the average percent difference due to improved training during the period while the training group is progressing to an ultimate performance level. A few firms may have record-keeping systems sensitive enough to estimate percent differences due to training. The majority of firms would likely rely on estimates of first line supervisors. Given that the chokersetting experiment produced average differences between the control and experimental group of 18%, the magnitude of expected differences would likely be in the 0 - 30% range (author's estimate).

The estimated average percent difference must be translated into dollar terms to develop a cumulative cost savings curve. Nearly all logging activity is viewed as a cost center from a business perspective. Within the firm, an average difference due to training may be translated into dollar terms as a percent of the cost saved for period of time, i.e. one day. The other significant influence on cost saving projections is the frequency of task occurrence for the task associated with the training. For chokersetting, the daily frequency for typical logging operations ranges from 40% to nearly 60% of the eight hour day. The third determinant of cost savings due to training is the hourly system cost of the system. For a single worker that may be as low as the direct hourly wages to as high as the entire logging system cost if an individual controls the entire production rate of the system. Finally, the last determinant of the training gains is the period of time along the curved portion of the learning curve until ultimate performance is reached by the control or comparison group.

A nomograph has been prepared to help estimate daily cost savings in Figure 21. Users enter the task frequency in an eight hour day, read across to the system operating cost, turn to the estimate of percent difference due to training, and turn to read the daily

cost savings. This figure is then multiplied by the estimated period of operating days that training gains could be expected. This value then is the raw estimate of the cumulative cost savings value. Plotted over time, the cumulative cost savings curve estimated in this fashion is a stairstep function in the discrete case and a straight line in the continuous case. While compounding of cost savings is necessary for theoretical completeness, logging firms are likely to use simple analysis without compounding or discounting.

Job Change Distribution

While considerable job leaving occurs within logging firms at the chokersetter level, firms lack records or have such a small sample size that development of a distribution is difficult. Where records exist covering sufficient job leaving activity, a distribution should be utilized as described above. Where records within the firm are not usable, the logging manager has at least two choices to incorporate job leaving (or staying) into the decision: industry-wide job leaving distributions such as those developed earlier, or the firm may develop its own subjective probability estimates for job leaving. The first approach assumes the firm mirrors the job changing activity of the entire industry of the past, while the second approach requires difficult probability estimation procedures. The logging manager who chooses to ignore the probabilities of job leaving in the decision is likely to make erroneous decisions associated with training investments. Unless sensitivity analysis of the job change component of the decision shows that it does not significantly alter training decisions, logging firms must cope with the risks of losing trained workers.
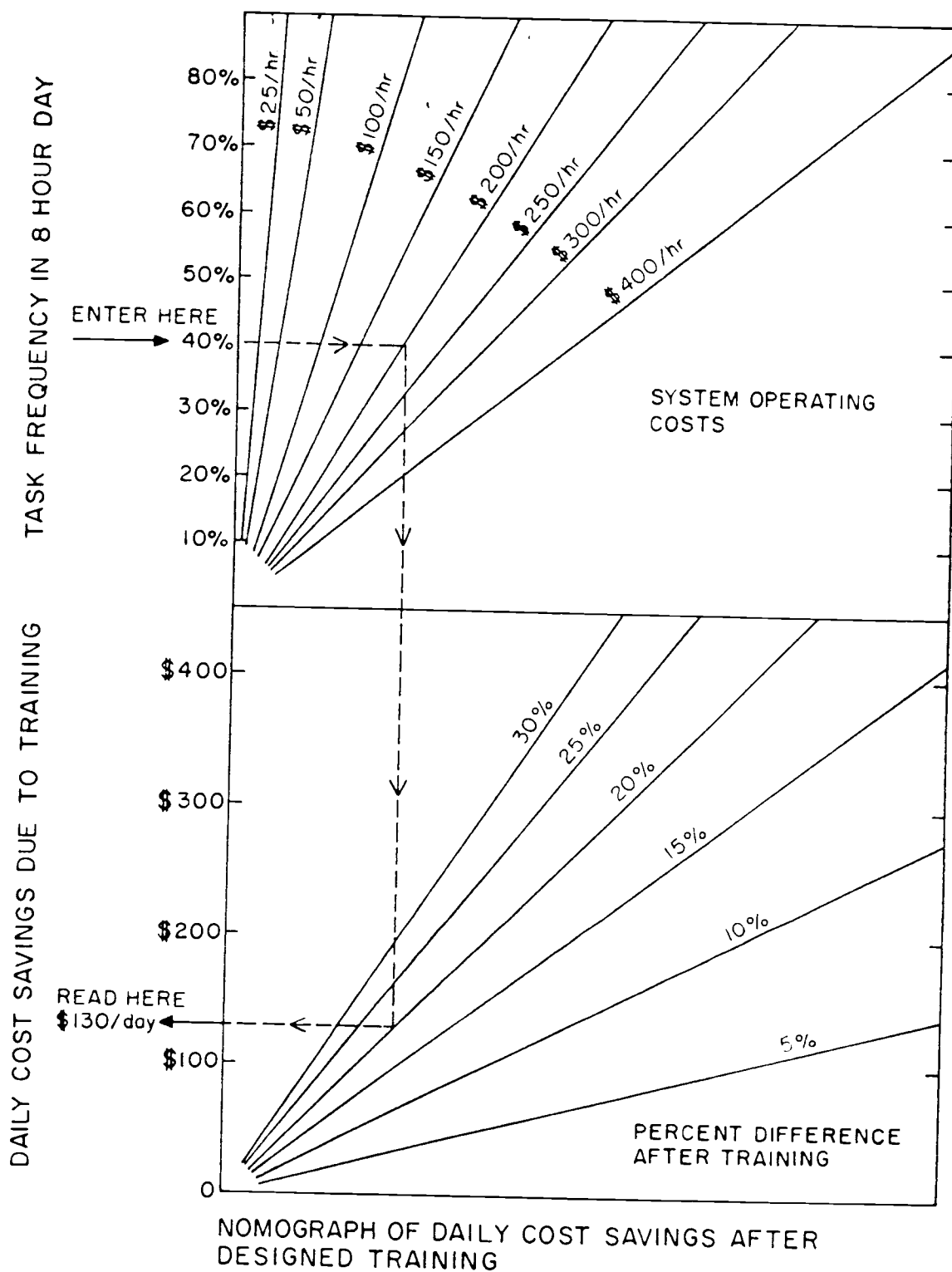
Figure 21. Nomograph of Daily Cost Savings After Designed Training

The Training Investment Curve for a Logging Firm

Estimating the training investment within a logging firm is likely to produce crude approximations until the firm gains some experience with logging training. There is no developed market place for training services to the logging industry that provides a schedule of services and fees for logging training purchased from outside the firm. The firm may need to estimate its own involvement and resource commitments at a crude level for assessment purposes and develop accounting procedures to refine the costs of training. For assessment purposes, a lump sum should be identified as the cost of training, Y, shown in earlier development of the $I(t)$ function. When the single cost of training or the investment in training is identified, the procedures for developing the $I(t)$ function are identical to those described earlier for the theoretical development and development associated with the experiment.

Expected Value of Logging Training for the Firm

Using the methodology of development for the firm as described above, the components associated with the training investment. Figure 22 shows the decision components viewed from the firm's perspective. The $C_o(t)$ curve is an upward sloping line to the point in time where the cumulative gains reach a maximum and then levels out at the point where a group not receiving the training has reached the same level of production (an assumption for the case under consideration). The $I(t)$ curve is a flat line of the training investment level. The $P_o(t)$ function is discrete probability estimates of job staying for the firm's future experience. The penalty cost function $W(t)$ is a uniform amount charged the firm for replacing a worker who left after training. The expected value of the decision requires determining a time horizon for analysis. The impact of the time value, t, has been determined earlier; the firm need only select an appropriate

time value, n, such as the total length of service as a chokersetter, one year, one logging season, etc. If the time value, n, is short relative to the effects of compounding, the time value of money may be ignored. The expected value then is given by numerical analysis from the form below:

$$E_v(n) = \sum_{t=1}^{n} [(\Delta C_o(t) - I(t))]P_o(t) - \sum_{t=1}^{n} [W(t)] (1.0 - P_o(t))$$

The decision to conduct logging training should be favorable if $E_v(n) > 0$. If the time value of money is included in the analysis and $E_v(n) \geq 0$, the interpretation of the decision is as follows: A positive $E_v(n)$ indicates that the training provides an expected return on funds used for training at interest rates at least as great as the interest rate used to compound the training investment.
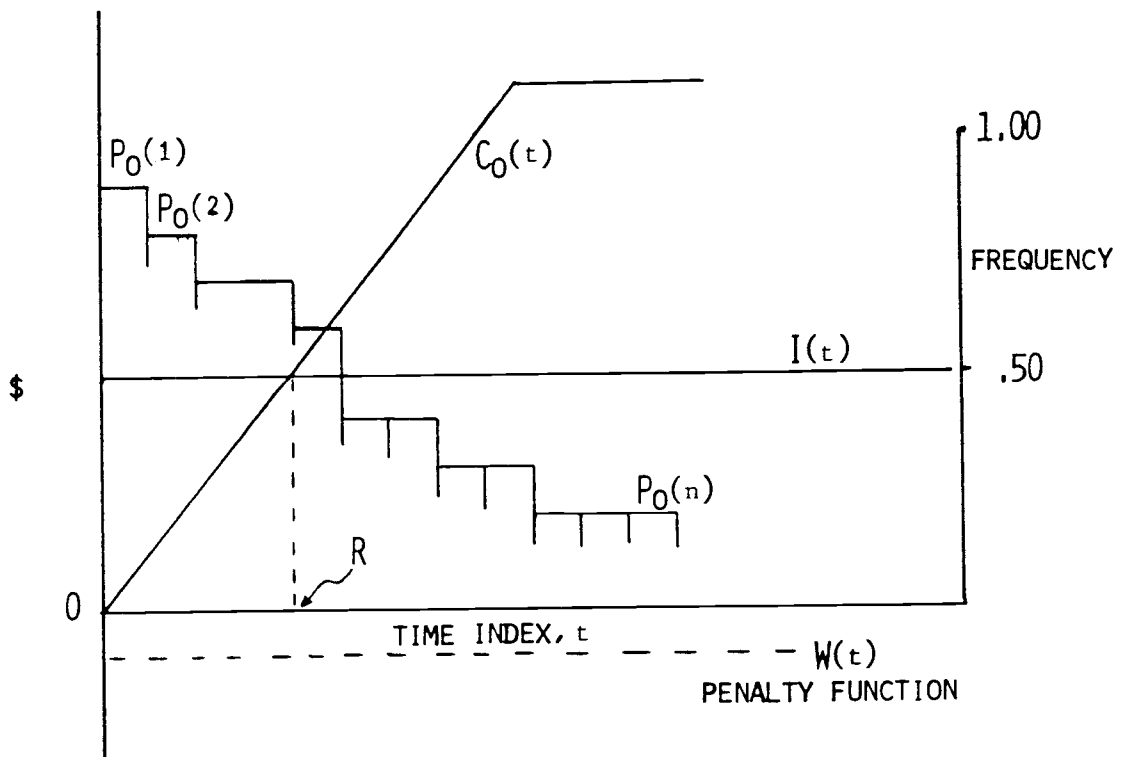


Figure 22. Logging Training Model for the Firm

# SENSITIVITY ANALYSIS AND EXTENSIONS THROUGH SIMULATION

The experiment provided a useful basis to better understand logging training within the firm. More can be learned from closer examination of the structure of the decision framework through sensitivity analysis. Also, simulation provides a powerful tool to extend knowledge of the experiment to expected actual conditions. This chapter first conducts sensitivity analysis and then extends results with simulation.

## Sensitivity Analysis

No decision is fully considered without assessing how changes in the magnitude of the variables influencing the decision affect the ultimate overall decision. This sensitivity analysis provides vital information to decisionmakers. For logging managers who are considering investments in logging training, sensitivity analysis shows where to place information gathering efforts for refining the decision. For purposes of this treatise, sensitivity analysis is conducted from two perspectives: the theoretical perspective and the perspective of the logging firm.

### Cumulative Cost Savings Curve, $C_o(t)$

The shape of the cumulative cost savings curve has been derived for theoretical conditions as a sigmoid shaped curve of the difference between two learning curves. The shapes of the two learning curves determine the cumulative cost saving curve. Possible learning curve shapes are roughly transformed into the cumulative difference function in Figure 23. Other curves may be examined in a sensitivity analysis exercise.

## Typical Form



## Experimental Reaches Higher Ultimate
## Level of Production Rate



## Experimental Starts at a Lower
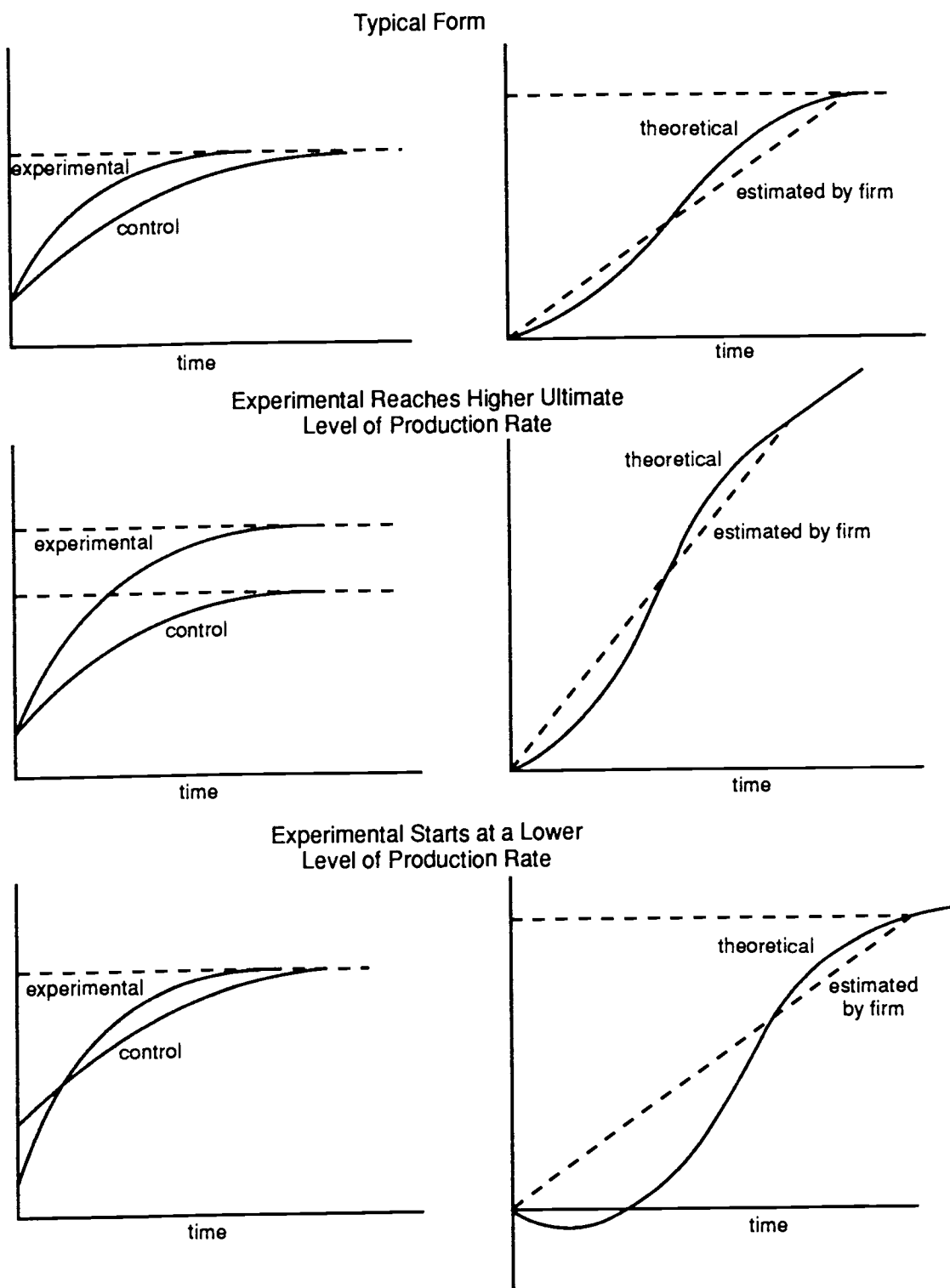## Level of Production Rate



Figure 23. Possible Cumulative Cost Savings Curve Forms

The cumulative cost savings associated with increased productive capacity due to training have to be converted into dollar values through some transformation function. The transformation function can be a simple cost multiplication or a complex valuation procedure. The hourly system cost and frequency of task occurrence are the major influences in the transformation function. The nomograph demonstrated earlier may be the easiest approach to considering these influences in the cumulative cost savings curve.

## The Training Investment Curve, $I(t)$

The sensitivity analysis for the level of training investment is largely a matter of shifting the curves up and down with various expected levels of training costs. At some level, the cumulative gains due to training will be insufficient to cover a particular training cost. If the expected value criteria is used, the training cost could be considerably less than the ultimate level of cumulative gain and still produce a negative $E_v$ value.

## The Penalty Function, $W(t)$

Associated with the job leaving probability and penalty function, $W(t)$, that has been assumed to be negligible or at least small and nonincreasing. It is assumed to be the replacement cost of a worker leaving after training. These assumptions are easily met for logging firms for the entry level position of chokersetter. From a theoretical perspective, if the penalty function cannot be ignored, then measures should be undertaken to either minimize the job leaving probabilities, i.e. a contract with reimbursement requirements, etc.

The Job Change Distribution, $P_o(t)$

The influence on the expected value of the training decision from the job change distribution is greatest for the periods immediately after training. If job leaving occurs before the training gains begin to accrue, the expected value is unlikely to become positive. A variety of creative arrangements are theoretically possible to reduce job leaving immediately after training, i.e. bonuses, contracts, promotions, etc.

Developing a simplified $P_o(t)$ curve is within reach of many logging firms with some assistance. Or perhaps, collections of like firms could pool their job change data to better understand past industry trends in turnover. In the future, more sophisticated probability distributions can be developed that utilize properties of conditional probabilities or Markov chains to better model worker job change behaviors (Barta, 1976). In fact, training workers could accelerate their job change behavior within the firm, to other firms in the industry, or even out of the logging industry.

Interest Rate Effects

For a firm to invest resources in logging training, the return on that investment should include a component that acknowledges the time value of money. Interest rate effects are evident in compounding the training investment and cost savings as they occur. As the interest rate increases, it influences the difference between the cumulative cost savings curve and the training investment as both are compounded forward. If the gains accrue rapidly the compounding aids in contributing to a positive expected value. If the gains are slow to accrue, the higher interest rate on the training investment further contributes to a negative expected value. The influence of the interest rate on the training decision is not negligible but is only moderate compared to the magnitude and timing of training gains.

The Expected Value, $E_v(t)$, and the Time Horizon

Earlier description of the influence of the decisionmakers time horizon on the development of the $E_v(t)$ curve has shown the significance of the time horizon selection. A short time horizon may yield expected values of the training decision that are negative. Longer time horizons yield continuously increasing expected values up to the point where the trained worker no longer occupies the position.

What time horizon is appropriate for the training investment decision? For jobs with relatively high job leaving rates, the time horizon should include the entire period of occupancy in the position. For jobs with characteristically low job leaving rates, the time horizon may be judged in relation to the deterministic recovery point R. Each firm has some notion of the acceptable payback period for invested resources. If the deterministic recovery point R exceeds the firm's payback period, the expected value recovery point R' will be larger than R and the decision to invest resources will be even less desirable. Most logging firms are unwilling to invest resources that cannot be recouped in less than five years. In the author's judgement, it is unlikely that a firm would commit resources to logging training that would be recouped greater than two years hence. A two year time horizon for the expected value analysis is a reasonable assumption for most logging positions and for most firms.

A Firm's View of Sensitivity Analysis

The nomograph of Figure 21 provides a basis for logging managers to conduct rudimentary sensitivity analysis. Various daily task frequencies, hourly system operating costs, and expected average training gains can be used to yield daily average cost savings from training. Combined with a time horizon of interest, a training cost, and a notion of the probability of a trainee staying with the firm, logging firms can

compute whether the expected gain is positive or not. This approach can be especially useful when considering whether training investments should be given higher priority for the firm.

What should be noted with this simplified sensitivity analysis are the weaknesses compared to better data collection or a trial of training. Average training gains mask the shape of the learning curve which could be significant. Also, developing a survivor curve $P_o(t)$ can be a useful exercise in studying job turnover of the firm. However, firms which undertake sensitivity analysis at all, show management skills not commonly found in small logging firms.

## Simulation Extensions

Simulation can provide experimentation on proposed model forms to enhance understanding of parameters (Pritsker, 1986). Holding other variables constant and assessing how an objective function varies with changes in a parameter of interest is typical of sensitivity analysis using simulation. Because many possible simulation trials are possible, it is necessary to select simulation runs of interest.

For the remainder of the chapter, simulation will provide insights on the parameters of the decision methodology through the following questions:

1. What is the effect of improved selection compared to training? Using the results of the experiment, would it have been better to try to select better woodsworkers for standard training procedures or use the procedures of the experiment?
2. Could experimental gains be duplicated on an actual logging operation typical of those found in cable thinning operations? Would comparable gains accrue from training if the limitations of actual yarding were imposed on the simulation? Are random effects significant?
3. What happens to training gains if timber conditions vary, e.g. tree size.
4. What happens to training gains if different yarding machines are used, e.g. different hourly costs or payload capacities?
5. How do training gains accrue if different logging tasks had the same magnitude of training gains as the experiment, e.g. loader operator training?

Basis for Simulation

There are two bases for simulation in the following discussion. First, Symphony
(™) Spreadsheets are used to scale the results of the experiment from time saved to
cycles of activity and to address the selection and task questions. Second, a Basic
program simulation of a yarding operation is used for questions relating experimental
gains to logging operations. Details of specific procedures are included in appendices
III and IV. Over 300 simulation runs help provide the general answers to questions
above. Because the cumulative difference curve is of primary interest, it is the focus of
simulation.

Selection versus Training

The role of selection and training and their contributions to productivity have been
recognized in many industries (Cascio, 1978; Wexley and Yukl, 1977). However, the
roles they might play has only been estimated for logging tasks. Garland (1981)
estimated the contribution to potential total productivity to be in the order of fifteen
percent.

With fifteen subjects each in the control and experimental groups in the
experiment who were originally matched, the question of selection can be addressed.
The learning rate parameter, T, of several in the control group are better than those in
the experimental group. Using the means of the parameters of each group as a basis for
normalizing the respective parameters of each subject, the modified parameters are
appropriately scaled from the base experiment.

Pairwise comparisons were made between each of the subjects to determine
whether performance by a given subject in the control group might exceed that of a
subject in the experimental group. Exactly 225 comparisons (15 by 15) were made with

spreadsheet comparisons similar to those of figure 18. For 17% of the pairings, the control subject performed better than the experimental subject because the cumulative difference function never became positive. In 32% of the comparisons, the control subject started better but was surpassed by the experimental subject. The cumulative difference function starts out negative but becomes positive as the rate of improvement increases faster for the experimental subject.

The majority of comparisons (51%) were of the type shown in figure 18. In all, 83% of the comparisons had trained subjects exceeding those learning by common industry practices. This comparison is a somewhat indirect assessment of the potential benefit of selection measures because the groups were selected together and then split based on a match of initial performances. All of the subjects came from the same recruiting pool. It may be argued that improved selection procedures actually shifts the recruiting pool from which to employ chokersetters. However, to the degree that the experimental subjects match available recruiting pools, the advantage of training over selection still holds.

Yarding Simulation

Various yarding simulators have demonstrated their usefulness in answering logging questions (Sessions, 1978; LeDoux and Butler, 1981). The author has not found any that dealt with issues of logging training. Several simulation approaches and languages are possible (Pritsker, 1986). For this analysis a Basic program outlined by Sessions (1988) has been modified by the author to consider training issues.

Details of the simulation are outlined in appendix IV. The fundamental yarding simulation defines a yarding corridor with tree distributions, log distributions developed from a bucking strategy, and the engineering and mechanical performance of a skyline

yarder. Topography considerations are handled similarly to well-known skyline analysis programs (LOGGERPC, 1986). The simulation distributes logs on the skyline corridor and then in a turn-by-turn (cycle-by-cycle) fashion, logs are yarded repeatedly from identical skyline corridors considering feasibility of skyline capacities and mechanical capacities of the yarder. Running skylines are used throughout this analysis although other skyline systems might be employed.

The chokersetting (Hook) phase is the portion of the overall yarding cycle where training gains are applied. The pattern of gains from the chokersetting cycles in the experiment are applied to the yarding simulator. The cost structure and basic learning parameters are first those of the mean performances of the control and experimental groups in the experiment. Skyline corridors are successively (conditions remaining identical) logged with gains accruing between experimental and control from each turn of logs yarded. The effect of training gains are tempered by the operating realities of the cable thinning operation.

Turn-by-Turn Gains

Using the parameters of the experiment to modify the hook element of a cable thinning operation yields results similar to those estimated for the experiment. After harvesting eleven corridors each for control and experimental groups, the cumulative difference function is similar in value to that derived from the experiment. At the end of eleven corridors (approximately 37 days of yarding), the cumulative difference function shows a positive gain of $1728.50 for the chokersetter trained in the fashion of the experiment (see Figure 18). Or conversely, the firm thinning in a fashion similar to the simulation could spend that amount on training and recoup its investment fairly rapidly.

Training gains would likely continue until the control group caught up with the experimental, but the changes in timber, topography, and other substantial operational changes would likely have occurred by then.

## Effects of Timber Size and Density

If the yarding simulation approximates training gains, the next question may be how would training gains differ if larger tree sizes were harvested? Figure 24 shows the cumulative difference functions for training gains when trees 8 to 18 inches are harvested. The results show an increase in training gains so that after similar yarding cycles, as much as $700 - $800 more gains are evident when larger timber is harvested. One could anticipate this effect because larger timber offers the potential for training gains to have larger effects.

## Different Yarding Machine Costs and Payloads

The straightforward effect of increasing the machine cost per operating hour is to steepen the cumulative cost savings curve. If the same results could be achieved with a lower cost machine, only the magnitude of the gains would be shifted proportionally lower. However, a lower cost machine would likely also have reduced payload capacity as well. How does this affect training gains?

Figure 25 shows effects of high system costs versus low system costs at reduced payloads from the simulation. High system costs accentuate the gains while low payloads and low system costs accrue gains much more slowly.

Different Logging Tasks

Using the spreadsheet simulation approach to assess training gains, it is possible to see potential gains from other logging tasks. The author has had experience with training of log loader operators (Weyerhaeuser, 1981). If certain parameters of the decision model are known or can be assumed, the potential gains from training may be assessed. If the relative gains from the experiment can be scaled to the loader operator task for the learning parameters and supervisor's judgements used for the beginning and ending levels, the gains from training can be estimated in a cumulative difference function.

Two critical assumptions or data are needed. First, the marginal value of an extra load produced must be known, calculated, or estimated as an average value over levels of production. For the example shown below, the value of an extra load of logs is estimated to be $200. Second, if partial loads are produced, there is value in sorting and preparing logs for loading proportionate to the partial loads produced. The value does not depend on whether the load is actually hauled away in discrete truckloads.

Figure 26 shows the result of one such simulation procedure. Training cost is assumed to be $12,000, and over a year's period, interest at 20% is included in the calculations. Over the year's period, the absolute cumulative gain level almost reaches $40,000 for a loader operating with a cable logging unit. The training costs are recovered by day 10. The level of $40,000 gain is similar to the level estimated in the Log Loader Project (Weyerhaeuser, 1981). The training model here provides the shape of how the gains accumulate.

Based on earlier assessment of low turnover for log loader operators (Sorenson, et. al., 1979), the expected value curve is assumed to be deterministic for this task. If the probability of staying in the job were a uniform distribution $P_o(t) = .90$, then the R'
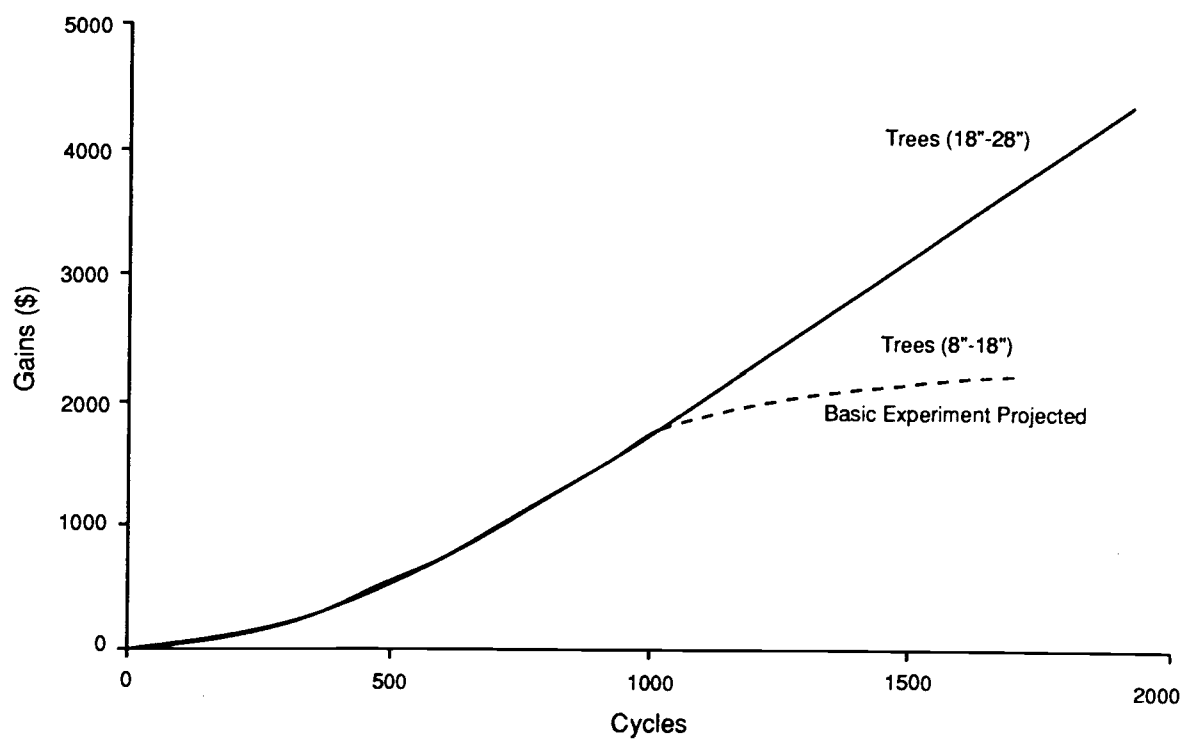
Figure 24. Cumulative Difference Functions
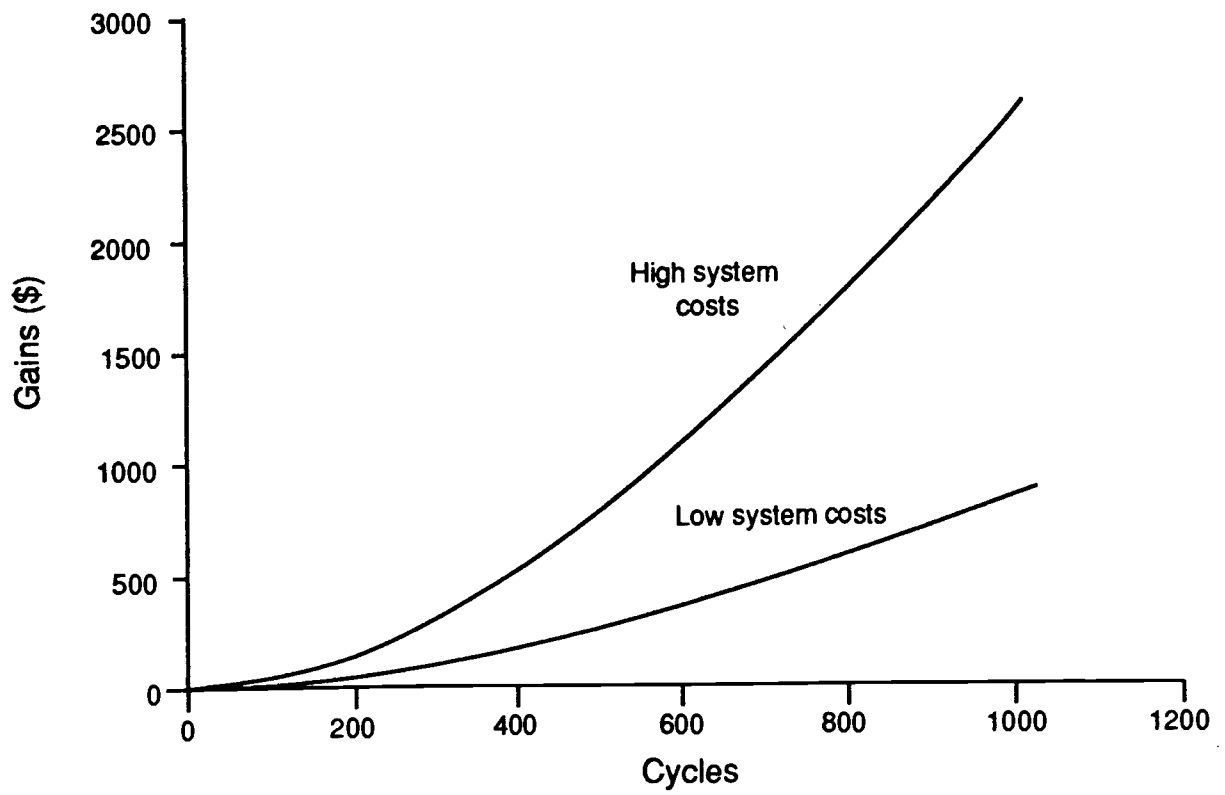on a turn-by-turn basis

Figure 25. Cumulative Difference Functions
for training gains influenced by machine costs

value would shift to 76 days and the expected gains would be reduced somewhat. The machine operator task is amenable to the same kind of anlysis as that developed for chokersetter training.
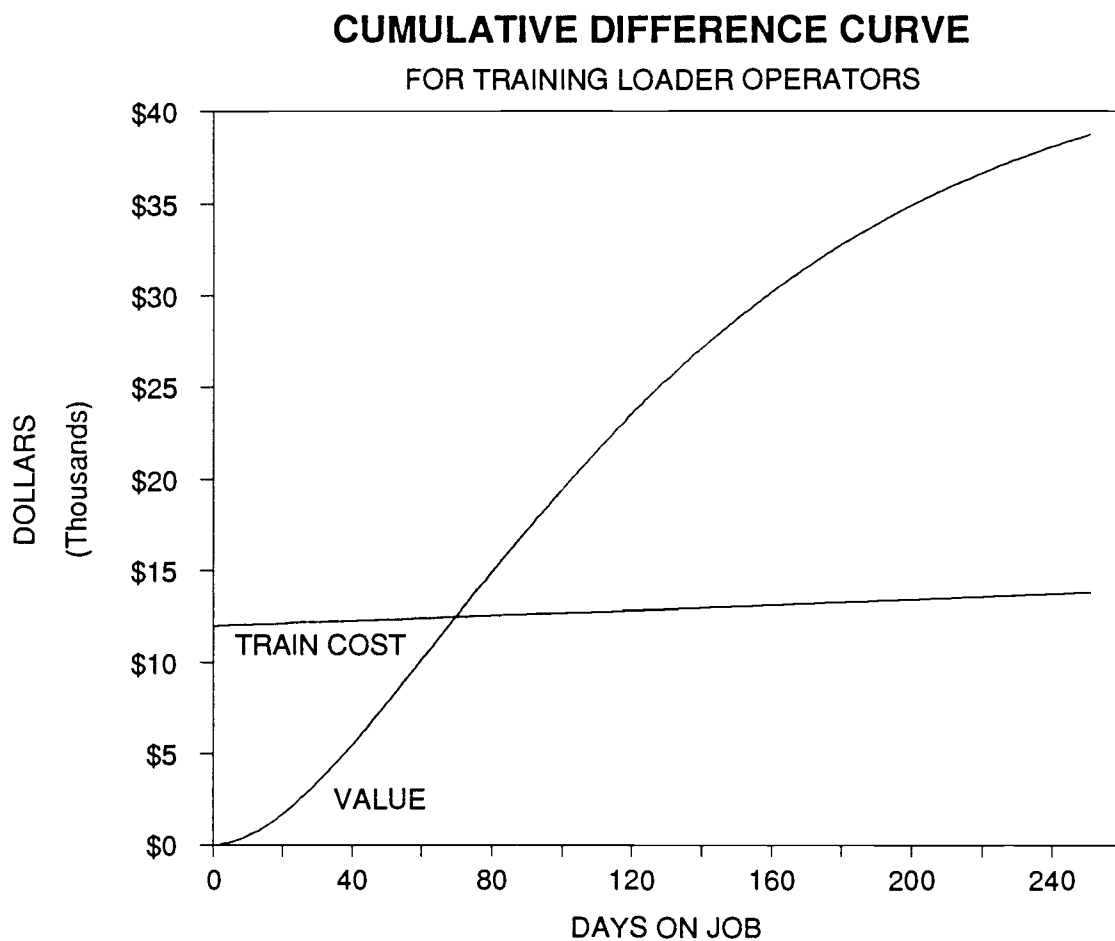
## CUMULATIVE DIFFERENCE CURVE
### FOR TRAINING LOADER OPERATORS

Figure 26. Cumulative Difference Curve For Training Loader Operators

# SUMMARY AND CONCLUSIONS

The need for a methodology to assess the training gains for the logging industry has been partially satisfied by this treatise. Continuing pressures on the logging industry from a variety of sources emphasize the need to assess training as a means to improve productivity and address other problems, e.g. safety performance. While the methodology presented here is simple conceptually, the implementation can become complex. Three viewpoints have been adopted to clarify the perspectives surrounding implementation and economic considerations. First, a theoretical perspective underlies the development of the methodology. Secondly, the firm's perspective was addressed as the viewpoint needed to ultimately implement the training assessment. Finally, a designed experiment was conducted and the methodology applied to the outcomes of the chokersetting experiment to bridge the gap between a theoretical perspective and the perspective of the logging firm.

## Complex, Repetitive Tasks

The author has characterized logging tasks, such as chokersetting as belonging to a class of tasks that can be termed complex, repetitive tasks. The learning of complex, repetitive tasks is not easily described through typical learning curves. Variation associated with the task may mask the learning effects. Only repeated experiments with like subjects and like conditions might yield typical learning curves for logging tasks -- an infeasible option for logging firms and a prohibitively costly research approach. The general approach described in this treatise can analyze complex, repetitive tasks found in logging from the standpoint of evaluating training gains. Other industries, such as the construction industry, have complex repetitive tasks that might be analyzed using the author's methodology.

## Learning Curves and the Cumulative Difference Function

Many researchers have used various curve forms to describe learning phenomenon. Towill proposes a learning curve form that has a cumulative difference function associated with it that can be used to compare two training strategies. The cumulative difference form contains the parameters of the individual learning curves for each training strategy. Thus, the cumulative difference function provides knowledge about the underlying learning curves producing a cumulative difference form. The cumulative difference form is used in the economic evaluation of two training strategies for logging tasks, even though the individual learning curve forms may not be known precisely.

## Model for the Economic Evaluation of Training Alternatives

Using the cumulative difference function as the cumulative gains due to training, the author has proposed a methodology that assesses training gains and costs in the light of job change characteristics of the logging labor force. In general, logging firms are reluctant to commit resources to training if those resources are not going to be recouped before the worker leaves the firm. The author's methodology explicitly identifies timing and pattern of gains due to training, the cost of training, the job leaving dimension of the decision, the time value of resources, a penalty function for replacing job leavers, and the decisionmaker's time horizon for the analysis. The expected value criterion is seen as the appropriate criterion for determining whether or not to commit resources to logging training.

Designed Experiment Conducted to Measure Gains Due to Logging Training

Because no prior studies have been conducted to measure the gains due to training in a logging task between a matched control and experimental group, the author conducted an experiment on the chokersetting task to establish the magnitude and timing of training gains. Thirty subjects were retained at half time for approximately six weeks. Subjects were matched on an initial task performance and randomly assigned to a control or experimental group. Over 3,000 chokersetting cycles were measured to form the cumulative difference function. The control group received training similar to the existing practices in industry, while the experimental group received a designed training effort that could be duplicated by nearly any logging firm.

Ten chokersetting stations were established that resembled the chokersetting tasks found in commercial thinning operations. About forty percent of the chokersetting cycles involved techniques that can be mastered through training; fifty percent were random log positions not associated with any particular technique. One station was termed FREE-PATH chokersetting in that the sources of variation were removed to the degree possible. The subjects set chokers on ten sets of logs on ten stations where logs were in different positions. The FREE-PATH chokersetting station established that the control and experimental groups performed at different rates along learning curves that could be established. Procedures using the well-defined learning curves on FREE-PATH chokersetting validated the parameter estimation procedures for the entire experiment and formed the cumulative difference function.

The experiment also provided insights on the chokersetting learning process relative to whistle errors, resets and carriage spotting errors, as well as the reduction in the variance associated with learning. Ratings and rankings were also reported for the experiment. Parameters were also estimated for the individual subjects.

## Economic Implications and Sensitivity Analysis

The heart of this treatise has been the application of the decision model using the results of the experiment. Using the expected value of the decision over a time horizon, the gains due to training chokersetters are sufficient to recoup the training investment even though there is some probability of workers leaving after receiving training. The decision model has been simplified for use by logging firms. In summary, positive expected values are projected for training chokersetters even though it might cost $1,000 and there exists a probability that the worker would leave the firm after training. The expected value function can recognize the time value of invested resources if needed.

The impact of changes in the influencing factors in the decision model are addressed through sensitivity analysis. The sensitivity analysis covers the magnitude and timing of training gains, the training investment, the job change probability curve, the time value of money, and the decisionmaker's time horizon. Sensitivity analysis using spread sheet approaches and yarding simulation have helped answer questions of worker selection, turn-by-turn yarding in thinning, changes in timber conditions, and differences in yarding machines. The decision model has been applied to one other logging task (log loader operator training) to assess how the model might work.

Overall results of applying the decision model using data from the experiment suggest that firms may make substantial productivity gains by designed training programs.

## Implementation and Other Obstacles

In earlier sections the economic framework was outlined along with obstacles preventing firms from implementing designed training. The proposed economic model

does not address all the obstacles cited by firms but the model does suggest some

insights on each of the obstacles cited in the survey of logging firms (Garland, 1979).

Obstacle Firm lacks time to train

Insight from model Significant gains from training merit a close look at allocating time to technical training

Obstacle Structured training is too expensive

Insight from model Training costs are incorporated in the model and can be quickly recovered

Obstacle Size of firm restricts training

Insight from Model The level of training activity in the experiment was scaled to be implemented by small firms, but not all issues associated with firm size have been addressed

Obstacle Firm prefers the informal "on-the-job" training

Insight from Model From the experiment and model framework, the opportunities of structured training should be compared to "informal" approaches.

Obstacle Firm lacks personnel to train

Insight from Model This obstacle is not addressed in the experiment or the model, although a demand for training should bring forth trainers

Obstacle Firm predicts union difficulties with training

Insight from Model Not addressed in the model, but training programs have been incorporated into collective bargaining agreements

Obstacle Firm foresees difficulty getting workers interested in training

Insight from Model Motivation was held constant in the experiment but is not addressed in the analytical framework

Obstacle Firm is concerned with trained workers leaving the firm

Insight from Model In the absence of policies to retain trained workers, job change may still occur. However, the model suggests that training costs are quickly recovered before the trained worker is likely to leave the firm.

There is no way to eliminate all of the obstacles to structured training in logging

firms, but the experiment and decision model allow the evaluation of some of the

obstacles cited by firms. The relative strength of the obstacles must be weighed in the light of expected gains from training. Until the present experiment and decision model, the obstacles to structured training could not be systematically and economically evaluated.

## Future Research Needs

The current research has focused on the chokersetting activity in logging which is a task involving a single worker and no complex machinery. There is a need to conduct a similar project with a man-machine task such as operating a log loader or yarder as well as to investigate logging tasks that involve crew interactions such as changing yarding roads. These research efforts may identify tasks that are relatively free of variance (akin to the FREE-PATH chokersetting station) that will provide identifiable learning curves while the entire task may be described by the cumulative difference function. In addition, simulators and simulated tasks may be analyzed for learning curve effects in the absence of the variation found in actual logging conditions. With proper analytical techniques the gains due to training for complex repetitive tasks can be assessed and evaluated in logging.

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Appendices

# APPENDIX I. CHOKERSETTING PRINCIPLES FOR THE EXPERIMENT

## CHOKERSETTING TECHNIQUES

Using the techniques shown can make chokersetting safer and easier but some of the techniques have hazards associated with them. You need to get in the clear in different locations depending on how the lines and logs will move. Try out some techniques when production pressures allow it even though they may not be needed immediately. This will let you see how the logs will move.

**SQUAW HITCH:** Used to move a log a short distance to create a choker hole.

**BRIDLE:** Used for oversize logs too big for one choker.
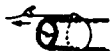
**SWEDE:** For large logs that need two chokers for pull.

**STRAP:** To move a log or rootwad a short distance.

**TAG:** To reach a log that cannot be reached with one choker.

**PARBUCKLE:** To move a log closer to the line with a tag to fill chokers or to move a log over a stump or obstacle.

**TONGS:** To move a tight log a short distance to create a choker hole.

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Communications
Organization
Maintain control
Positioning
Expectations
**TRAINING**

## STUMP SELECTION AND NOTCHING

You must maintain the strength of the selected stumps by proper notching techniques. The notch must be only deep enough to prevent the line from slipping up (1.5 times the line diameter). It must be on solid wood inside butt flares and in lead with the line. Check the Safety Code for allowable attachments and rigging.

**PROPER NOTCHING**

Cut to good depth and in lead with line

**IMPROPER NOTCHING**

Shallow notch not in lead with line

**IMPROPER NOTCHING**

Too close to top of stump

**IMPROPER NOTCHING**

Mushrooming cut too deep.

## CHOKERSETTING TECHNIQUES

The first job for most new woodsworkers is setting chokers. Setting chokers is more than just attaching a cable to the end of the log, there are specific techniques that are used to solve problems. But new chokersetters may have difficulty seeing how these techniques are used with new terms, brush obstacles, time pressure to get the turn set, getting in clear, etc. Common techniques are shown and uses briefly described. Many are used with cable logging but they are useful for ground-based logging as well.

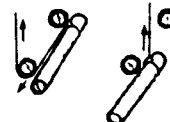**NORMAL:** Set choker tight, close to end of log with notch on bell next to log.

**ROLL:** Make choker roll log past or over obstacle or get easier start.

**KICK OR JUMP:** Place line between log and obstacle to kick past or jump over obstacle.

**RUB** (stump or tree): Set line around rub stump or tree to move log short distance past obstacle. Then reset choker or throw line over stump.

**BONUS:** Two or more logs in single choker.

**FIGURE 8:** To choke two logs with ends in opposite direction tightly.

**Artwork:
Don Poole**

## STUMP SELECTION AND NOTCHING

Stumps for anchors of guylines, skylines, and running lines need to be properly selected and then notched for the loads placed on them. They should be looked at when first loaded and then inspected periodically. Stump capacity varies with the type of wood, how long it has been cut, where it is located, and the size. You can get more support if needed by rigging multiple stumps and using tiebacks.

### AVOID USING THESE TYPES OF STUMPS

**STUMP DISTURBED BY ROAD CONSTRUCTION**

**STUMP OF A SNAG**

**STUMP ON ROCK**

Shallow topsoil, Weak surface roots

Solid rock

**PARTIALLY BURNED STUMP OR WITH ONLY SHELL OF WOOD**

**STUMP AT WATER LEVEL**

Creek

**STUMP ON TOP OF LOOSE ROCKS**

# APPENDIX II. SPREADSHEET SIMULATIONS

Spreadsheets may give simulation results by their rapid recalculation of values and their associated ranging functions. For purposes of this dissertation, several results are found using spreadsheet simulation

## Normalizing Data and Scaling Results

Data from the experiment produce a pattern of training gains in actual minutes saved. Further, the curve fitting procedures for the learning curves of subjects on FREE PATH chokersetting provide parameters that express the training gains for the experiment. It is possible to find a set of parameters from actual logging conditions that closely match the pattern of gains from the experiment using the ranging functions for the parameters of interest. A simpler approach of matching the graphical results is however quicker. This normalizes the data from the experiment to a set of actual expected conditions and provides numbers one could expect from logging operations. The closeness of match from spreadsheet values to experimental results could be tested with statistical tests such as t-tests. However, because the purpose is only to set a scale for the values and not to precisely match parameters, a reasonable judgement or visual match is sufficient.

## Comparison of Paired Subjects to Assess Selection Effects

A natural question in any training experiment is whether the effects of selection alone would have been a major factor in the experimental outcomes. Because the experiment was designed to eliminate selection effects by pairing the subjects first and then allocating them to control or experimental groups randomly, selection effects are removed from the experiment to the degree possible. However, with spreadsheet simulation it is possible to gain information on selection effects.

For the experiment, control and experimental groups had a mean value for the learning parameter and each subject had a learning parameter for FREE PATH chokersetting. Using the scaling and matching procedure above, a typical training situation can be established for the mean values of each group and then individuals' parameters can be normalized for the situation. Pairwise comparisons can then be made for the 15 subjects in each group based on the cumulative difference function for the pair.

Two hundred and twenty five comparisons are possible in this fashion. If the cumulative difference function never is positive, then the control subject would have outperformed the experimental subject even with the training effect present. If the cumulative difference function begins negative and then becomes positive later, then the control subject would have started better than the experimental subject but presumably training and other effects of the experimental subject would have allowed the subject to progress more rapidly. If the cumulative difference function is always positive, then the experimental subject would have outperformed the control.

## Comparisons with Other Logging Occupations

If certain parameters are known for training effects in other occupations, spreadsheet simulation can be used to assess possible results with the model developed. Based on a large project on log loader operation in the western United States, the model parameters could be estimated and assessed in a spreadsheet.

For log loader operators who would begin production at 7 loads per day and progress to a common level of 15 loads per day, the rates of training improvement could be cut from one year to six months with a designed training program. The production of an additional load or partial load was valued by logging supervisors as adding $200 to operation profit. With these figures, the model described earlier has been implemented

and results shown elsewhere in this dissertation. Bottom line results from simulating a designed training program are remarkably similar to those estimated by logging supervisors independently.

# APPENDIX III.  FORMAT OF YARDING PRODUCTION SIMULATOR WITH

## TRAINING EFFECTS FOR CHOKERSETTING