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Statistical Process Control techniques have been successfully implemented in the mechanical fabrication and chemical manufacturing industries. The techniques consist of the application of statistical theory in conjunction with quality control procedures. To date the Forest Products industry has yet to apply these techniques toward lumber drying. This thesis focuses on the application of Statistical Process Controls to evaluate the final moisture content of dried lumber and the accuracy of sticker placement by stackers.

Computer models, based on real data, were used to produce the necessary quantitative information required to construct X-bar, Range, group, and p charts. These models were modified to reproduce drying and stickering processes that were under control or out of control. From the computer, simulated data control charts were drawn to graphically prove that such charts can be used for quality control purposes when drying or stickering lumber.

An Application of Statistical Process Control Measures for Maintaining Optimal Quality from Dry Kiln Operations

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INTRODUCTION

Lumber must be dried to a predetermined, uniform moisture content (MC) to minimize dimensional changes in service and enhance gluing and machining properties. Careful stacking of the wood in the kiln helps to minimize warp. Grading agencies such as the West Coast Lumber Inspection Bureau, Western Wood Products Association, and Southern Pine Inspection Bureau have established upper limits for MC and warp; however, mills can improve productivity, product quality, and customer satisfaction by closely controlling the stacking and drying processes so that final product quality exceeds these standards. To date, only imprecise estimates have been made about the average final MC for a charge of lumber. Very few producers track charge MC in a consistent manner or statistically evaluate the reliability of their estimates. No producers monitor their stacking operation using statistical principles.

Quality control is the procedure of inspection, analysis, and application of corrective policies to maintain a desired consistency and quality in a manufactured product (Clements, 1989). The use of small samples of the product being produced are examined with specific standard procedures so the quality of the product is maintained within established standards. Should corrective measures be required of the manufacturing process, they can be made in a timely and effective manner with minimal loss in product material and quality.

The use of statistics and the application of quality control measures in manufacturing industries is called Statistical Process Control (SPC). The quality control methods used in different industries range from simple record keeping to complex statistical quality control measures like sequential sampling plans (Grant and Leavenworth, 1988). The mechanical fabrication industry has successfully used graphical techniques called control charts to maintain tolerances of machine parts. The chemical manufacturing industry has also used control charts to monitor and control such properties as density, percent solids, viscosity, and hardness.

This thesis focuses on the application of SPC to evaluate the final moisture content of dried lumber and stickering accuracy. Tests of lumber moisture content (MC) and the assessment of sticker placement were conducted to arrive at base case situations representative of normal mill practices and procedures. From these base cases, computer models were developed to provide the data necessary to generate control charts for the drying and sticker placement processes.

Preliminary investigative studies of three different kiln charges of lumber were conducted to determine package MC distributions. A hand-held, resistance-type moisture meter was used to measure the MC of boards selected randomly from the outer edges of the packages. An average MC for each package was then calculated. This average MC was then compared in a regression analysis to the average MC of all boards contained in the package, as determined by an electronic in-line moisture meter. The results of this regression analysis were used to decide if there existed a practical method by which one person using a hand-held, resistance-type moisture meter could accurately determine the average moisture content of a package by randomly sampling only boards on the outer edge of a stack of lumber.

A computer program that simulates the drying of boards inside of a kiln was used to generate MC data for X-bar and Range control charts. The computer program was adjusted to simulate the MC distribution of a kiln charge of lumber that was properly dried in a kiln believed to be correctly operated. Various drying scenarios, demonstrating maintenance and control problems, were simulated and the effects shown on control charts.

The accuracy of sticker placement was investigated by two different methods. The first method was to count the number of stickers misplaced or missing versus the total number of stickers. The data was used to produce percent defective or p charts.

In the second method, the displacement of stickers from a reference line was measured. This was done on two stackers, one operating properly and the other malfunctioning. These distributions of sticker displacements formed the basis for computer-generated sticker displacements which simulated stacks of lumber. The displacement values generated were then classified as "misplaced" or "not misplaced," and a tally was made of each situation. This count was then used to generate two p charts: one with a stacker "in-control" or in proper operation; one with a stacker "out-of-control" or only capable of producing inaccurate sticker placements.

OBJECTIVES

Communicating how well a dry kiln and stacker are operating to mill management, and operating personnel is very important. An ideal situation is to know exactly what is happening in a kiln or at the stacker at all times. Often, however, conflicting information presents itself, making decisions for future operations or adjustments difficult. Four specific objectives were undertaken, which will lead to statistical methods that minimize the amount of information collected and correctly interpret it based on statistical quality control (SQC) principles. These objectives are as follows:

1) Establish how many hand-held MC readings are needed to estimate the MC of a lumber package after it leaves the dry kiln.
2) Determine the relationship between hand-held MC readings taken on the sides of a lumber stack and the average package MC as determined by an in-line moisture meter.
3) Determine if control limits for both out-of-kiln board MC and the accuracy of sticker placement can be produced.
4) Develop a visual aid chart system (control chart[s]) to convey drying and stickering SPC information to mill personnel.

LITERATURE REVIEW

INTRODUCTION

SQC methods have been used in the forest products industry for about 40 years. The methods of SQC range from crude record keeping to complex statistical analyses of MC distributions between and within boards in a stack of lumber. This literature review will first examine the history of SQC and then go into detail about issues concerning SPC. MC and its evaluation, quality control programs for MC, sticker alignment considerations, and quality control programs for sticker placement will also be discussed.

HISTORY OF SQC

A deliberate attempt at quality control can first be found in the ancient Egyptian pyramids and in Roman works of sculpture and buildings (Halpern, 1978). The Egyptians had developed a decimal system and established a value for pi, while the Romans built high quality masonry buildings that last till today (Banks, 1989). By the Middle Ages craft guilds were established to set standards and regulate the quality of goods produced (Encyclopedia International, 1980; cited Banks, 1989).

During the late 1800's to the 1920's industrialization began, greatly increasing the complexity of manufactured products. This made the existence of a supervisor for quality control necessary (Banks, 1989). By 1924, Bell Telephone Laboratories established the Inspection Engineering Department of which Walter A. Shewart was a member (Banks, 1989). Shewart developed the first "control charts," sometimes known as

"Shewart control charts" (Grant and Leavenworth, 1988). From 1925 to 1926 the Western Electric company, under contract to Bell Telephone company, developed such concepts as "Consumer's Risk," "Producer's Risk," and "type A" and "type B" risk (Banks, 1989). In 1925, Harold Dodge developed statistical quality inspections based on attributes or discrete quantitative characteristics (flaws) of a product (Banks, 1989).

Statistical quality control emerged once again in the 1940's (Feigenbaum, 1983). At this time the American Standards Association (ASA) became interested in statistical quality control measures for manufactured products at the request of the U.S. War Department (Halpern, 1978). Sequential sampling and analysis was first proposed by A. Wald in 1943 while working at Columbia University (Schilling, 1982). Unfortunately, these statistical quality control measures did not achieve a lasting stay in American industries. In 1955, K. Ishikawa, however, introduced control charts with great success in Japan (Banks, 1989).

From the 1940's up until the 1980's quality control concerns in the United States fluctuated. Industries in the U.S. were at a disadvantage by not implementing statistical quality control, but by the 1980's an increased concern for quality control was seen with the emphasis of "quality slogans" from almost all U.S. industries (Banks, 1989).

SQC IN LUMBER DRYING

As early as 1951, Latimer showed how the use of trend charts and control charts by the kiln operator could assist in visualizing when the kiln was in- or out-of-control. Should an "out-of-control" situation occur, the result would be improperly dried lumber. The author suggests that the control chart be based on the range or standard deviations of MC readings.

By 1976, an accept-reject criterion for making changes in the kiln schedule had been reported by the Canadian Forestry Service (1976). The MC of two hundred pieces of dried lumber was measured; if x or more boards in a certain number of consecutive charges were over 19 percent MC, the drying schedule was modified to give more or less drying time. Should x number of boards not be reached in the consecutive charges, the drying schedule is left alone. The method does not require complex statistical calculations, but does necessitate numerous MC samples to be taken. In addition, it does not provide a comprehensive historical record of past drying performance or give any indication of the MC quality of future charges. The only advantage to using this technique is to determine how a kiln schedule should be modified (either by increasing or decreasing the drying time) when improperly dried lumber has occurred.

Wengert (1986) developed a statistically-based quality control method for drying "typical softwood" lumber to a final MC below 19 percent. From a stack of lumber, the MC of 10 to 15 boards is measured at 3 to 5 locations per board. Calculations are made for (1) average board MC, (2) within-board standard deviation (SDW), (3) between-board standard deviation (SDB), and (4) total standard deviation (TSD).

Wengert has established numerical "Acceptance Ranges" for the average MC, SDW, SDB, and TSD. Unfortunately, these numerical ranges apply only to softwood lumber. The technique has not been applied to hardwoods, nor does it give an early warning indication of when a kiln may go "out-of-control" and produce improperly dried lumber. However, for the limited species of wood to which it does apply, it could be used as a cumbersome mathematical method to isolate problems in a kiln producing dried lumber of poor quality.

A sequential sampling plan to determine whether to accept or reject a lot of softwood lumber based on PS 20-70 specifications has been developed by Ismail Hashim (1988). The process consists of taking successive moisture meter readings and adding them together until one arrives at an accept or reject cumulative numerical value. The advantages of this testing scheme are as follows: significant reduction in the number of MC samples needed to reach a decision, greater sensitivity to MC grade rules, and a reduced chance of operator error due to sampling fatigue. The testing method only indicates whether or not more than five percent of all boards are wetter than 19 percent MC. This SQC scheme does not prevent over drying and degrade.

STATISTICAL PROCESS CONTROL

SPC is a group of statistically-based quality control techniques that track the processes through which an item, such as lumber, must go to be readied into a final finished product. To use these techniques, sample sizes must be established along with a method for taking the samples. Once this has been established, a number of different charts can be produced based upon the type of data being collected.

SAMPLING

A sample is a subset of the entire population (universe) or entire collection of items, components, measurements, or individuals under consideration (Devore, 1986). Statistical inferences are estimates of the population's parameters based on samples taken from that population (Grant and Leavenworth, 1988). Two different methods exist for taking samples, random sampling and stratified sampling. Most SPC methods are based upon random samples.

Random sampling requires the independent selection of samples from the population (Devore, 1986). Samples can be taken either with replacement or without replacement of the previously-selected sample back into the population. Only small samples sizes are needed for SPC charts, (Enrick, 1985) so sampling without replacement is acceptable.

Should sampling be done according to ASTM Standard D 2016-74, all the MC samples must be from a random selection of boards. Similarly, Grant and Leavenworth (1988) state that SPC theories are based on random sampling schemes. Geisel (1990) clearly advises samples be randomly selected, otherwise false conclusions will be derived. Before any SPC techniques can be implemented for MC or the accuracy of sticker placement, one must decide how to sample and how large of a sample to take.

SAMPLE SIZE

Sample sizes recommended in the literature vary considerably. ASTM Standard D 2016-74 (1988a) requires any package of lumber to be tested for its MC must have 10 percent of the lot or 20 samples, whichever is greater, tested with a resistance-type meter. Bramhall and Warren (1977) suggest measuring MC on every fifth or tenth board until 200 boards have been tested. However, Rice (1976) says to test roughly nine percent of the boards and Wengert (1986) indicates 10 samples are needed to estimate the MC of a package of lumber. Juran (1988) has developed Equation 1 to estimate sample size in quality control situations. The formula establishes sample size (N) based on maximum allowable error in the estimate (E), the level of significance (α) for the normal distribution coefficient (K), and the standard deviation of the population derived from a pilot study (σ). The formula is as follows:

$$N = \frac{K_{\alpha/2}\sigma^2}{E^2} \tag{1}$$

This equation is the standard formula for a confidence interval half-width after solving for N.

SAMPLE ACQUISITION

All SPC techniques are based on random samples from normally distributed populations (Grant, 1988). For lumber McMahon (1961) states a normal distribution can be produced from sample MC readings when the MC values are transformed into logarithms.

Where and how to obtain random samples for SPC in a mill is an important consideration. For MC sampling the Canadian Forest Service (1976) claims that MC readings should be taken randomly at the dry chain. Further Bramhall and Warren (1977) advise against taking MC samples only along the top or sides of a lumber package. This procedure is to prevent an over representation or unusually high probability of dry boards in the sample. The most practical location to take MC readings is at the dry chain, but the speed at which normal operation occurs may be too fast for accurate hand-held meter readings.

CHARTS

SPC control charts can track either "variables" or "attributes" over a time span. Data classified as "variables" are numerical measurements such as temperature, pressure or MC; data classified as "attributes" denote the existence or absence of a condition, such as acceptable versus not acceptable or in alignment versus out of alignment (Contino, 1987).

There are many types of control charts used in SPC. Some of the more common are X-bar and R charts, X-bar and moving range charts (MR), percent defective (p) and (np) charts, and nonconformities per unit (c) and (u) charts (Geisel, 1990; Grant and Leavenworth, 1988). In addition, there is the group control chart. This chart tracks the performance of the two extremes among the many machine centers that are all producing the same product (Enrick, 1985). The most common, simplest and most often used charts are the X-bar, R (range), and p charts, provided the types of data lend themselves to be used in these charts (Grant and Leavenworth, 1988). Representative examples of these three types of charts can be seen in Figures 1a to 1c. Whenever a point occurs above the upper control limit (UCL) or below the lower control limit (LCL), the situation is classified as being "out-of-control" or in a state of malfunction. The drying process (variable data) can be monitored with

Figure 1a. X-bar Chart

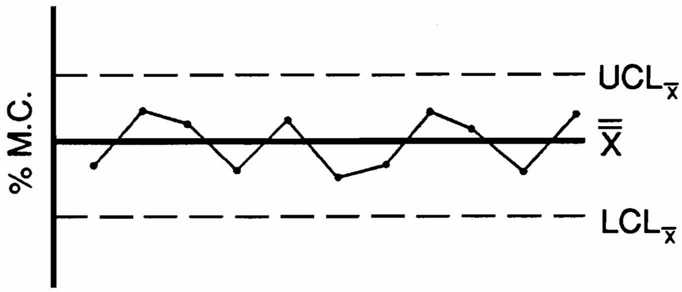


Figure 1b. Range Chart

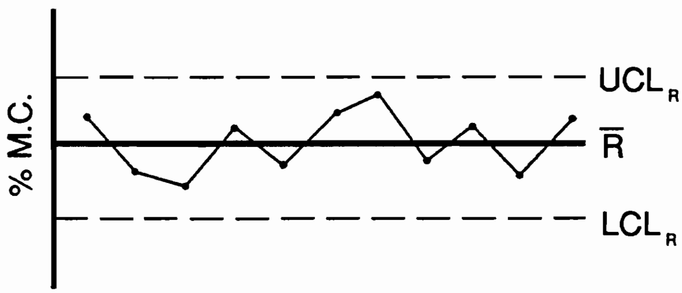


Figure 1c. P Chart

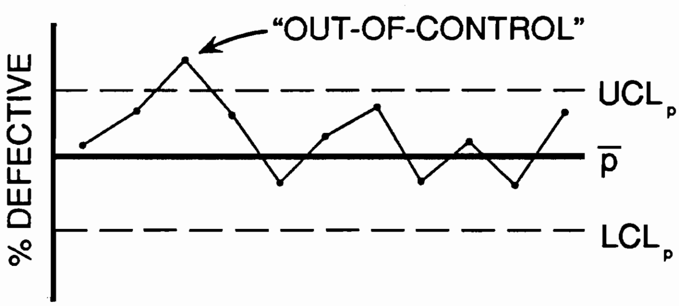


Figure 1. Examples of common control charts

the use of X-bar and R charts; the accuracy of sticker placement (attribute data) can be monitored with the use of p charts.

The calculations for the average (X-bar), group, and range (R chart) statistics are well established and straight forward. Grant (1988) provides the following equations to be used for calculating the required statistics (see nomenclature table for definitions of terms):

CENTRAL LINE OF X-BAR AND GROUP CONTROL CHARTS

$$\overline{X}_i = \sum_{j=1}^{n} \frac{X_{ij}}{n} \tag{2}$$

$$\overline{\overline{X}} = \sum_{i=1}^{k} \frac{\overline{X}_i}{k} \tag{3}$$

CENTRAL LINE FOR R CHART

$$R_i = X_{i,max} - X_{i,min} \tag{4}$$

$$\overline{R} = \sum_{i=1}^{k} \frac{R_i}{k} \tag{5}$$

CONTROL LIMITS FOR X-BAR AND GROUP CHARTS

$$UCL_{\overline{X}} = \overline{\overline{X}} + A_2\overline{R} \tag{6}$$

$$LCL_{\overline{X}} = \overline{\overline{X}} - A_2\overline{R} \tag{7}$$

CONTROL LIMITS FOR R CHART

$$UCL_R = D_4\overline{R} \tag{8}$$

$$LCL_R = D_3\overline{R} \tag{9}$$

Calculations for the p chart statistics are likewise well established and readily available in most statistical quality control textbooks. Grant and Leavenworth (1988) define the formulas as follows (see nomenclature table for definitions of terms):

MEAN P

$$\bar{p} = \frac{\sum r_i}{\sum n_i} \tag{10}$$

CONTROL LIMITS FOR P CHART

$$UCL_p = \bar{p} + 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n_i}} \tag{11}$$

$$LCL_p = \bar{p} - 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n_i}} \tag{12}$$

According to Enrick (1985) and Grant and Leavenworth (1988), control limits need to be updated or recalculated weekly, monthly, or at some regular time interval. The control limits should be updated (recalculated) using recent data to determine if the drying or stickering processes have undergone any changes over time. This should save wood, increase kiln productivity, and reduce degrade.

Enrick (1985) and Grant and Leavenworth (1988) have described what control charts can tell an operator. When control limits (UCL or LCL) lie outside of the product specifications, they indicate that the machine center is not capable of meeting the specifications. In the case of lumber MC, this control chart would indicate that drying practices need to be modified or repairs made to the kiln. Stacker repair or adjustment would be required in the case of sticker placement. When a point lies outside of the control limits, it indicates cause for immediate action.

If points exhibit an "abnormal arrangement," such as a sequential series of points all lying above or below the control chart centerline, the drying process or stickering process should be examined for causes, and changes made. When a normal random variation exists among the plotted points, the drying or stickering process should be left alone. Suspicion of a malfunction will be verified when a series of points all lie very close to the center line (CL), or if a group of points all lie beyond either the first or second standard deviation warning limits called σ.

ERROR AND RISK

Only routine quality control sample testing will assure that only rare lots of unacceptable quality products are produced (Enrick, 1985). Sampling is not foolproof; but with proper scientific sampling techniques, the risks of error are greatly reduced. Enrick (1985) describes the two types of errors that exist: Type I error, or "Producer Risk," and Type II error, or "Consumer Risk." The Producer Risk is defined as the probability of an acceptable charge of dried lumber being rejected or considered improperly dried due to variances in sampling. This risk causes either a halt in the drying process until a decision is reached, or requires needless inspection of the kiln instruments and unnecessary performance of maintenance. Consumer Risk is described as the chance of accepting a poorly dried package due to the "luck of the draw" and not to human or mechanical error. With this type of risk, wet lumber may be shipped resulting in the possibilities of stains, warp or degrade in service, or structural failure. Another possibility would be consumer complaints or financial penalties levied against the mill.

MOISTURE CONTENT

The MC of green wood varies greatly and can range from above 200 percent to 25 percent on a dry basis. Moisture in wood below the fiber saturation point (FSP), about 30 percent MC, is called bound water, while water in wood in excess of the FSP is called free water. The physical and mechanical properties of wood begin to change after all free water is removed. Wood's resistance to decay and stain also increases when dried below the FSP. Thus, the drying of lumber to a uniform MC that is below the FSP will greatly increase its durability, usefulness, and value. However, lumber drying defects can often occur whenever wood is over dried (Panshin, 1980). Degrade becomes excessive when wood MC falls below 10 percent (Kozlik, 1972). SPC measures may help prevent both over dried and wet boards through the use of control charts and their upper and lower control limits.

NBS Voluntary Product Standard PS 20-70 (1970) for softwood lumber requires 95 percent of the pieces to be at or below 19 percent MC with an average of not more than 15 percent MC. The Southern Pine Inspection Bureau requires kiln dried lumber graded "KD 15" to have a maximum MC of 15 percent and "KD 19" graded lumber to have a maximum 19 percent MC (SPIB, 1977). Other inspection agencies have different requirements for different species and products. Unfortunately, lumber is often over dried so the wet lumber constraints are met (McMillen, 1974; Wengert, 1986).

The Weyerhaeuser Company, Tacoma, Washington estimated that every sixth kiln load was over dried by 0.5 percent MC. The average loss due to over drying was four to six dollars per thousand board feet (MBF) per one percent MC (Steinhagen, 1979). If these figures are applied to data for the Western United States for 1989 (WWPA, 1990), overdrying means that approximately 4.5 million dollars was lost due to over dried lumber. Culpepper and Wengert (1982) reported that for each one percent MC that southern pine was dried below the 15 percent MC required average, a loss of three dollars per MBF was incurred. The forest products industry cannot afford to lose such significant quantities of money due to improperly dried lumber. In addition, should the wood be too wet, the lumber will not meet inspection agency standards; if over dried, the mill will lose money, because of excessive degrade.

MEASURING MC

The determination of the MC of lumber, especially for SPC purposes, requires a rapid, nondestructive, and reliable method (ASTM, 1988a). This requirement is best met by the use of electronic moisture meters; although other, more time consuming, techniques do exist (ASTM, 1988a). Among these techniques are the following: oven-drying of test samples, distillation, and hygrometric methods (ASTM, 1988a).

HAND-HELD METERS

Portable, hand-held, electronic, resistance-type moisture meters are commonly used in mills. Power-loss moisture meters are used for reinspection (Bramhall and Warren, 1977). ASTM Standard D 2016-74 allows MC readings to be taken with either a resistance- or power-loss-type, electronic moisture meter.

The hand-held, resistance-type meter estimates MC by measuring the electrical resistance between two pins that are driven into wood. The electrical resistance of wood is very dependent on MC below the FSP, decreasing as MC increases (Rasmussen, 1961). To account for the MC gradient in recently-dried lumber, the pins must be driven into the wood to a depth equal to one-fifth to one-quarter of the board's thickness (ASTM, 1988a). Pins which are electrically insulated, except for the tip, should be used when a MC gradient exists or when the surface of the lumber is wet (ASTM, 1988a). Pin alignment must be parallel to the wood grain (Can. For. Ser., 1976). Meter readings should be taken quickly after the needles have been driven into the board, otherwise "drift" will occur in the meter a short while after insertion, which gives false readings (ASTM, 1988b; Can. For. Ser., 1976). Readings from the meter are made to the closest one percent MC (Wengert, 1986). For the greatest accuracy, the wood should be at room temperature (77° F); otherwise a correction factor for temperature is required (ASTM, 1988b; Rice, 1976). A correction factor for wood species is also required for proper use of the meter (ASTM, 1988b).

Power-loss or capacitance meters generate radio-frequency (RF) waves or alternating electric fields that penetrate into wood to various depths, depending on meter type and settings (Can. For. Ser., 1976; ASTM, 1988a). The loss of power as these currents pass through the wood is measured by the meter (Can. For. Ser., 1976).

Wood that has had its surface dampened by dew, high humidity, or other sources of moisture should not be metered with a power-loss or capacitance MC meter, as the meter will give excessively high MC readings

(ASTM, 1988a). Wood samples should be separated from other samples by at least 1 in. to prevent sensing a second sample underneath a test sample (ASTM, 1988b). Just as for resistance-type meters, power-loss or capacitance meters require correction factors for temperature and wood species (ASTM, 1988a; ASTM, 1988b).

The power-loss meter readings are greatly affected by wood density and in general give poorer results than a resistance type meter; however, the power-loss meter is reliable for readings up to 25 percent MC, provides quick readings, and does not make holes in the wood surface like resistance-type meters (Can. For. Ser., 1976). A properly calibrated resistance type meter can be relied upon to give accurate readings of MC for six to 30 percent with an error of two to three percent MC (ASTM, 1988a; ASTM, 1988b).

The hand-held, resistance-type meter would be the best choice for quality control. This type of meter is the more reliable of the two and is relatively easy to use (Bramhall, 1977). Although the process of taking MC readings with a resistance-type meter may be more time consuming than for a power-loss-type meter, the disadvantage is not great when considering the better accuracy of hand-held resistance meters.

IN-LINE METERS

In-line moisture meters are used by some mills to do a complete MC test on all boards dried (Bramhall, 1977). These meters are typically placed behind the planer or in the dry chain (Bramhall, 1977). The MC of every board is indirectly calculated by measuring a physical property of the board that is affected by MC (Can. For. Ser., 1976). Based on MC set points in the device, lumber is either diverted to another location or is sprayed with paint to be sorted into loads that are to be redried (Bramhall, 1977; Can. For. Ser., 1976).

The in-line meter must be capable of a fast response for lumber feed speeds of 1000 lineal feet per minute (5.1 m/sec.) and kept correctly calibrated to prevent drifting (Can. For. Ser., 1976). These meters typically suffer inaccuracies from changes in temperature, wood density, and board size and cannot simultaneously meter different wood species (Can. For. Ser., 1976). Many of the points regarding hand-held power-loss or capacitance meters made earlier also apply to in-line meters.

The in-line moisture meter is capable of testing all boards in a kiln charge, or sampling the entire board population for a 100 percent inspection rate. The advantage is a complete inspection for wet or dry boards that need to be rejected.

Unfortunately, a heavy reliance on 100 percent inspections to catch manufacturing (drying) mistakes may provide a disincentive for the manufacturer (mill) to improve the process (Grant and Leavenworth, 1988). The objective of SPC techniques is to predict when drying mistakes are about to occur, and when to take preventative actions. This technique is in lieu of conducting a 100 percent inspection with the in-line meter for drying mistakes after they have been made.

QUALITY CONTROL PROGRAMS FOR MC

RECORD KEEPING

Diamond International Corporation has used a simple record keeping technique to track the MC of boards going to the planer and the grade coming out of the planer (Huber, et al., 1976). Records were also maintained of the kiln schedule used, the position of the crib in the kiln, and type of defects found in samples, in addition to board MC. This basic quality control information has built a data base from which kiln maintenance, schedules, repairs, kiln performance, and process modifications are analyzed and justified. The quality control data has also shortened kiln schedules and reduced overall MC ranges (Huber, et al., 1976).

The Canadian Forestry Service (1976) suggests the use of a record sheet for each kiln charge that tracks kiln number, charge number, species, quantity, dates in and out, final MC, total length of drying time, final average MC, and percent "overs." These were all found to be critical parts of information needed to maintain and produce quality dried lumber.

CHARTING

Frequency distribution and probability plots of board MC have been used as a quality control technique (McMahon, 1961; Pratt, 1953; Rice, 1976). The overall shape and or skewness of a curve for a MC distribution has been used as a check to see if drying has been performed within established standards, and a log-normal probability plot of MC has been used to assess the percentage of boards over and under dried (McMahon, 1961; Pratt, 1953). Log-normal probability plotting was done to make rough linear estimates of board MC which had a MC greater than that which could be taken with a moisture meter. This technique allowed for extrapolation of data beyond the moisture meter's sensitivity.

These quality control techniques, like many of the others, just describe what has already occurred. What is needed is a program or technique that not only tells what has happened, but what is likely to occur in the future and what consistency of MC a mill is capable of maintaining or achieving. Simple SPC control charts, which have already been described, are capable of this.

SCREENING

Enrick (1985) would describe screening at a lumber mill as the inspection of every board with defective lumber downgraded, redried, chipped, or discarded. This process is a 100 percent inspection rate of all boards. However, this does not assure an acceptable board MC for all lumber at mills that do not make use of an in-line moisture meter to test all of their dried lumber.

PROCESS INSPECTION

Process inspection of a dry kiln involves a check on the equipment and operational procedures by following the lumber from the green chain to the planer. The reason for a process inspection should be to pinpoint any trouble spots and have the mill take corrective actions.

A major drawback to process inspection is that one inspector can not be at all machine centers at all times, thus a great amount of defective material (lumber) may be produced before the error(s) is noticed and corrected (Enrick, 1985). The use of a control chart system and statistical analysis will provide continuing information for the inspector, about mill equipment, so he can quickly determine when something is about to go wrong or has malfunctioned in the process (Enrick, 1985; Latimer, 1951). This system is far better than an occasional and often infrequent spot check performed during a simple process inspection.

STICKER ALIGNMENT

Sticker alignment is concerned with the proper placement of stickers (narrow strips of wood used to separate layers of lumber) in a package of lumber so that stickers are vertically aligned in columns over a kiln car or bunk support. Misplaced stickers cause uneven weight distributions in a lumber package, with the end result being warped and kinked boards (Rasmussen, 1988; Milota et al., 1990). By following the correct stickering procedures in the stacking process, a mill can reduce lumber degrade by five to 10 percent and cut drying time by 15 to 20 percent (Huber, 1973).

PROCESS INSPECTION FOR STICKER ALIGNMENT

Proper sticker placement can be determined by holding a sticker vertically, and on its narrowest edge, against a column of stickers so as to cover the tier of stickers. A tally is then made of all stickers not covered by the vertical sticker. Milota et al. (1990) suggest testing a total of 15 randomly-selected columns of stickers from a variety of different packages and package locations. An attempt should be made to check for a pattern that would lead to a cause for the misaligned stickers. In terms of an actual count of misaligned stickers, missing stickers, and stickers on edge, a target goal of no more than two per category out of 15 sample columns of stickers is good (Milota et al., 1990).

MEASURING STICKER ALIGNMENT WITH A CONTROL CHART

P charts or percent defective charts can be used to evaluate stacker performance by plotting the fraction of misplaced, missing, and stickers on edge versus time. By looking at the upper and lower control limits on the chart, the p chart will give the operators an idea of what is obtainable given the circumstances. These control limits should be based on a time span of at least 20 to 25 sequential sampling periods, days or shifts (Contino, 1987; Enrick, 1985; Grant and Leavenworth, 1988). As time passes and repairs or adjustments are made to the machine center (stacker), new control limits should be recalculated. In all likelihood these newer control limits will be narrower due to increased precision and better operation of the machine center (stacker) (Enrick, 1985).

SUMMARY

Presently there exist a number of quality control methods for MC control and stickering procedures. Unfortunately, most of the methods that have been developed and used are just summaries of what has occurred in the drying or stickering process. Many SPC methods that are capable of predicting future drying or stickering performance in addition to summarizing past performance have not been tested or implemented in mills. An added advantage to SPC control charts is that they are simple graphical representations of historical performances and future drying and stickering process capabilities. These SPC charts can be understood by people who do not have strong statistical backgrounds.

SPC quality control measures (control charts, p charts, group charts) are on-going quality control measures. An insight into the past, the present, and the future is much more valuable to a mill then just knowing the past and present. Certainly SPC control charts can provide the key to maintaining and improving the quality of drying MC and lumber stickering practices.

PROCEDURE

STICKER PLACEMENT

The accuracy of the sticker placement of four different stackers was studied. Sticker placement was measured by two different techniques. For the first method, a vertically aligned sticker was positioned in a location so as to cover as many stickers as possible in a column. This technique was similar to that described by Milota et al., 1990. In the second method, the distance of the sticker from the desired location was measured. From this data computer simulations were performed to reproduce representative sticker placement positions. The data from both of the methods used were plotted on p charts.

There were three reasons for measuring the accuracy of sticker placement: (1) to determine if the method could be accomplished in an amount of time reasonable for regular quality control; (2) to obtain an estimate of the variation in sticker placement; (3) to develop data that could be used in a computer model to simulate a number of different stacking and sticker placement scenarios.

To date, no mills track or evaluate the accuracy of sticker placement on a continual basis. The ability to do so by counting the number of misplaced stickers out of the total number examined and plotting them in a p chart format can provide valuable quality control information. One quick look at a p chart will show if sticker placement is occurring correctly or if some error is occurring in the process, such as a broken component in the stacker or improper operation of the stacker by the operator. The use of a computer model provided the means by which p charts of in- and out-of-control situations could be reproduced.

Finally two histograms, each based on sticker thickness (in.) or width (in.) from randomly selected stickers, were produced. The histograms were drawn to see if they could help distinguish different sticker sizes. A simple histogram of sticker width or thickness can provide an easy visual check on sticker size uniformity.

ALIGNMENT USING THE STICKER

Sticker placement was studied on two stackers (A and B) over a three-day period. A straight sticker with a plumb level attached to its side was positioned vertically with its narrowest edge outward. This sticker was then moved to the left or right to cover as many stickers as possible, as shown in Figure 2. Those stickers that were not at least partially covered by the vertical sticker were tallied as out of alignment. This procedure was performed randomly 14 to 16 times over the three-day duration. The sample size for each observation (subgroup) period varied. The control limits for the p charts were calculated according to Equations 10 to 12 and were plotted with Statgraphics (Ver. 3.0) software.

DISPLACEMENT SIMULATIONS

The displacement distance of each sticker from the best possible sticker location in a stack was measured on lumber from stackers C and D. The best possible sticker location was assumed to be at the

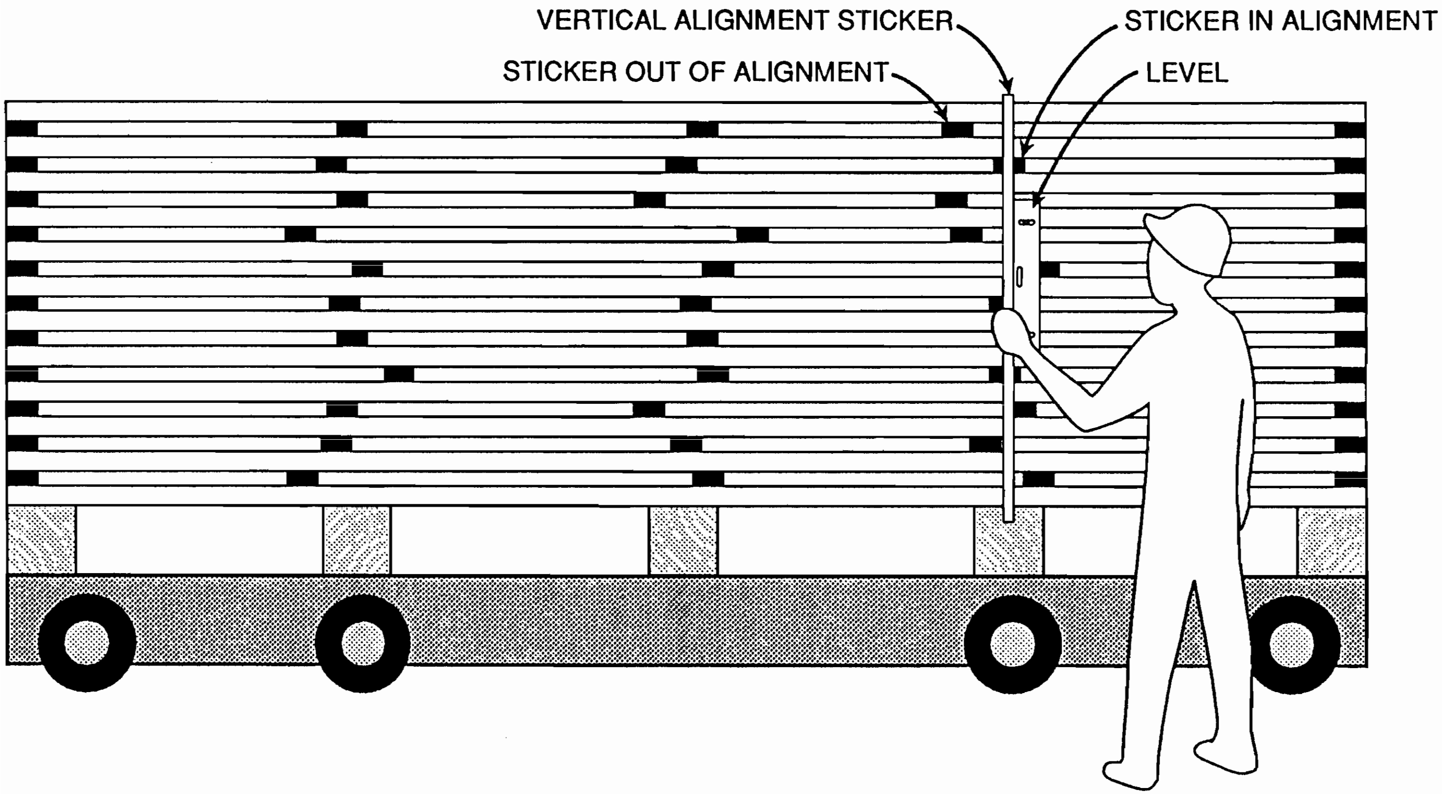


Figure 2. Method used to assess sticker placement accuracy.

horizontal center of the sticker column. This implies that the stacker places the center of the column of stickers at the correct spacing (2 ft. or 4 ft. for example). A string, secured at each end by tacks, was strung vertically in the estimated best position for a given column of stickers. The distance to the left or right (negative or positive) from each sticker center to the string (displacement distance) was recorded. The displacement distances were measured for 302 stickers from stacker C and 256 stickers from stacker D. From the sticker displacement data, the median sticker displacement distance was calculated for stackers C and D. This median sticker displacement distance for each stacker was subtracted from all the measured sticker displacements to arrive at the true sticker displacements produced by each stacker. From these mathematically-adjusted true sticker displacement distances, the averages and standard deviations were calculated for each sticker column under measurement.

A computer model was developed to simulate the sticker displacement distances produced by a stacker. This was done to be able to produce data that could be used in p charts. The goal was to produce p charts illustrating in- and out-of-control situations and to test which edge of the vertically-aligned sticker should be used in evaluating sticker placement.

Equation 13 was used to approximate a normal distribution (Abramowitz, 1972) using the random number generator in Lotus 1-2-3 (Rel. 3.0). See nomenclature table for definitions of terms.

$$x_p = t - \frac{2.515517 + .802853t + .010328t^2}{1 + 1.432788t + .189269t^2 + .001308t^3} \qquad t = \sqrt{\ln\frac{1}{p^2}} \tag{13}$$

A random number between zero and one, P_1, is used to calculate X_p, the random normal deviate. From X_p, the displacement is calculated according to Equation 14.

$$\text{Displacement} = \text{Mean} + \text{Standard Deviation} * X_p \tag{14}$$

The mean and standard deviation come from the corrected sticker displacement data for stackers C and D. Figure 3 shows an example of the typical sticker distribution. The y-axis, called probability, represents the random seed value. The x-axis indicates the stickers' actual displacement distance in inches. From this sticker displacement distribution, the computer then mathematically evaluates what percent of stickers are out of alignment.

A sticker is out of alignment if it has an absolute value of displacement distance greater than the "critical rejection distance." The critical rejection distance (Figure 4) is the sum of one half the thickness of the vertically aligned sticker (A) plus one half the width of the sticker (B) in the stack of lumber, (A+B)/2.

Two values for the critical rejection distance were selected, 1.25 and 1.50 in. The first represents placing the vertically-aligned sticker on edge (A=1.0 in.); the second represents placing the vertically-aligned sticker flatwise (A=1.5 in.). B=1.5 in. in both situations.

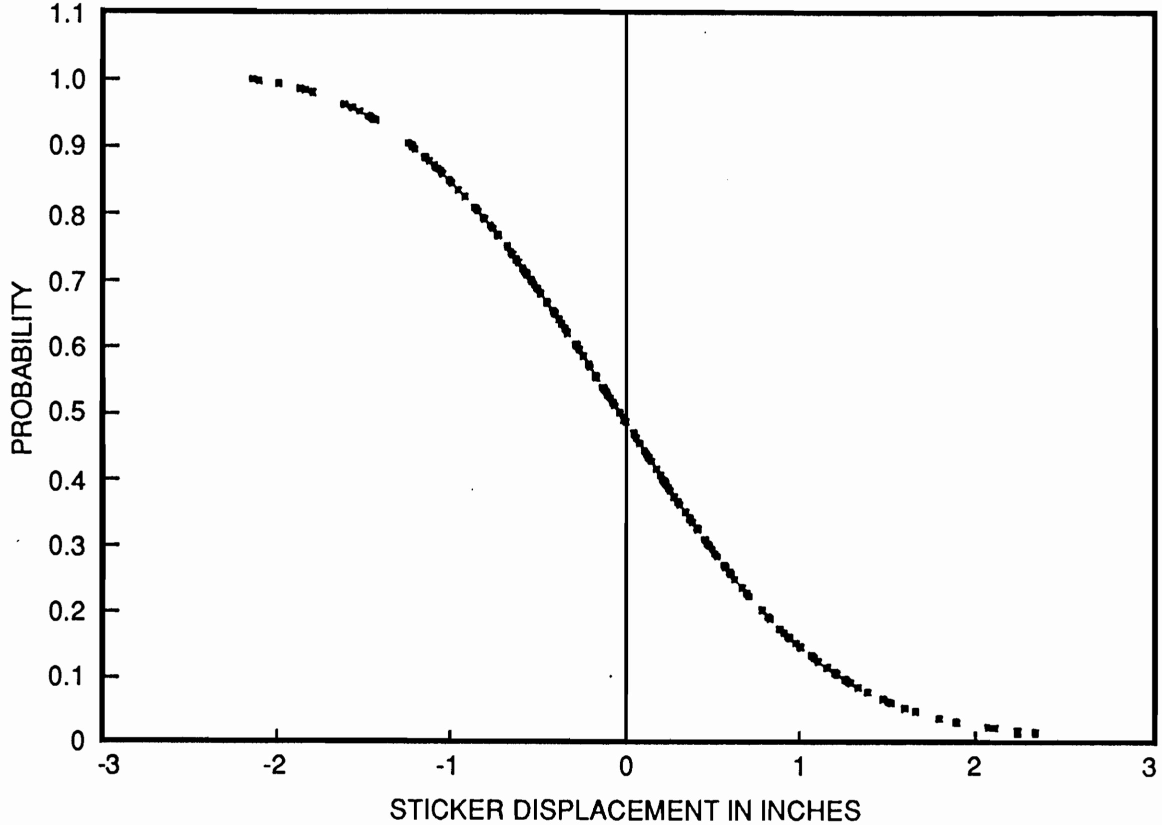


Figure 3. An example of a distribution of sticker displacements produced by the computer model.

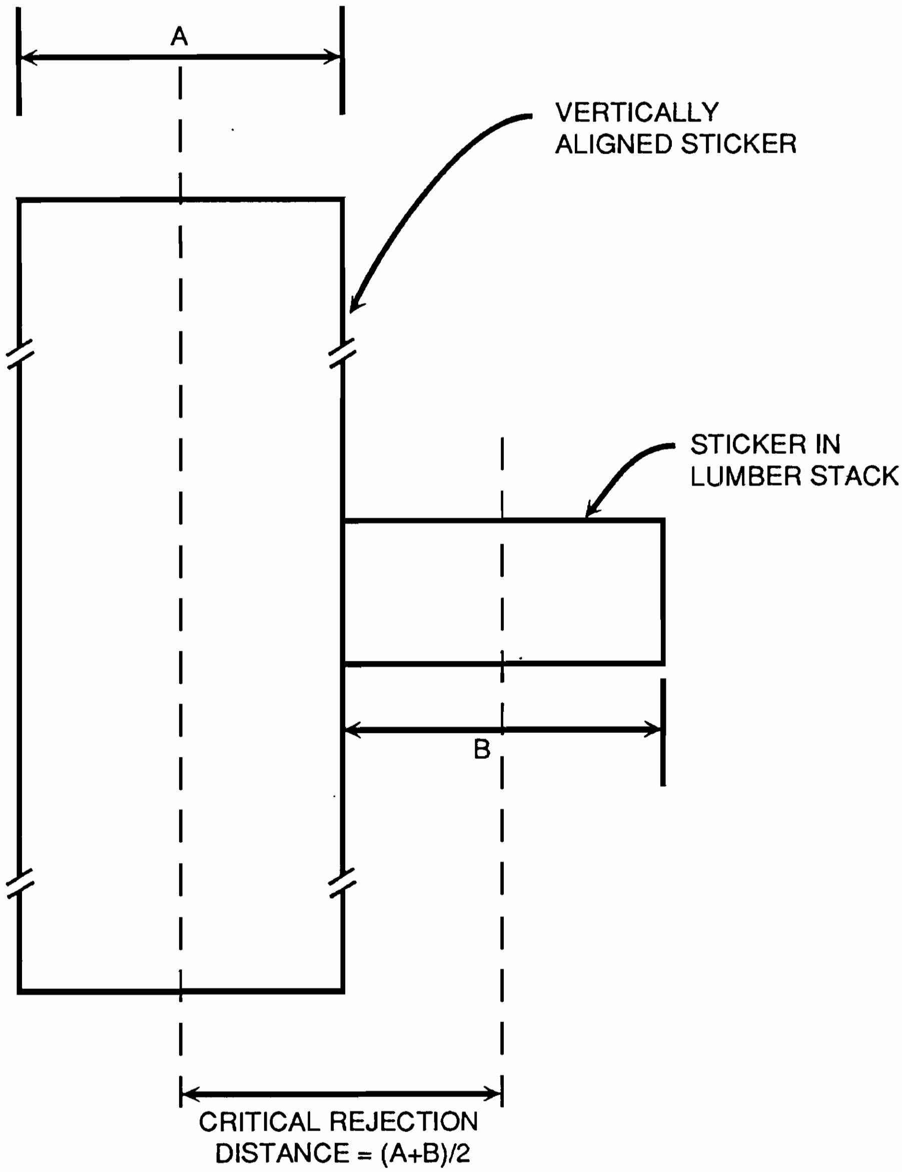


Figure 4. Schematic showing how critical rejection distance was computed.

For each critical rejection distance considered, 200 sticker displacement values were generated for each of 25 subgroups. A mean sticker displacement of -0.050 in. and a standard deviation of 0.942 in. were used. These were representative of the data from stacker C, and are based on a vertically aligned sticker placed in the median position of a sticker column. For each subgroup, the fraction defective was determined and p charts were produced using Statgraphics (Ver. 3.0).

One computer-generated, out-of-control p chart was constructed using the computer model with average and standard deviation values from stacker D. This particular stacker was not operating properly. The same procedure as described in the above paragraph was followed, but unique averages and standard deviations were used in each computer run (subgroup). A critical rejection distance of 1.25 in. was used . This p chart was developed to demonstrate a typical out-of-control situation.

Two p charts which were initially under control, went out of control, and were brought back under control were also produced. For subgroups in which the process is in control, the mean was -0.050 in. with a standard deviation of 0.942 in. Subgroups which represent an out-of-control situation were based on the same mean value and a standard deviation of 1.461 in. Critical rejection distances of 1.25 in. and 1.50 in. were used for the first and second p chart, respectively. The control limits represented periods in which the charts were in control and were, therefore, taken from the previous in-control charts corresponding to the two critical rejection distances.

STICKER THICKNESS DISTRIBUTIONS

The thickness and width of a random sample of thirty stickers was measured with digital calipers to evaluate sticker size uniformity. This was done because drying straight lumber requires that consistently sized stickers be used throughout a package of lumber. One measurement of width and thickness was made per sticker approximately 2 in. in from the sticker's end. The data was then used to produce one histogram each for sticker width and thickness in Statgraphics (Ver. 3.0) software.

ESTIMATION OF PACKAGE MC

If estimates of package MC could be accomplished in a reasonable amount of time, a kiln operator could then accurately determine the package's overall MC. This person could then decide if the lumber needed more drying or if it was over-dried before the entire stack of lumber went to the unstacker and was metered by an in-line moisture meter. Ideally, a person could locate areas or zones in a kiln where wet or dry lumber was occurring. Maintenance could then be performed to remedy the problem before numerous improperly dried charges of lumber were produced.

A hand-held moisture meter was used to randomly sample the boards on the outer edge of packages of lumber from three different mills (A, B, C). The average MC was estimated for each package. The average MC for each package of lumber was also determined by a 100 percent inspection of boards in the package with an in-line moisture meter. This procedure was done to determine how good of a relationship exists between estimates of the package MC based on hand-held MC readings and the MC based on an in-line meter. A regression analysis procedure was attempted to verify the relationship exists between the two methods of estimating MC.

Three hand-held resistance (1 in. pins, Delmhorst RDX-1 meter) MC readings were taken on each of 10 randomly chosen, outer edge boards, each on the exposed edge of twelve stickered and stacked packages of Douglas-fir (Pseudotsuga menziesii) from mill A. This 2"x8"x18' and 2"x8"x20' lamination grade lumber was stacked 20 to 23 layers high per package. All lumber metered was at 70° F. One meter reading was taken two feet in from each end of the board and one meter reading was taken at the board's midpoint. The total time required to take these three MC readings was recorded for future assessment of practicality.

All MC readings were averaged to arrive at the "dependent variable," known as the average hand-held meter percent MC. The average package MC, the "independent variable," was then determined by a 100 percent screening with a Wagner in-line moisture meter with nine sensory pads. A regression of the dependent variable on the independent variable was then performed in Statgraphics (Ver. 3.0).

In another package MC study, two hand-held resistance (3/4 in. pins, Delmhorst RDM-1 meter) MC readings were taken from every third board, each on the exposed edge of 24 stickered and stacked half-cribs (the upper and lower halves of the cribs will be referred to as packages) produced by a crib stacker. Each meter reading was taken at least two feet in from the board's end. The packages consisted of 5/4 random width 16' long ponderosa pine (Pinus ponderosa) at an ambient temperature of about 70° F. Two kiln charges, one from each mill (B and C), were examined according to this method.

Two subsets of data were selected from the mill B MC readings. This procedure was done to check the strength of the relationship between hand-held and package MC readings as the sample size was decreased. One subset consisted of 10 randomly-selected, outer edge boards. Each board MC was the average of the two meter readings per board. The random selection process was performed so that five boards came from each side of the package. The second subset of data consisted of four randomly selected, outer edge boards. Two boards came from each side of the package.

The hand-held meter readings from the full data set and each subset were then averaged to give estimates of the package MCs based on various sample sizes. The average package MCs were also determined by a 100 percent screening with a Wagner, one-sensory-pad, in-line moisture meter.

For the ponderosa pine data sets a total of four regression analyses were performed in Statgraphics (Ver. 3.0). The independent and dependent variables were average MC based on the in-line moisture meter and the average MC based on the hand-held mositure meter, respectively.

STATISTICAL ESTIMATION

NORMALIZATION

MC distributions taken from kiln dried lumber packages are positively skewed. This skewness was verified from MC distributions taken with an in-line meter from three different kiln dried charges of lumber. The MC distributions from two additional kiln charges of lumber were tested for skewed distributions. Testing for skewness was done mathematically and graphically.

Two wood species were tested. These consisted of two-inch Douglas-fir from mill A, 5/4 ponderosa pine from mills B and C, and 2" ponderosa pine from mill D. MC data from two charges of lumber from mill D, each dried in a different kiln, were tested. The lumber from mill D was metered for MC by sampling every third board at three locations per board with a hand-held, capacitance-type moisture meter (Wagner L600). One meter reading two feet in from each end of the board and one reading at the midpoint of the board were taken. These were averaged to obtain the MC of each board.

To use MC data in a control chart, the skewed MC distribution must be mathematically transformed to produce a normal distribution. This transformation was performed to avoid the "serious mistakes" referred to by Grant and Leavenworth (1988) when the distribution of a "quality characteristic" such as MC is assummed to be normal. Also the required sample size for a normal distribution can be less than that required for the skewed distribution. Each set of MC data described above and the computer-generated MC data that is discussed in the section on "COMPUTER MODEL" were transformed using a log transformation as suggested by McMahon (1961), in addition a reciprocal transformation of the same MC data was performed. The skewness and kurtosis of these MC distributions were calculated in Statgraphics (Ver. 3.0).

Box-and-Whisker plots were made of the untransformed and transformed MC distributions for mills B and D data. Normal probability plots of untransformed and transformed MC data from one correctly-dried lumber charge, simulated by the computer drying model, were also produced. These two graphic techniques and data were chosen to help visualize the effect each transformation had on the dried MC distributions of ponderosa pine. All calculations for transformations and graphic plotting were done in Statgraphics (Ver. 3.0). Skewness and kurtosis of the MC distributions from mills A and C were similarly calculated and compared to the results from mills B and D.

SAMPLE SIZE

The sample size required to properly estimate the variations in MC found in packages of lumber can be calculated by using the standard sample size formula shown in Equation 1.

To calculate the sample size required for control chart usage, a target MC of 10 percent was selected. This target is the selected final dried MC that the mill will try to achieve. After selecting the target MC, a level of accuracy must be established. For this study a maximum allowable error of ± 1.0 percent MC was selected. Knowing the target MC and accuracy level, the normal half-width confidence interval may be established. The half-width confidence interval distance was selected to be the difference between 1/9.0 to 1/10.0 or 0.0111 such that $1/(.1+.0111)=9.00$ to $1/(.1-.0111)= 11.25$ percent MC. A smaller normal confidence interval could have been chosen by using the other half of this uneven confidence interval. One could have chosen the difference between 1/10.0 to 1/11.0 or 0.0091 such that the normal half-width confidence interval ranged from 9.17 to 11.00 percent MC.

For this thesis the chosen normal confidence interval will be 9.00 to 11.25 percent MC. A 95 percent confidence level will also be used in Equation 1 with the standard deviation of the transformed pilot study MC data being 0.0226 1/%. The standard deviation value used was the standard deviation of the percent MC after the MC data was transformed using the reciprocal of the percent MC.

For illustrative purposes, required sample size calculations were also calculated for a target MC of 10 percent $\pm$1.5 percent MC and $\pm$0.5 percent MC such that their respective normalized confidence intervals ranged from 8.50 to 12.14 and 9.50 to 10.56 percent MC. Both calculations were made using a 95 percent confidence level and a standard deviation of 0.0226 1/%.

CONTROL CHARTS

Computer simulations of a number of different drying scenarios were conducted by using a model to produce MC distributions similar to those that occur in a real dry kiln. These computer simulations provide the data necessary to generate control charts.

The purpose of conducting a variety of drying scenarios with this computer model was to test the feasibility of using control charts to track the quality of board MC and the operation of a dry kiln. The computer model provided data that was nearly identical to actual kiln operations. With this model the computer operator can deliberately reproduce incorrect drying conditions inside a kiln without destroying valuable lumber. Known drying conditions inside the kiln can easily be reproduced or simulated by programming the computer model.

COMPUTER MODEL

A computer model, developed by Dr. Michael Milota of Oregon State University, that mathematically calculates MC of each board in a kiln as a function of time was used to produce the MC distributions necessary to construct control charts. The first requirement necessary to use the model was to input all known data about the kiln charge. This information included the kiln schedule, initial moisture distribution, board properties and the drying time. Then, two parameters were adjusted to force the final MC distribution from the model to match that measured at mill B. The known data for the simulation were a wood density of 23.7 lbs./cu.ft.; board thickness 1.23 in.; board length 192 in; board width 8.5 in.; an initial board temperature of 70° F; sticker thickness of 7/8 in.; a barometric pressure of 92200.0 pascals; a fan reversal time of three hours; a package 63 boards high and 12 boards wide; and a total drying time of 68.5 hours. The initial board MCs were represented by a log-normal distribution with a mean log of 3.94 and a standard deviation log of 0.55. The first adjustable parameter controlled the drying rate of individual boards during the constant rate period. The second parameter was a proportionality constant which was related to the dependence of drying rate on moisture content as the MC approaches the EMC. Values of 0.085 lb./hr./ft^2 and 70 lbs./hr./ft^2/%MC, respectively, were selected. The dry- and wet-bulb temperatures and air velocities used in the simulations are given in Appendix A. The output from the program is the final moisture content of each board. This MC was the untransformed MC data used in constructing the control charts.

X-BAR AND RANGE CONTROL CHARTS

All the sample MC data used to generate the X-bar and Range control charts described below were randomly selected from the computer generated MC distributions. The subgroup size used in making the data selections for each point on the control charts was based on that size calculated by using Equation 1 with a confidence interval of 9.00 to 11.25 percent MC and a standard deviation of 0.0226 1/%. The MC data used in all control charts were transformed by taking the reciprocal value of the MC before the control charts were plotted. Five different drying scenarios were simulated and control charts produced.

In-Control Situation

The first drying scenario run consisted of 20 charges of lumber being dried under a drying process that is in-control. This procedure was performed to establish the UCL and LCL against which all drying processes were to be evaluated.

Out-of-Control Situations

The next four drying scenarios all began with the same first 20 charges that were under control; however, each of the four pairs (X-bar and Range) of control charts depicted out-of-control drying situations after charge number 20.

Drying Scenario 2: Charges or subgroups 21 to 30 were dried in a kiln in which the dry-bulb sensor was 5° F in error, resulting in a kiln that was too cool.

Drying Scenario 3: Charges or subgroups 21 to 30 were dried in a kiln in which the dry-bulb sensor was 5° F in error, resulting in a kiln that was too hot. Charges 31 to 40 were brought back under control because the dry-bulb sensor was fixed.

Drying Scenario 4: Charges or subgroups 21 to 30 were dried with too low a fan velocity (300 FPM). Charges 31 to 40 were brought back under control because the fan velocity was corrected to 600 FPM.

Drying Scenario 5: Charges or subgroups 21 to 40 were dried in a kiln in which one dry-bulb sensor was 5° F in error, resulting in one end of the kiln being too hot.

GROUP CHARTS

The last type of control chart investigated was the group control chart. Each individually-controlled heating zone within a kiln was called a "quality zone." Every quality zone inside a kiln was given a specific number. The quality zone producing the wettest and driest lumber MC for each kiln run was plotted on the control chart. That quality zone number and its estimated MC are signified by the location where it is plotted on the control chart.

The control limits were the same as those calculated for the X-bar chart that was under control in the section titled "In-Control-Situation." Likewise, the estimated MC in a quality zone was the average of the randomly-selected MC data used to generate the X-bar and Range charts.

The data for the first group control chart came from the same computer scenarios in which all the charges or subgroups are under control. Each subgroup consists of 16 randomly-selected MC data points that have been transformed in the same manner as the data used in the X-bar and Range control charts. These MC data points were then averaged together to arrive at the subgroup's average MC point on the group control chart.

The second group control chart shows an example of quality zone number 3 being out of control. The data for quality zones 1, 2, and 4 came from the computer scenarios where all the charges were under control. The data for quality zone number 3 came from the scenario where the dry-bulb was too hot by 5° F.

The last group control chart shows a situation where quality zone number 2 was consistently out-of-control. The data for quality zones 1, 3, and 4 came from the computer scenarios where all the charges were under control. The data for quality zone number 2 came from the scenario where the dry-bulb was too cold by 5° F.

RESULTS

STICKER PLACEMENT

ALIGNMENT USING THE STICKER

The p charts shown in Figures 5 and 6 indicate that stackers A and B are not in a constant state of control or are incapable of consistently placing stickers accurately. Stacker A, shown in Figure 5, began the study period with a high percentage of incorrectly placed stickers in subgroups 1 and 2. The presence of an evaluator checking on sticker accuracy may have resulted in improved performance of the stacker operation in subgroups 4 to 10. Stacker performance improved in subgroups 11 to 13, which was better than the stacker's LCL capability. Subgroups 14 and 15 show a regression back to within the UCL and LCL.

The p chart for stacker B, Figure 6, again shows that at the beginning of evaluation the sticker placement was out of control. Subgroups 1,2 and 3 lie above the upper control limits depicted by the dotted line. Subgroups 4,5,7,8,12, and 13 are within control limits, thus indicating sticker placement is occurring at an acceptable precision. Subgroups 9,10 and 11 are beneath the lower control limit. This indicates that better sticker placement is achievable with this stacker. Subgroup 14 shows proper sticker placement practices were forgotten or ignored, resulting in the fraction of misplaced stickers being greater than the upper control limit.

Most of the points do not fall within the UCL and LCL for stackers A and B because the stackers are in need of repair and adjustment, in

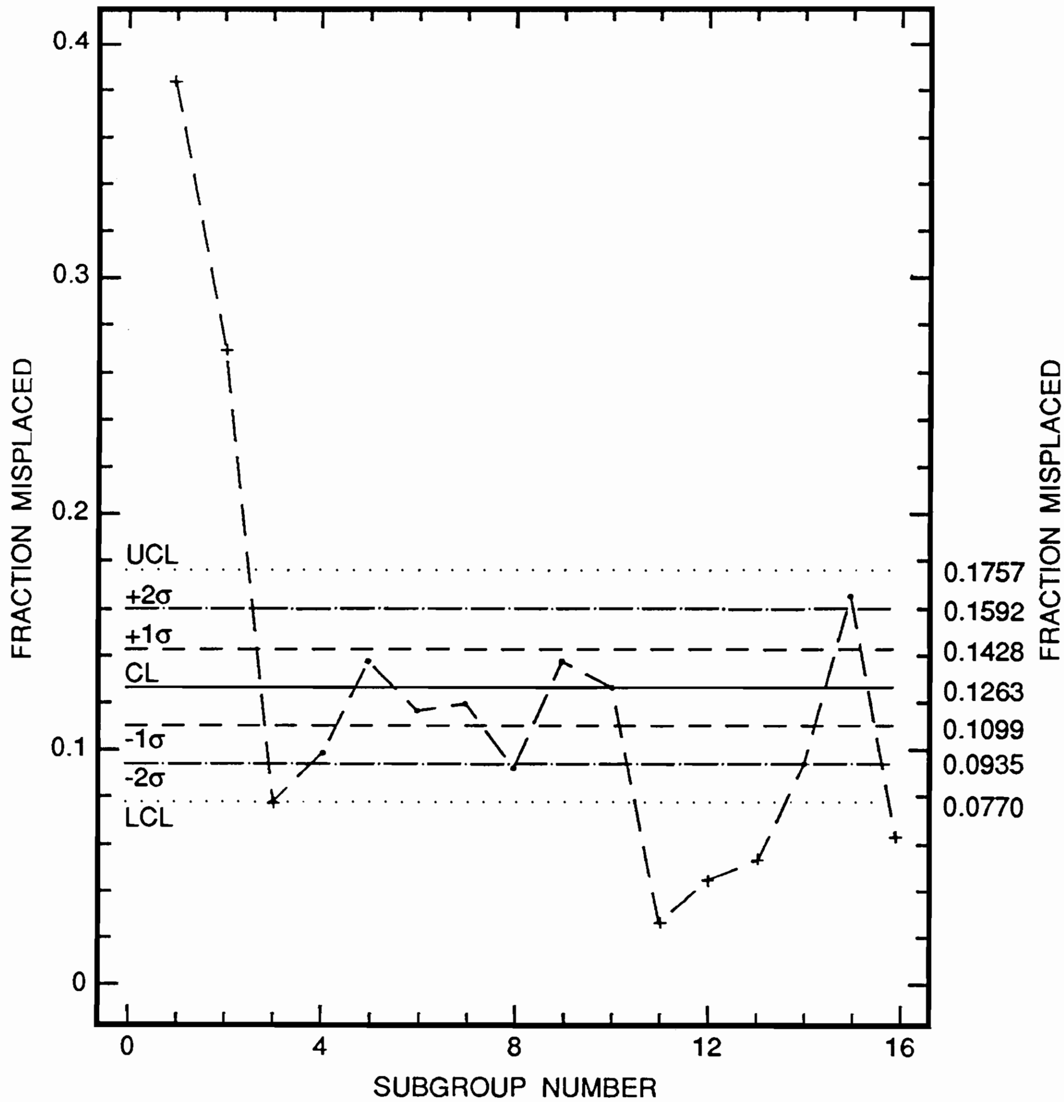


Figure 5. P chart that is representative of a stacker (A) which is not under control.

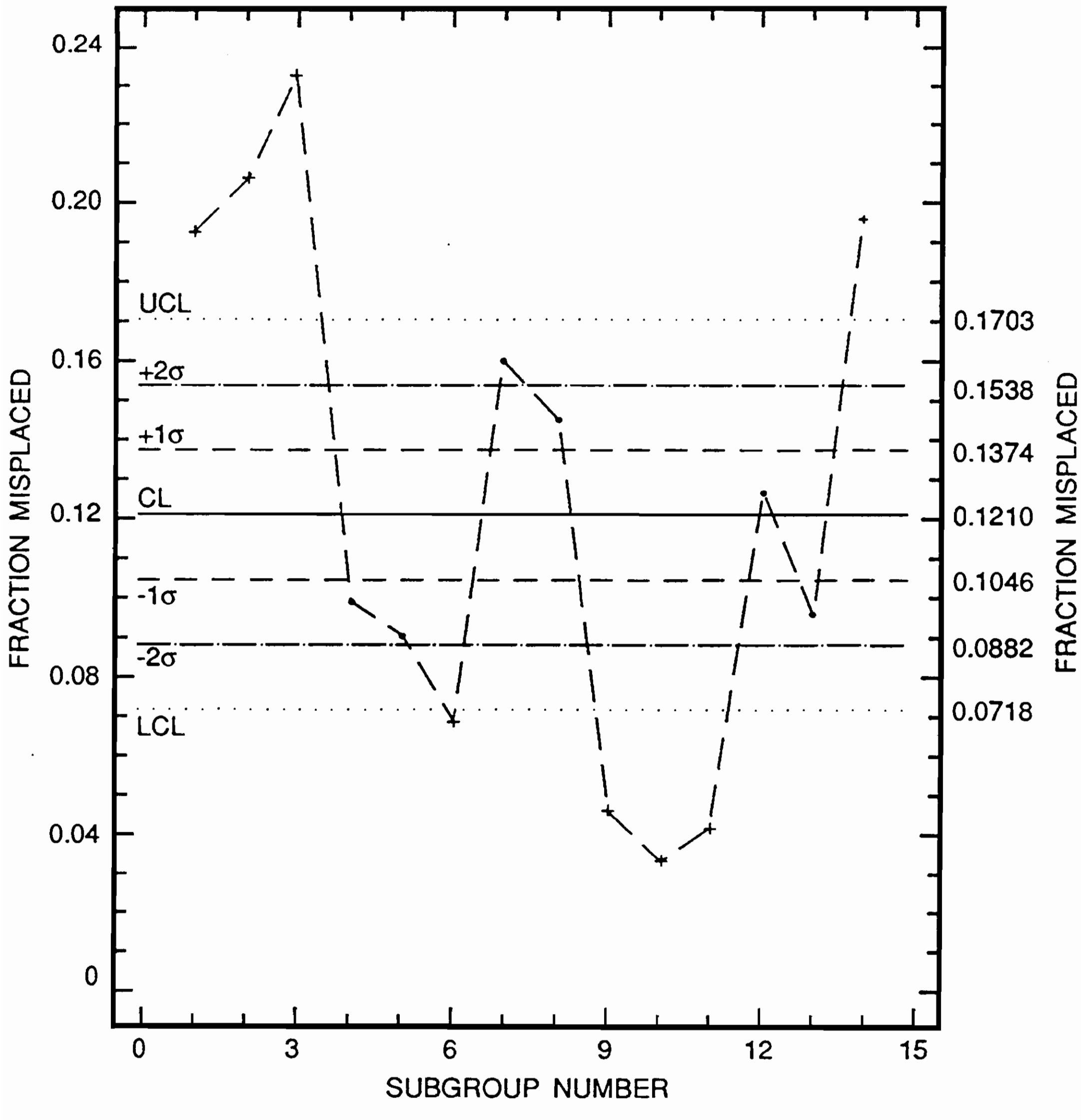


Figure 6. P chart that is representative of a stacker (B) which is not under control.

addition to improper operation. Important mechanical components are worn or need adjustment or calibration.

This practical test of counting the actual number of stickers out of alignment with a vertically positioned sticker and the plotting of control limits proves that the procedure can be done on a day-to-day or shift-to-shift basis. A reasonable time span, about 10 minutes per subgroup, was all that was required to complete this task.

DISPLACEMENT SIMULATIONS

Two p charts that use computer data to simulate sticker placement situations that are under control are shown in Figures 7 and 8. The data for these charts are based on the stacker performance statistics for stacker C. The first p chart, shown in Figure 7, is a control chart for 25 consecutive sample periods (subgroups 1 to 25) consisting of 200 stickers examined per period. None of the points are above or below the upper and lower control limits of 0.2530 or 0.0926. To be counted in the fraction misplaced, a sticker would not be touched or covered by a vertically aligned sticker placed on its narrowest edge. The critical rejection distance used was 1.25 inches. The fraction of stickers expected to be misplaced from this stacker using this technique would be 0.1728.

The p chart in Figure 8 shows a process under control if a critical rejection distance of 1.5 in. was used, that is, if we used the widest edge of the vertically aligned sticker for the evaluation of stickers in or out of alignment. The expected average fraction of misplaced stickers would be 0.1080. For practical purposes the use of the widest edge of

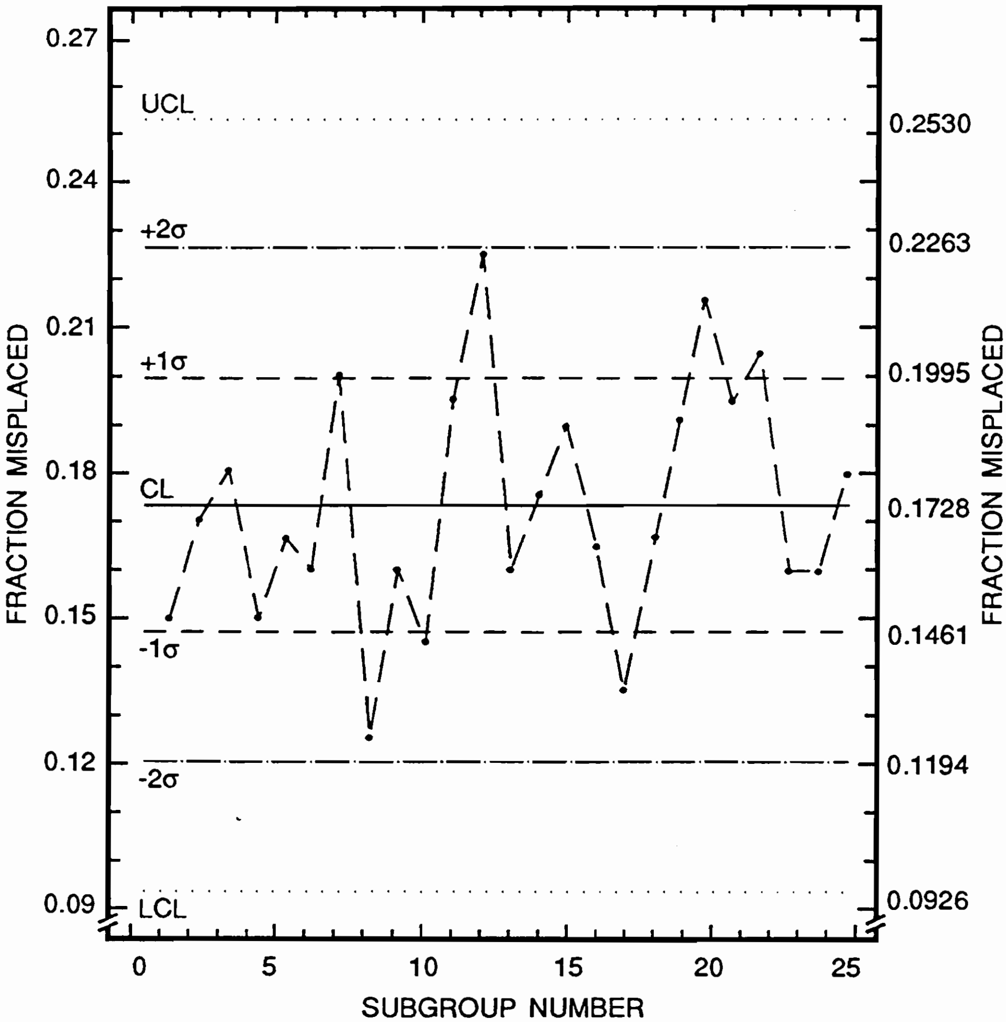


Figure 7. P chart for sticker placement. The data is from a computer model simulating a process which is in control. A critical rejection distance of 1.25 inches was used.

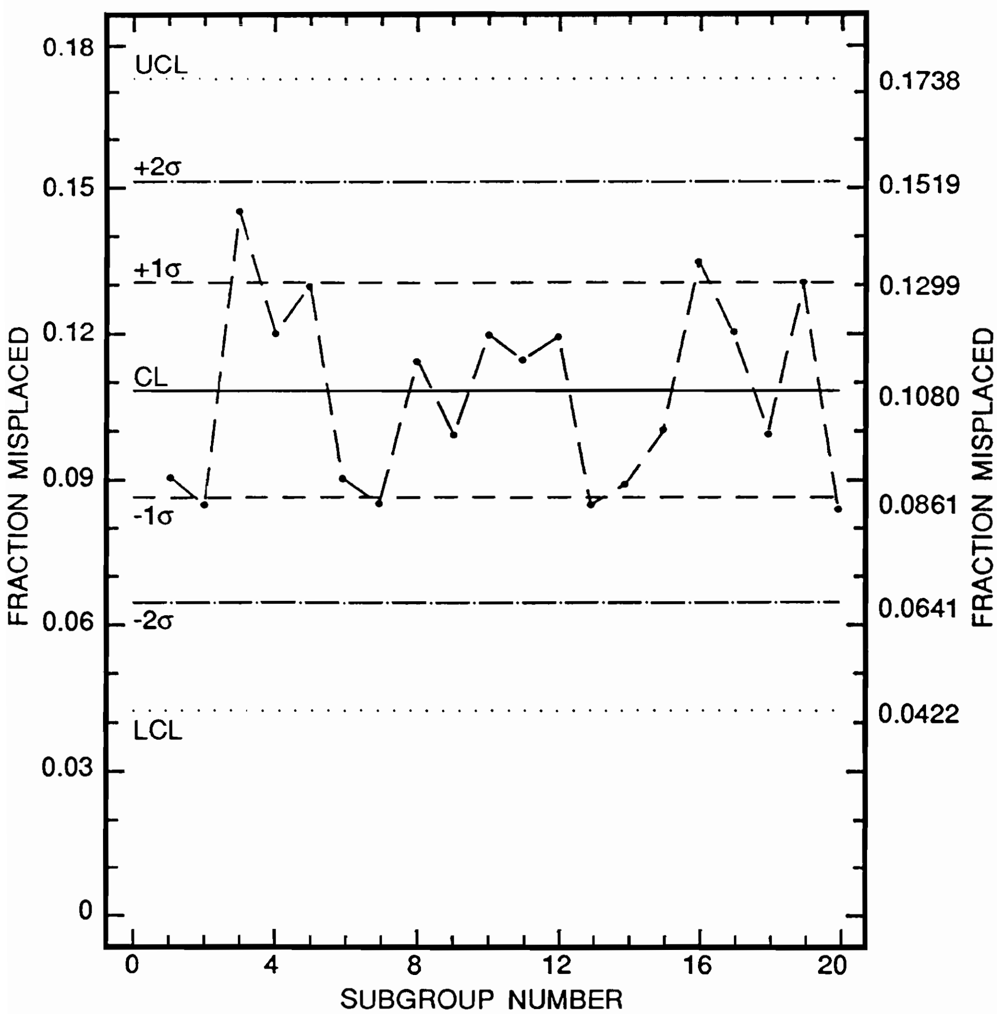


Figure 8. P chart for sticker placement. The data is from a computer model simulating a process which is in control. A critical rejection distance of 1.50 inches was used.

a sticker is a more realistic measure for evaluating sticker placement performance. A stacker under control is more likely to be operating at a low 10 percent sticker misplacement rate rather than at a 17 percent misplacement rate.

Both of the p charts in Figures 7 and 8 show all points to be within the upper and lower control limits. Each point on both charts occurs randomly. There are no runs or trends of plotted points to indicate possible trouble in sticker alignments. Likewise, there are no consecutive sets of subgroups at or beyond the 1σ or 2σ warning limits. These two charts are typical of stackers that are in control, or in other words, properly operating. However, the goal of misplaced stickers should be closer to two percent for a stacker that is operating to ultimate precision. The stacker used as the basis for the computer-generated data in this study (stacker C) was 40 years old and probably was not capable of achieving better sticker placement accuracy because of worn components.

Figure 9 shows what a typical control chart would look like for an out-of-control situation or an improperly operating stacker. This chart was produced from a computer simulation based on data from stacker D. The stacker was not functioning properly. Most of the points lie either above or below the initial study control limits defined at 0.3004 and 0.1266. A number of points are below the LCL. This chart indicates that the stacker is capable of better performance if proper adjustments or calibrations could be maintained. The phenomenon is most likely due to worn parts not staying within calibrated standards. In addition, there are a number of sets of subgroups beyond the 1σ and 2σ warning limits.

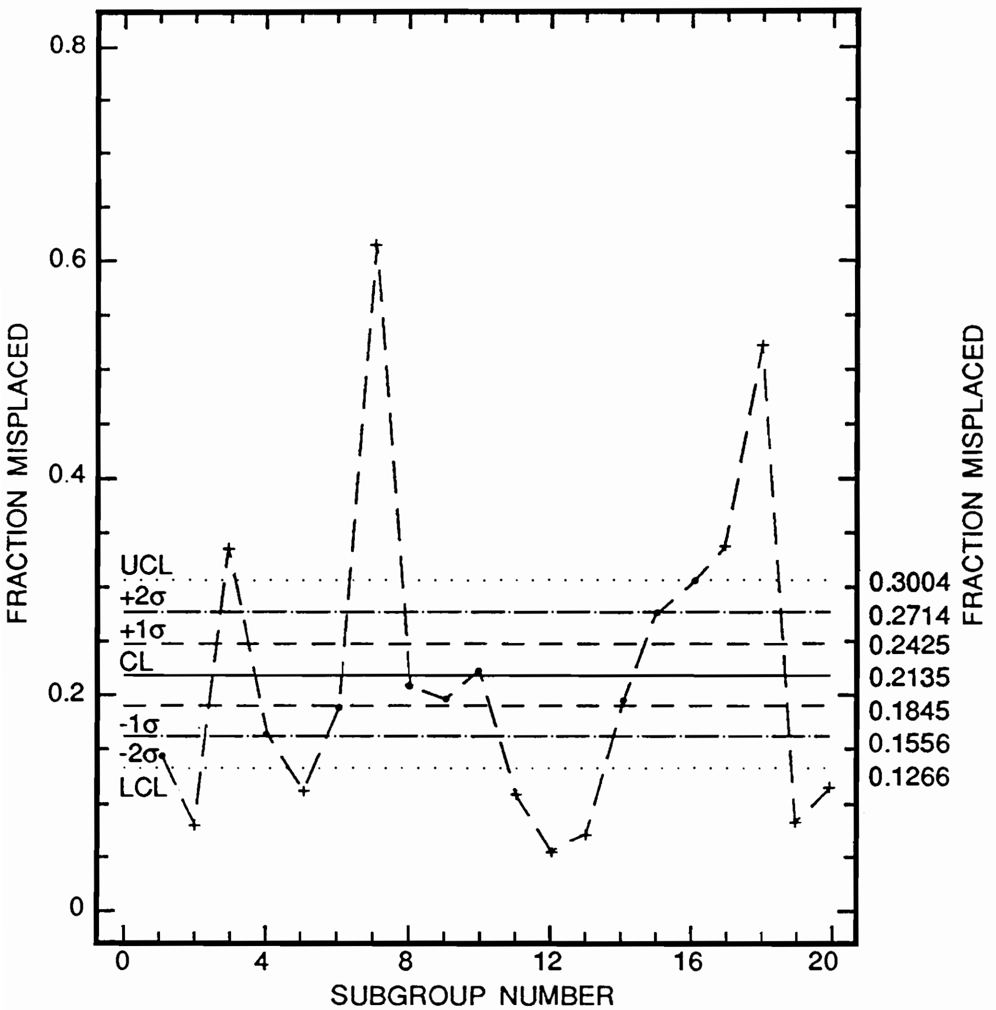


Figure 9. P chart representative of a stacker that is not under control. A critical rejection distance of 1.25 inches was used. The data comes from a computer model.

These subgroups provide further evidence that this stacker is out of control. The occurrence of sets of subgroups beyond warning limits is not typical of a machine center that is under control. The critical rejection distance used for this situation was 1.25 inches or the method by which the narrowest edge of the alignment sticker was used to test for in- or out-of-alignment conditions.

P charts illustrating situations brought under control are shown in Figures 10 and 11. The purpose of these two charts is to show what a typical p chart would look like if a stacker arm broke. The two critical rejection distances discussed in the prior procedure section were used. These charts are based on data from computer simulations.

Figure 10 shows a control chart for a stacker initially under control for subgroups 1 to 10. Then, one of the stacking arms on the stacker malfunctions, simulated by a larger standard deviation for the sticker placement locations. This broken arm results in points above the upper control limit of 0.2530 for subgroup periods 11 to 20, after which the stacker arm was repaired. Future points occur within the upper and lower control limits for subgroups 21 to 30. This chart makes use of the more stringent critical rejection distance of 1.25 inches. The upper and lower control limits were based on the standards established previously in Figure 7. Figure 11 shows the same situation as above, but the UCL and LCL were based on the more liberal method of using the widest edge of a sticker for evaluation purposes.

The results of these two p charts clearly show that stacker performance can be accurately assessed with this type of control chart. A broken component in the stacker, such as a stacker arm, will produce

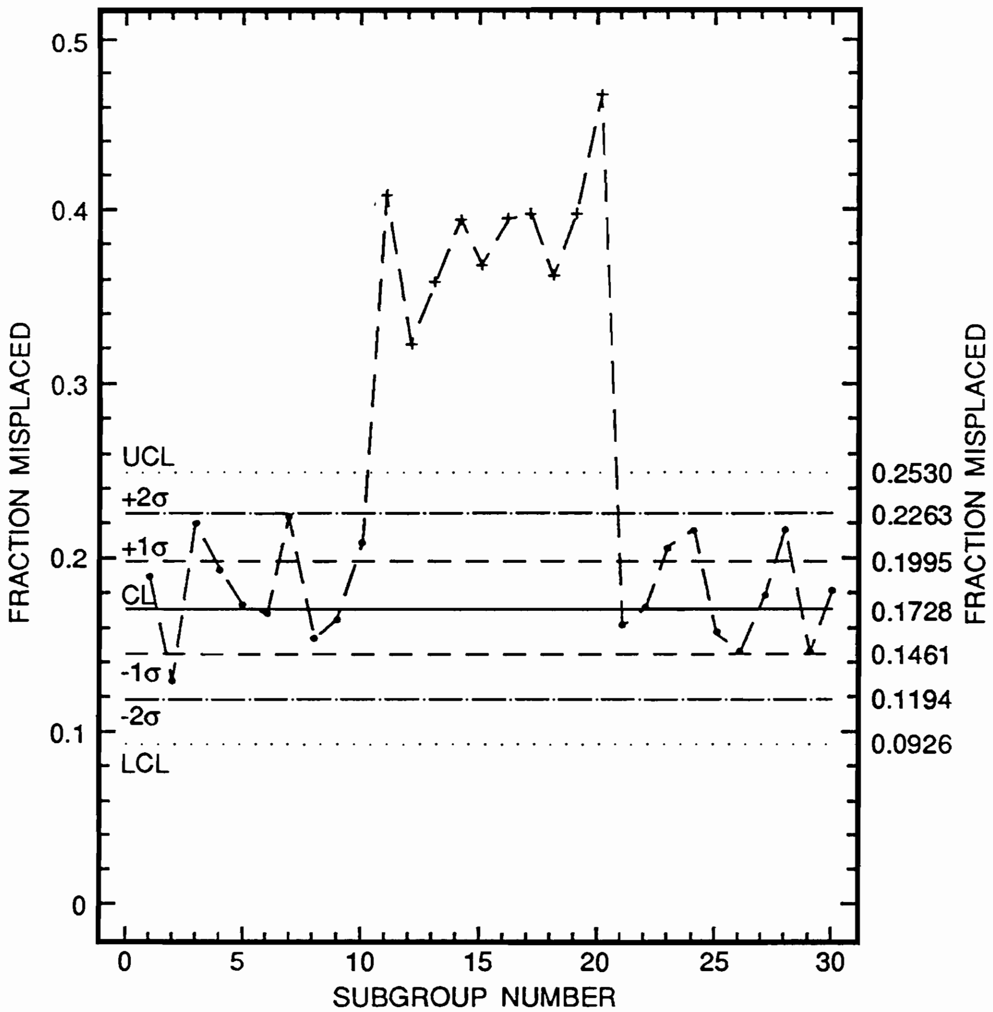


Figure 10. P chart representative of a stacker brought under control from an out-of-control situation. The data comes from the computer model making use of a 1.25-inch critical rejection distance.

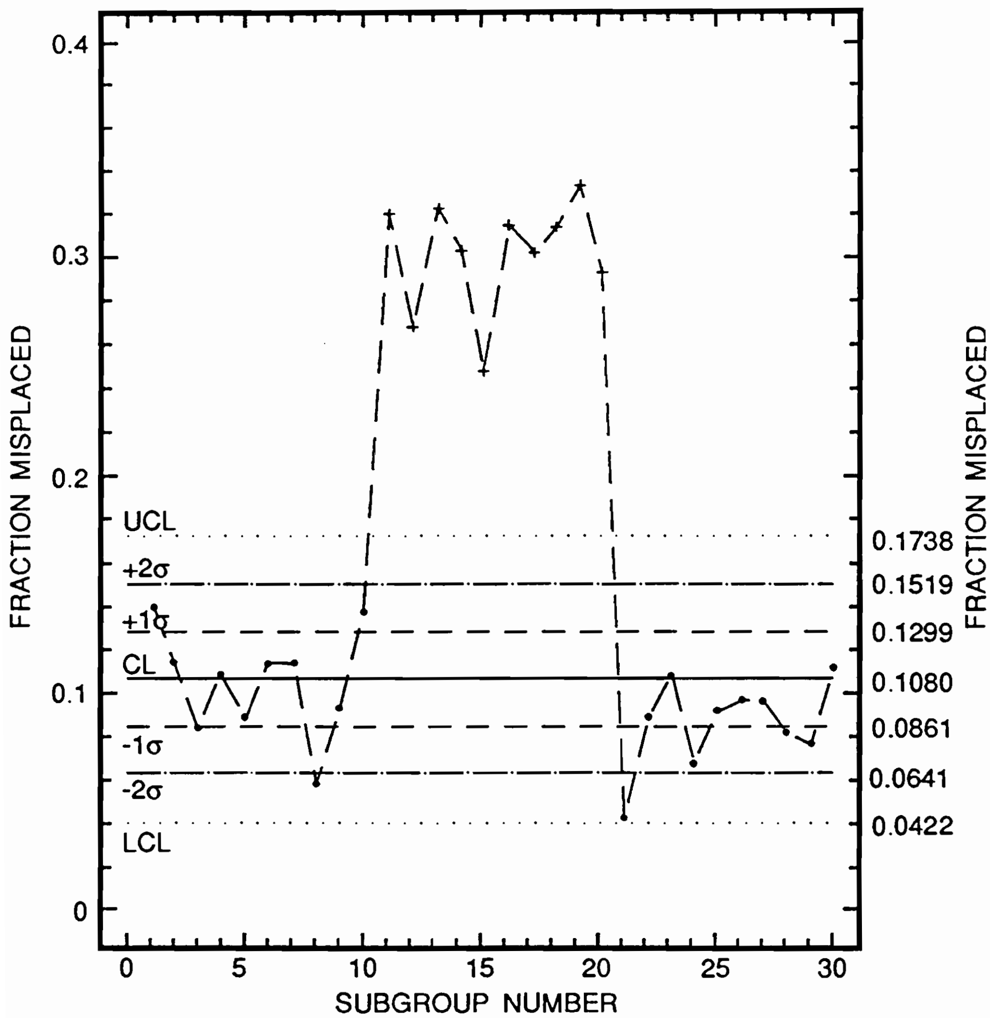


Figure 11. P chart representative of a stacker brought under control from an out-of-control situation. The data comes from the computer model making use of a 1.50-inch critical rejection distance.

such a significant change in stacker performance that the errors in sticker placement will produce points outside the control limits. This observation proves that p charts can be relied on to check stacker performance.

STICKER THICKNESS DISTRIBUTIONS

Sticker size uniformity for thickness and width is shown in frequency histograms Figures 12 and 13. In both cases a bimodal distribution can be observed. This means that stickers of two different sizes are being used to stack lumber. The sticker population should either be sorted so only one size sticker is used to stack a pile of lumber or new stickers, all of the same dimension, should be purchased.

ESTIMATION OF PACKAGE MC

The regression of hand-held meter readings on in-line meter readings by package for Douglas-fir data from mill A is pictured in Figure 14 along with 95 percent confidence and prediction limits. The regression analysis of the MC sampling of lumber was unsatisfactory because a correlation coefficient of 0.58 was calculated.

A weak relationship does exist between the readings of the boards from the outer edge of a package to the package's overall average MC. To improve the relationship, a larger range of package MCs would be helpful.

The average time required to accomplish the hand-held MC readings per package for mill A was 15 minutes. One hour was required for one

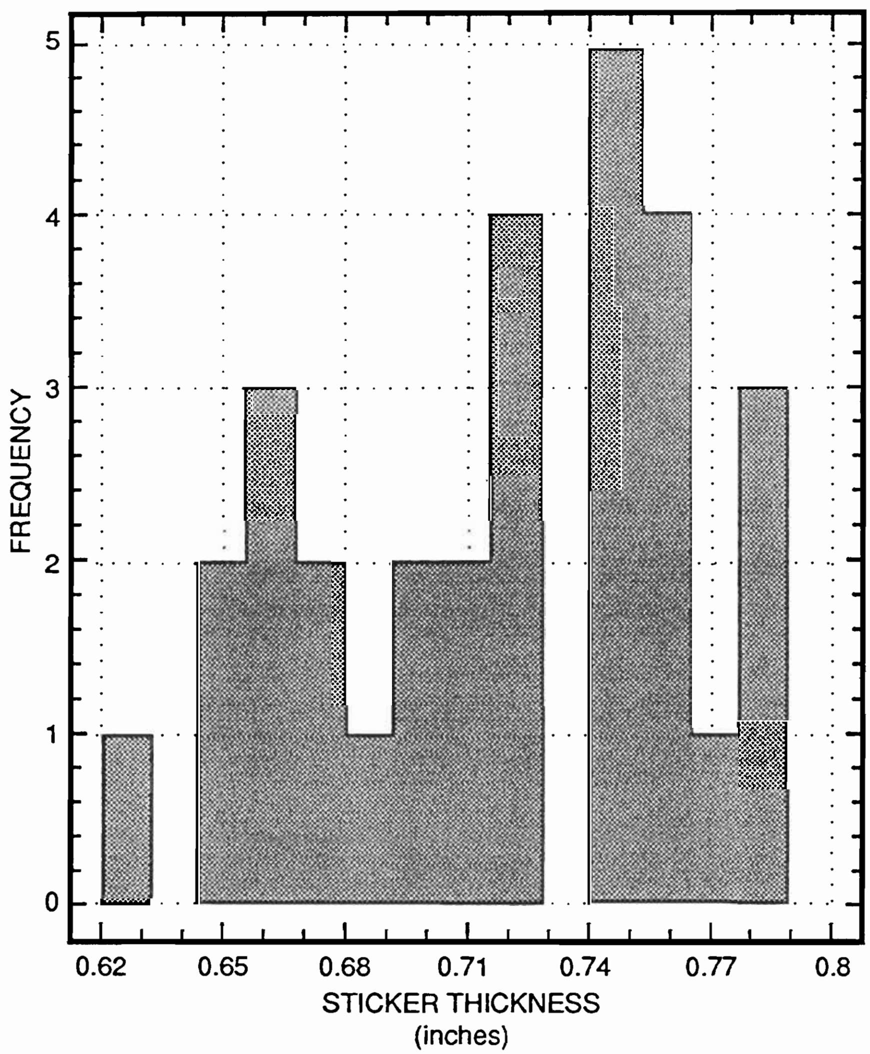


Figure 12. Frequency histogram for the thickness of 30 randomly-selected stickers.

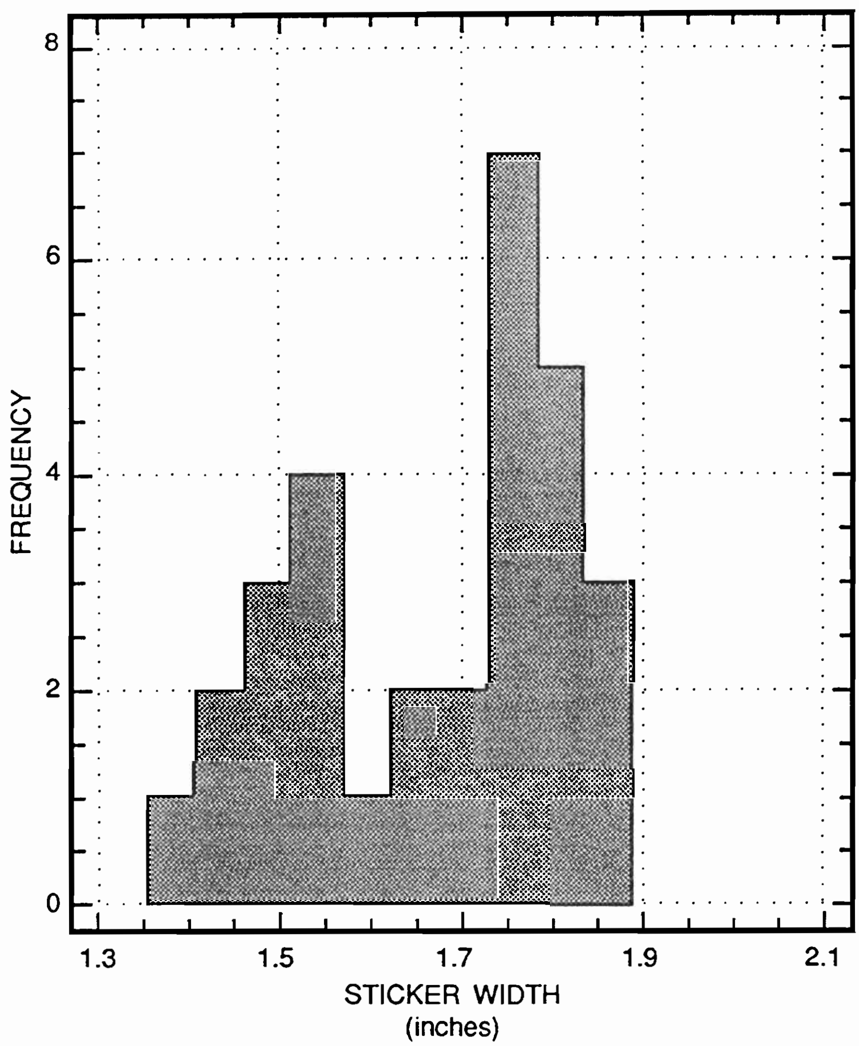


Figure 13. Frequency histogram for the width of 30 randomly-selected stickers.

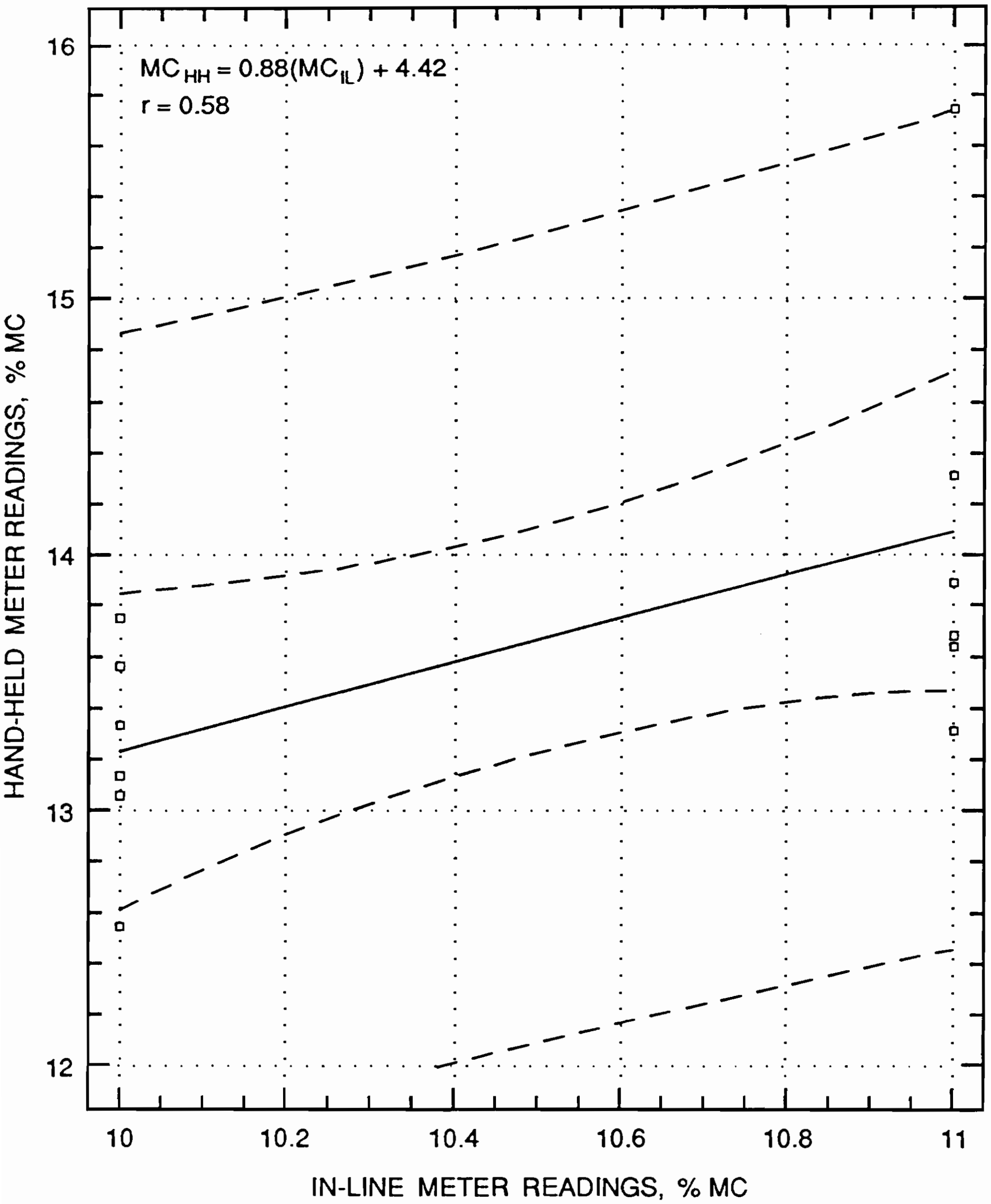


Figure 14. Plot showing results of regression of hand-held meter readings versus in-line meter readings by package. The data comes from mill A, which dried Douglas-fir lumber.

unit of lumber consisting of four stacked packages. This calculates to be an average time requirement of 30 seconds per reading (3600 sec./120 readings). The time requirement per reading is acceptable, but the overall time for one package of lumber is too long to become a practical, everyday technique for quality control.

Figure 15 shows a plot of the results of average package MC based on hand-held meter readings versus average package MC based on in-line meter readings for 24 packages of ponderosa pine examined at mill B. Included in this graph are the 95 percent confidence and prediction limits. The correlation coefficient for this linear regression analysis was 0.90. A plot (not shown) of the residuals against the independent variable (average package MC based on the in-line meter) readings showed random scatter. This plot indicates that a linear regression analysis was appropriate.

The same procedure used to collect the MC data at mill B was used at mill C. However, the regression analysis of the MC data from mill C did not give the same degree of correlation. The correlation coefficient for this study was only 0.47. The graph for this regression analysis and the 95 percent confidence and prediction limits are shown in Figure 16.

The above data were obtained by metering every third board at two locations. Each meter location was two feet in from the board's end. Regression analyses were performed on subsets of mill B's MC data to see how a reduction in sample size would affect the regression.

A subset of mill B MC data consisting of 10 randomly selected outer edge boards (5 per package side) MC per package was used as the data

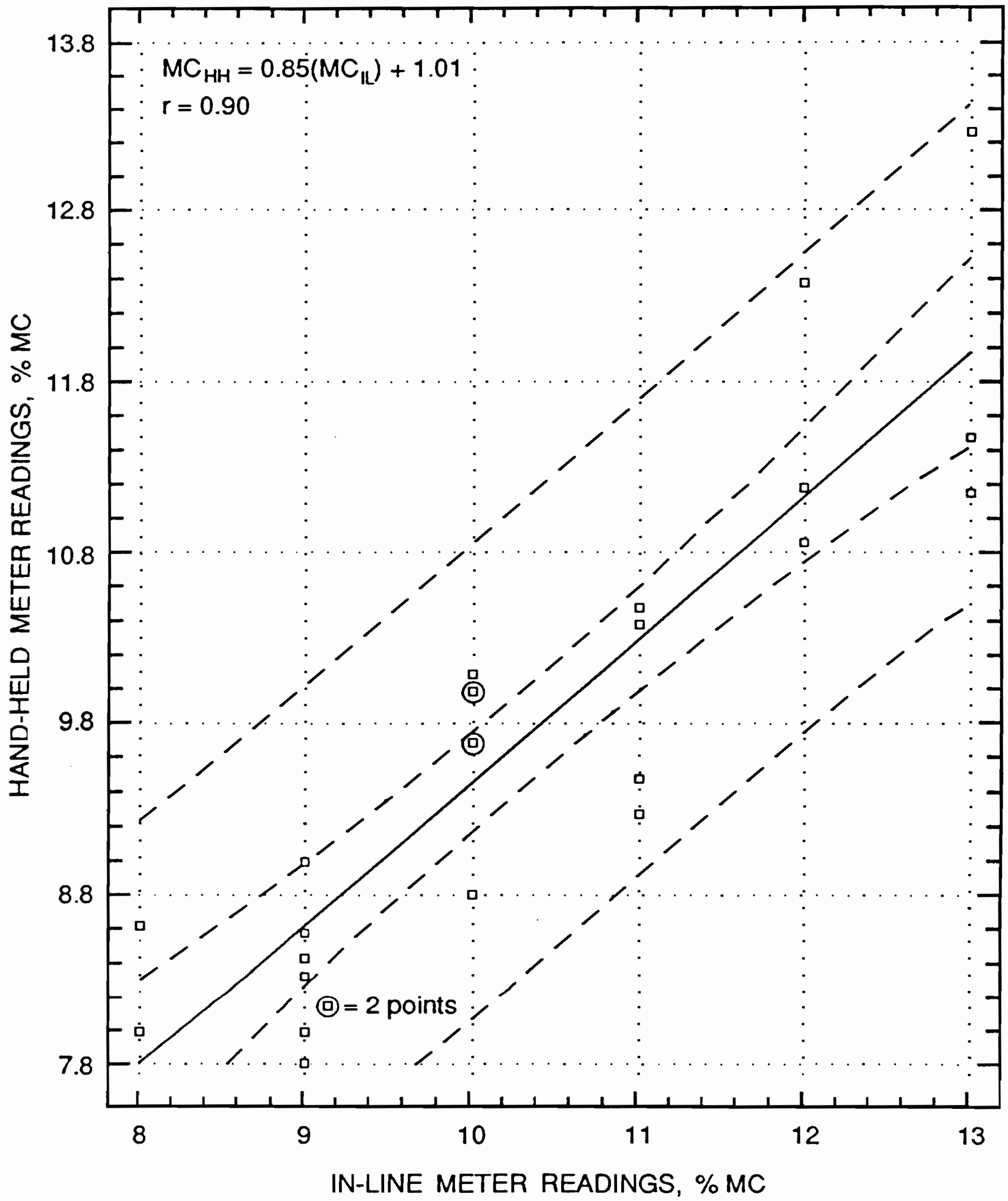


Figure 15. Plot showing results of regression of hand-held meter readings versus in-line meter readings by package. The data comes from mill B, which dried ponderosa pine. Every third outer-edge board was metered to collect this data.

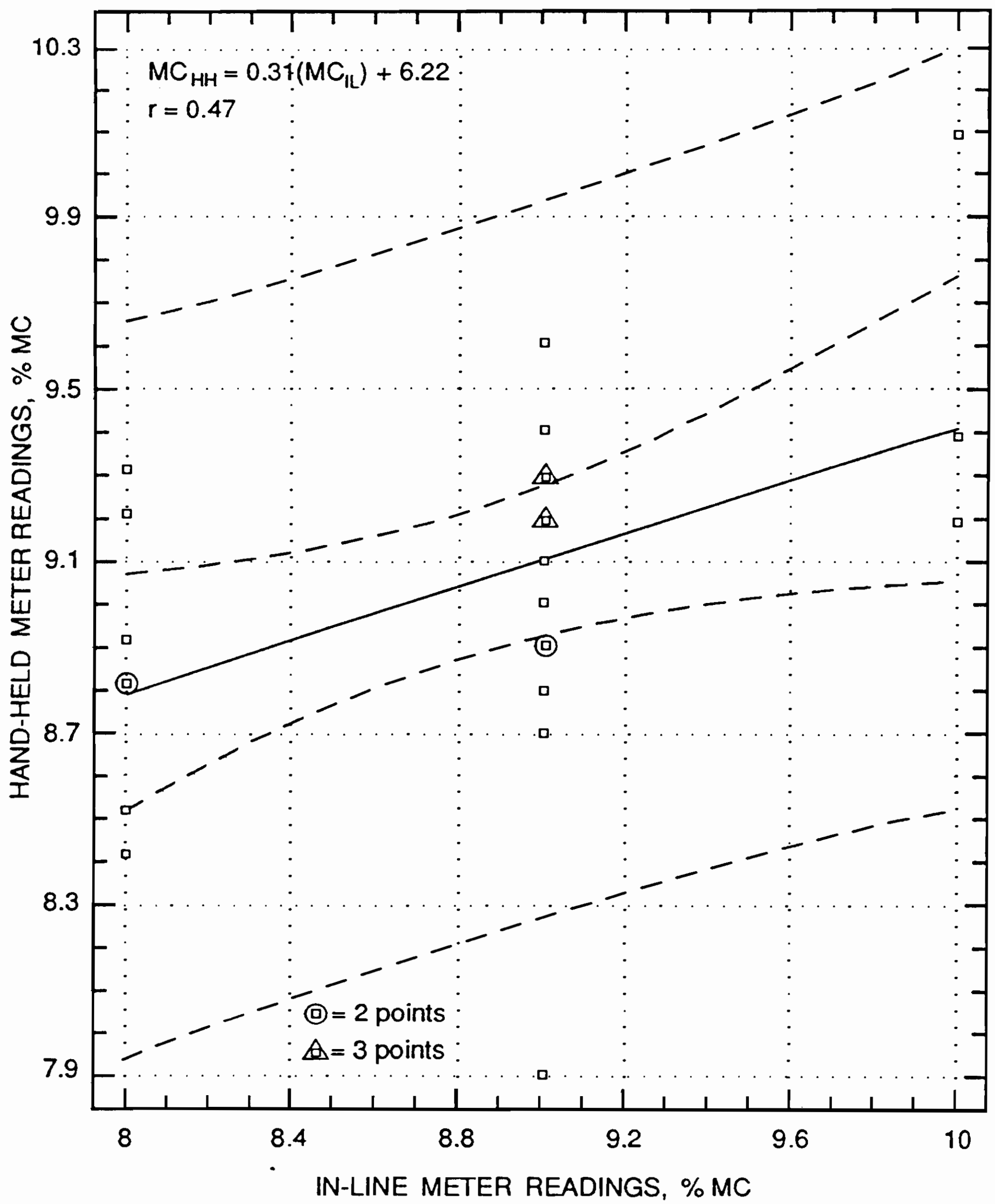


Figure 16. Plot showing results of regression of hand-held meter readings versus in-line meter readings by package. The data comes from mill C, which dried ponderosa pine. Every third outer-edge board was metered to collect this data.

source for a regression analysis. The graph for this regression analysis and the 95 percent confidence and prediction limits are shown in Figure 17. The correlation coefficient for this regression analysis was 0.88. This coefficient is slightly less than the correlation coefficient of 0.90 when every third board was measured for MC.

The graph for the regression analysis of the data from mill B when only four randomly selected outer edge boards (2 per package side) were used per package is shown in Figure 18. Included in this graph are the 95 percent confidence and prediction limits. The regression analysis on these data resulted in a correlation coefficient of 0.69. A weaker relationship exists here due to the smaller sample size.

The results of the regression analysis in trying to accurately estimate the MC of a package of lumber by metering only boards on the outer edge before unstacking was very poor. Table 1 summarizes the results of the regression analysis by number of MC readings per package and mill. In all likelihood every single outer edge board would have to be metered at multiple locations on the board and put through a regression analysis procedure to improve the correlation between average hand-held and average in-line MC readings. The time required to do all the metering plus the analysis would be too long. At best only poor estimates of average package MC can be obtained. For quality control purposes this technique does not have any great benefit.

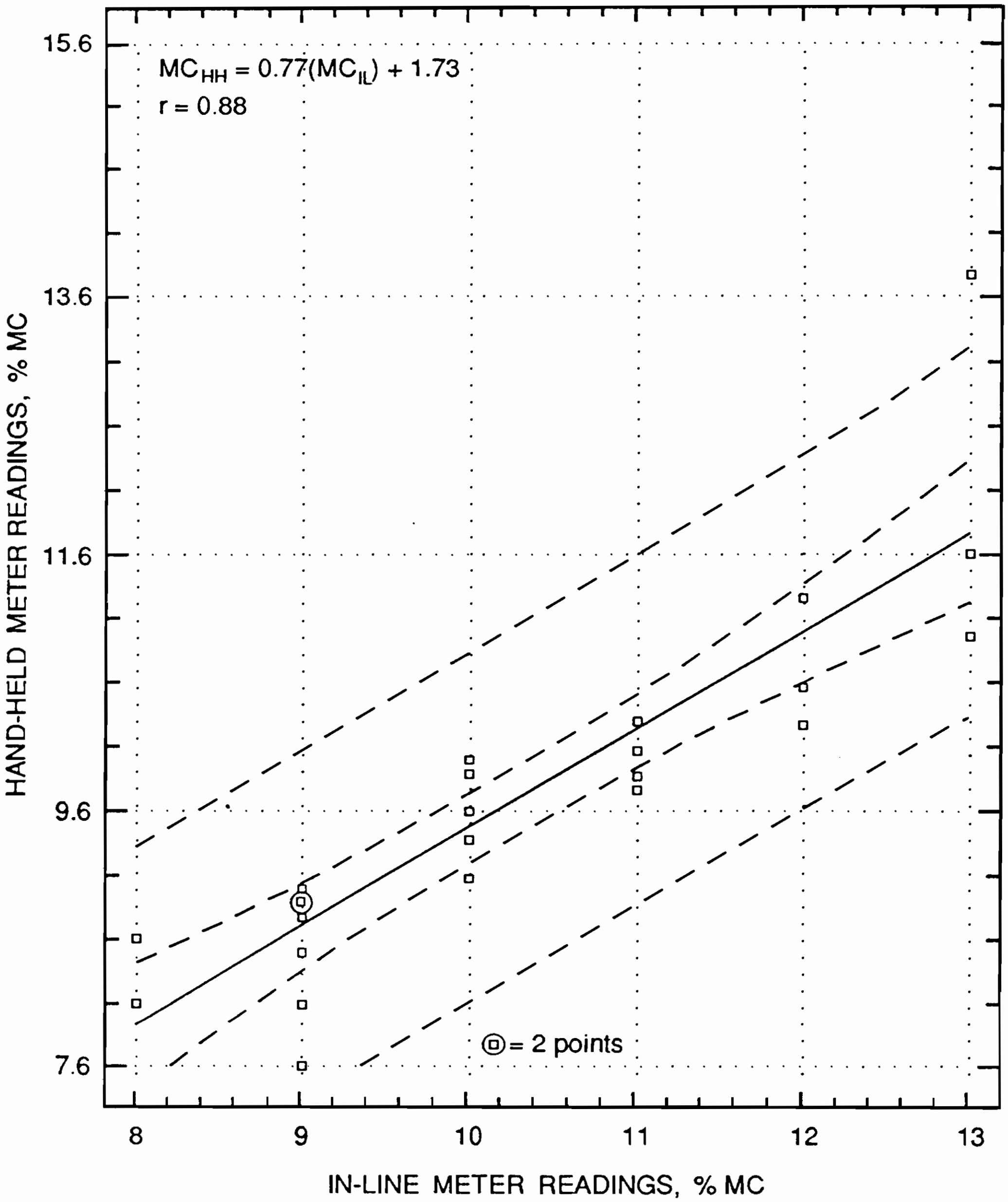


Figure 17. Plot showing results of regression of hand-held meter readings versus in-line meter readings by package. The data comes from mill B, which dried ponderosa pine. Ten outer-edge boards per package were metered to collect this data.

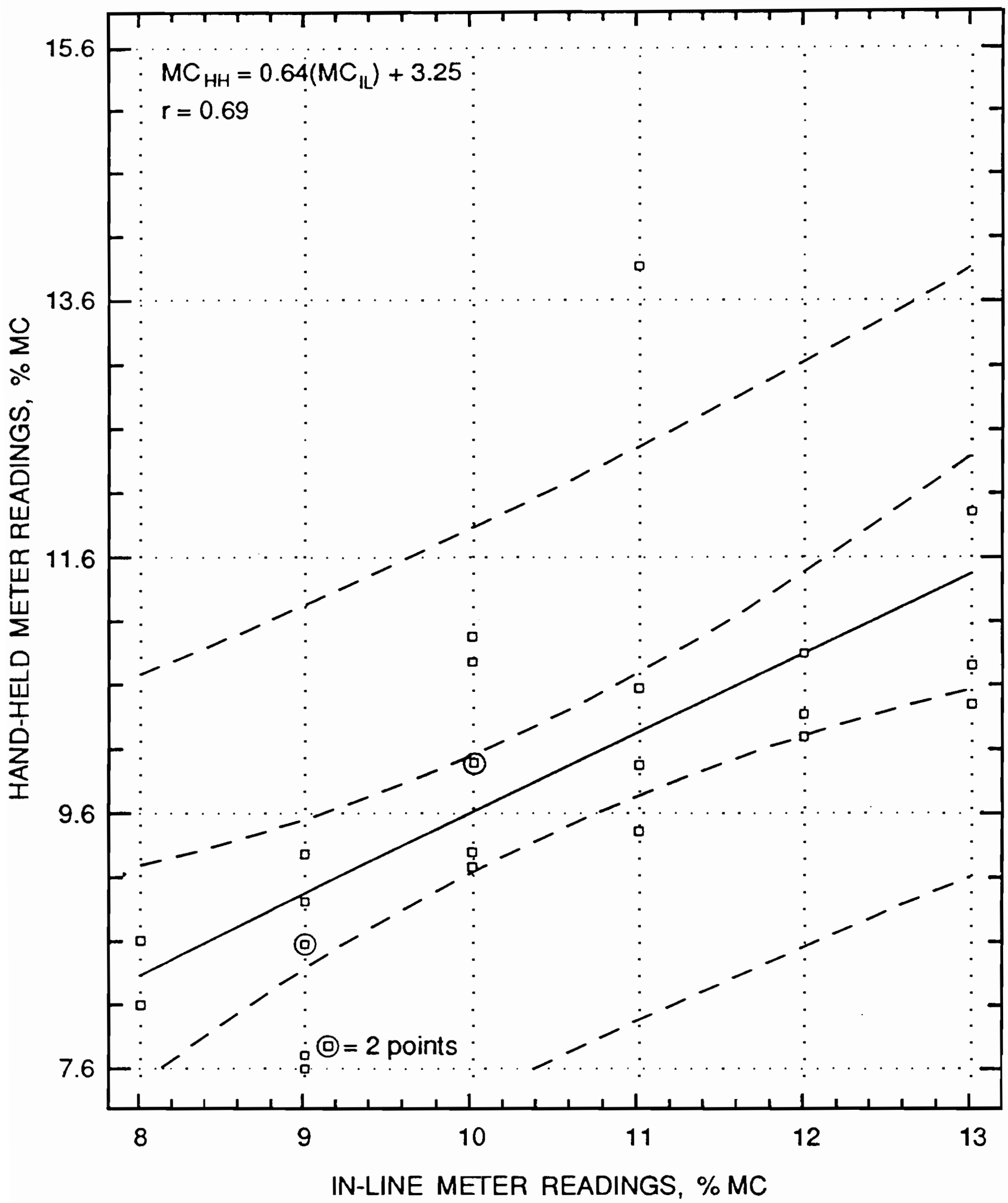


Figure 18. Plot showing results of regression of hand-held meter readings versus in-line meter readings by package. The data comes from mill B, which dried ponderosa pine. Four outer-edge boards per package were metered to collect this data.

Table 1. Summary of relationships between in-line MC and hand-held MC. These values are based on the number of readings per package.

Mill	Boards Metered Per Package	MC Readings Per Package	Correlation Coefficient
A	10	30	0.58
B	20 to 22	40 to 44	0.90
B	10	20	0.88
B	4	8	0.69
C	14 to 16	28 to 32	0.47

STATISTICAL ESTIMATION

NORMALIZATION

In Table 2 the effects of log and reciprocal transformations on the distributions of MC data taken from five different kiln charges of lumber are summarized. The skewness coefficient and the kurtosis coefficient are used to evaluate the distribution for normality. Statgraphics (Ver. 3.0) reference guide defines the two measures in the following manner. The skewness coefficient is used to evaluate how symmetric the MC distribution is. A value of zero is indicative of a normal distribution. A positive value for skewness indicates that the upper tail of the distribution curve is longer than the lower tail. A negative value for skewness indicates the opposite. The kurtosis coefficient is used to evaluate the flatness or steepness of the distribution compared to a normal distribution. When the kurtosis coefficient is less than zero, the distribution will be somewhat flat with short tails. A kurtosis coefficient larger than zero indicates a distribution curve that is steep at its center with long tails. Caution should be used in comparing kurtosis values when the skewness is not zero.

The MC distribution for the kiln charge of Douglas-fir lumber dried at mill A had a skewness of 0.4955. The log transformation of this MC data resulted in a distribution with a skewness of -0.2917. This is better than the skewness produced by the reciprocal transformation of this MC data. However, neither of the two transformations produced a good near-normal distribution with a skewness of near zero. The data are

Table 2. Effects of log and reciprocal transformations on MC distributions.

Source	Samples Size	Normal Data Skewness / Kurtosis	Log Transformation Skewness / Kurtosis	Reciprocal Transformation Skewness / Kurtosis
Mill A	1619	0.4955	-0.2917	1.4513
		2.1815	2.5347	9.6800
Mill B	5361	1.0722	-0.0494	1.0898
		2.2281	0.3047	1.6811
Mill C	6728	1.2076	0.3282	0.4226
		3.6107	1.0926	1.0823
68' Kiln	872	2.3009	0.8870	-0.1292
		8.5065	0.6353	-0.7951
84' Kiln	1113	2.6015	0.9642	0.0487
		9.6781	1.3934	-0.3438
Computer	756	1.9666	0.9910	-0.3212
		5.7381	1.2379	-0.3078

inconclusive for determining which transformation is correct for Douglas fir. This data indicates that possibly some other type of transformation is required, or that this particular charge of lumber is not a typical charge of kiln dried lumber.

The MC distribution for ponderosa pine dried at mill B had a skewness of 1.0722. The log transformation of this data produced a near normal distribution (zero skewness) of -0.0494. This transformation technique was better than the reciprocal transformation, which had a skewness of 1.0898. Similarly, the log transformation for lumber dried at mill C had less skewness than the reciprocal transformation of the same MC data. This skewness suggests the better of the two transformation techniques to be the log method. However, a graphical display of the normal MC distribution and the two transformed MC distributions for the data from mill B indicate otherwise.

A number of large outliers are present in the Box-and-Whisker plot (Figure 19) of normal data from mill B. The log transformation of this same data shows an improvement in reducing the number of outliers, but is skewed. Although not indicated to be the best transformation by measuring skewness, the reciprocal transformed MC distribution (Figure 19) appears more normal in appearance than the log transformation. Only one lone outlier exists in this plot.

The evidence for which transformation is best at producing a normal distribution is still inconclusive. Skewness measures for MC distributions using the data from mill B suggest the log transformation to be the best. However, graphical analysis suggests the reciprocal transformation to be better at producing a normal distribution. Neither

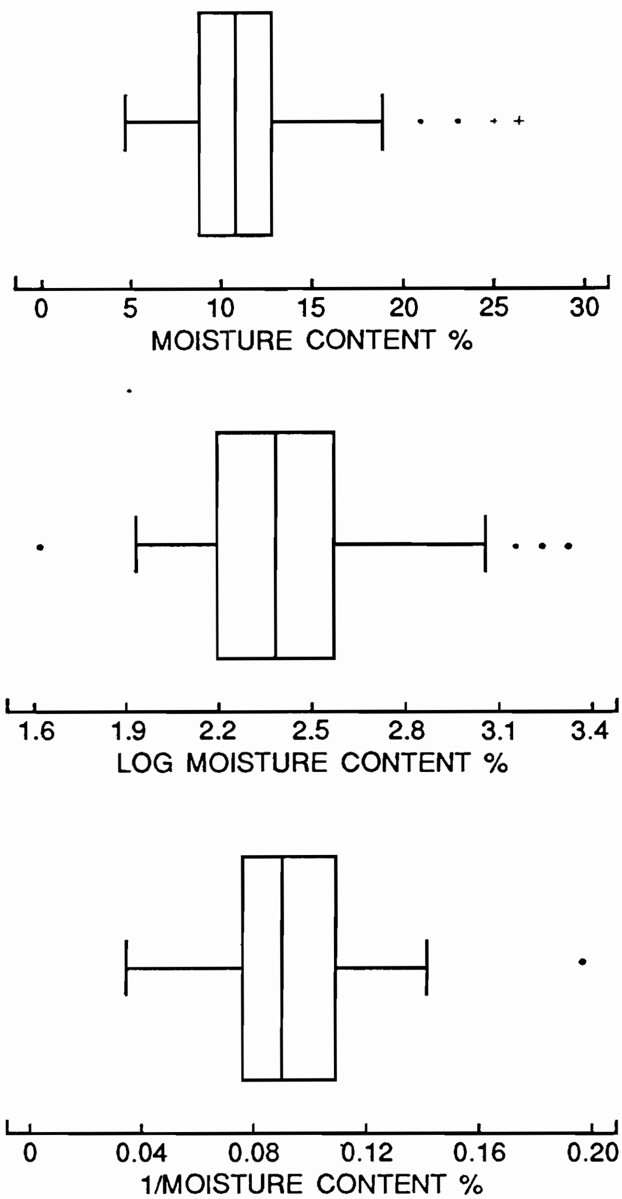


Figure 19. Box-and-Whisker plots of transformations made on mill B moisture content data.

skewness coefficients for the transformed MC distributions for mill C showed any great difference between themselves. Deciding which transformation technique is best using skewness coefficients and graphical analysis still remains inconclusive at this point.

Mention should be made that the MC data for mills B and C came from in-line moisture meters. These meters operate at high speeds and can only make quick estimates of board MC, thus they are prone to error as suggested by the Canadian Forestry Service (1976). Also, the meters only categorize MC data into two percent MC intervals. In addition board MC readings were only taken at one location on each board by the in-line moisture meter. Clearly, this evidence alone does not suggest which transformation is the best. Further studies from two kilns at mill D were performed to decide which transformation was better.

The MC data from both kilns at mill D were taken with a hand-held moisture meter with three MC readings per board. A more accurate MC reading was probably made using this slower process, compared with an in-line moisture meter.

For the data from the 68′ kiln at mill D, the reciprocal transformation was more normal than the log transformation. Although the skewness of the reciprocal transformation is not as near zero as the log transformation of the MC data from mill B, a larger and more representative sample size from the 84′ kiln does suggest the better transformation to be 1/%. The larger MC sample size, when transformed using the reciprocal, had a skewness of only 0.0487.

Figure 20 graphically shows the effects each transformation had on the 68′ kiln MC data. These data were chosen to be displayed pictorially as it is believed to be the more accurate MC data from the three mills drying ponderosa pine. Figure 20 shows the original MC data, the log transformed data and the reciprocal transformed data from the smaller 68′ kiln. Improvements towards a near normal distribution are seen by looking at the top plot then to the middle plot to finally the bottom plot. The 84′ kiln MC data, and the transformation effects on this data are shown in Figure 21. Skewness and numerous outliers are present in the top plot. The log transformation of the MC data improves the situation slightly, but the reciprocal transformation results in a near perfect normal distribution, as pictured in the bottom plot.

The best transformation technique was also found to be the reciprocal of MC values when test transformations were conducted on the computer model data generated by matching the computer MC distribution to that of mill B. Table 2 shows the numerical results of the two transformations under the caption "Computer."

Normal probability plots of the untransformed and transformed MC data that was originally generated by the computer model are shown in Figures 22 to 24. This graphical technique was used as another method to illustrate the same conclusions reached with the Box-and-Whisker plots. A nonlinear MC probability plot of nontransformed MC data is shown in Figure 22. The same data transformed using the log values improves the probability plot, but is still not very linear. See Figure 23. A more linear plot, indicating a normal distribution, is pictured in Figure 24. This linear plot is evidence that the preferred

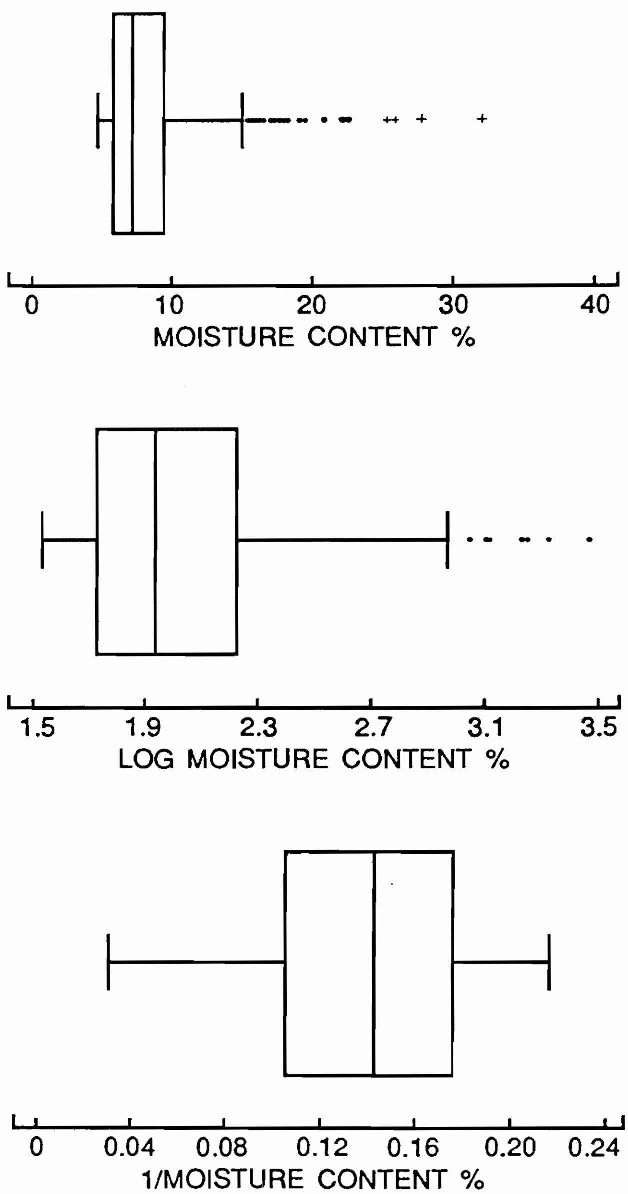


Figure 20. Box-and-Whisker plots of transformations of kiln moisture content data from 68′ kiln at mill D.

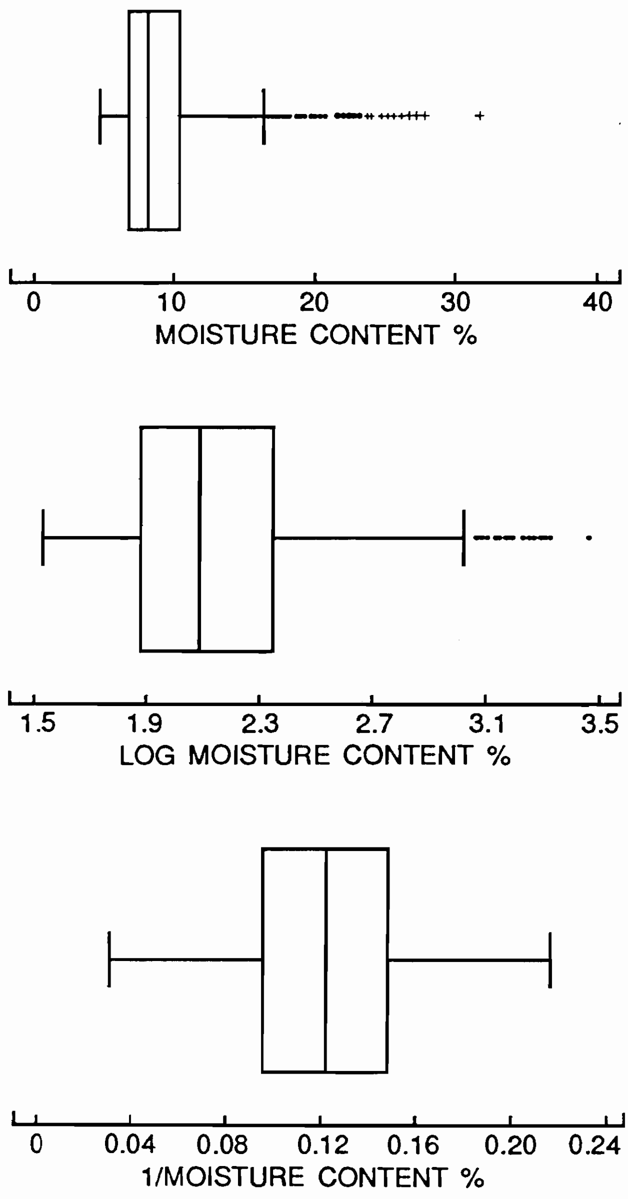


Figure 21. Box-and-Whisker plots of transformations of kiln moisture content data from 84′ kiln at mill D.

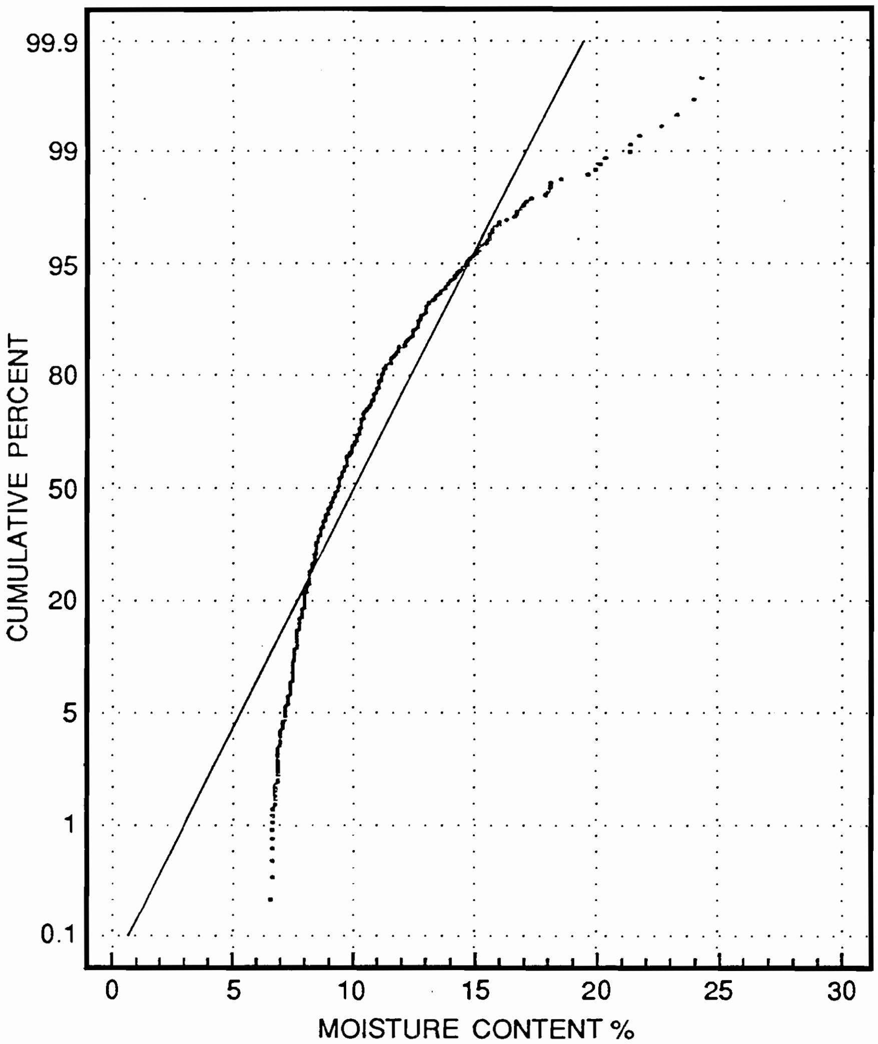


Figure 22. Normal probability plot of untransformed MC data from one computer simulated kiln charge of ponderosa pine.

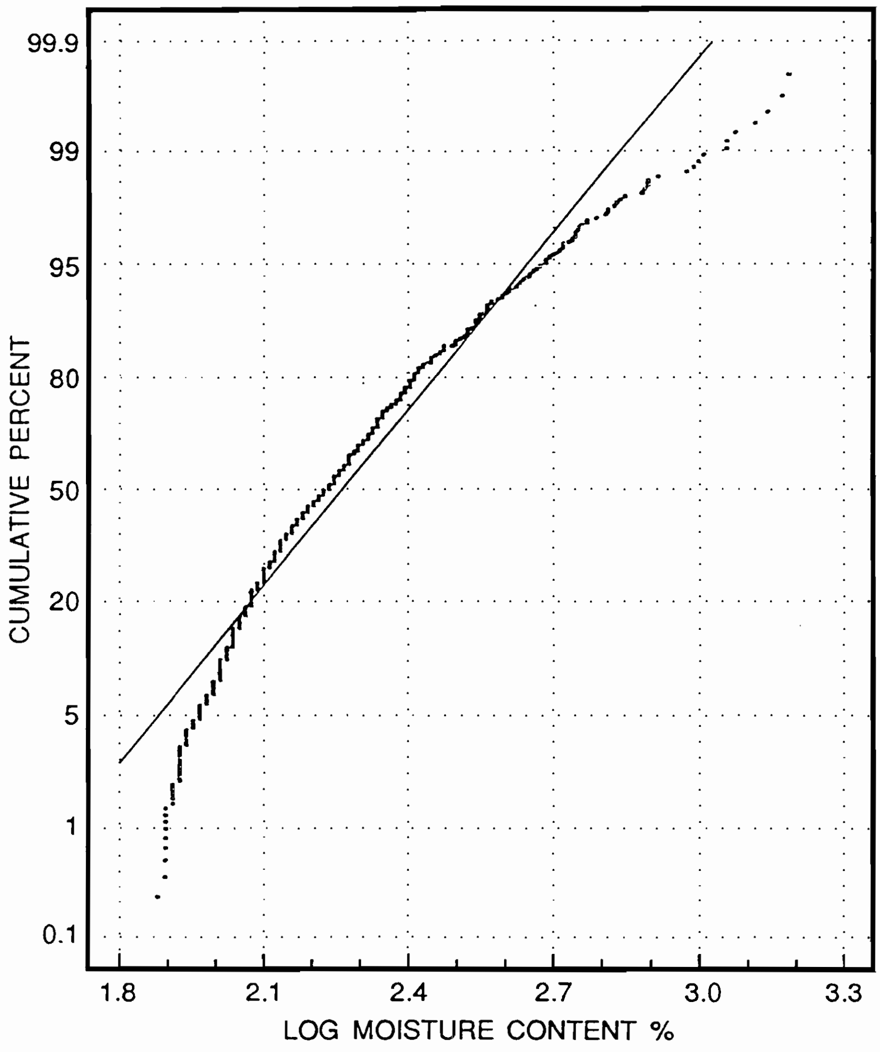


Figure 23. Normal probability plot of log transformed MC data from one computer simulated kiln charge of ponderosa pine.

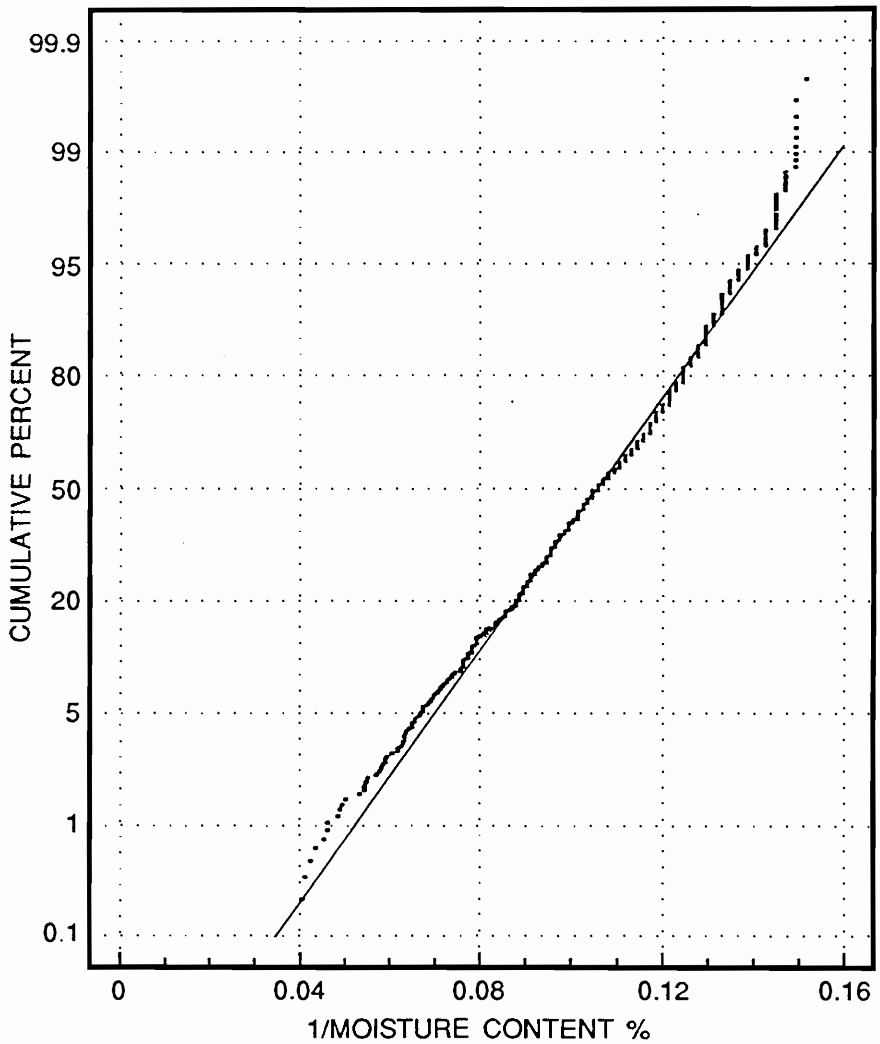


Figure 24. Normal probability plot of reciprocal transformed MC data from one computer simulated kiln charge of ponderosa pine.

transformation is the reciprocal method when using MC data generated by the computer drying model.

SAMPLE SIZE

Figure 25 illustrates the sample size required versus the confidence interval half width when using reciprocal transformed data. The sample size required to estimate a target MC of 10 percent $\pm$ 1.0 percent such that the normal confidence interval contains 9.00 to 11.25 percent MC with a 95 percent confidence level was calculated to be 16. This is in reasonable agreement with a sample size of 10 boards per package suggested by Wengert (1986). However, only six samples would be required if the confidence interval were expanded to $\pm$ 1.5 percent or 8.50 to 12.14 percent MC. Similarly, for an estimate within $\pm$ 0.5 percent and a confidence interval from 9.50 to 10.56 percent MC, the required sample size becomes 71. This is a 9.39 percent sample size for a package of 756 boards, and is very similar to what Rice (1976a) suggested. He proposed a sample size of 9.0 percent. In addition, ASTM Standard D 2016-74 requires a 10.0 percent sample size.

CONTROL CHARTS

The computer simulations of different drying conditions provided the data necessary to generate a variety of control charts. The construction of these different control charts tested the feasibility of using control charts to track the quality of board MC and the operation of a dry kiln.

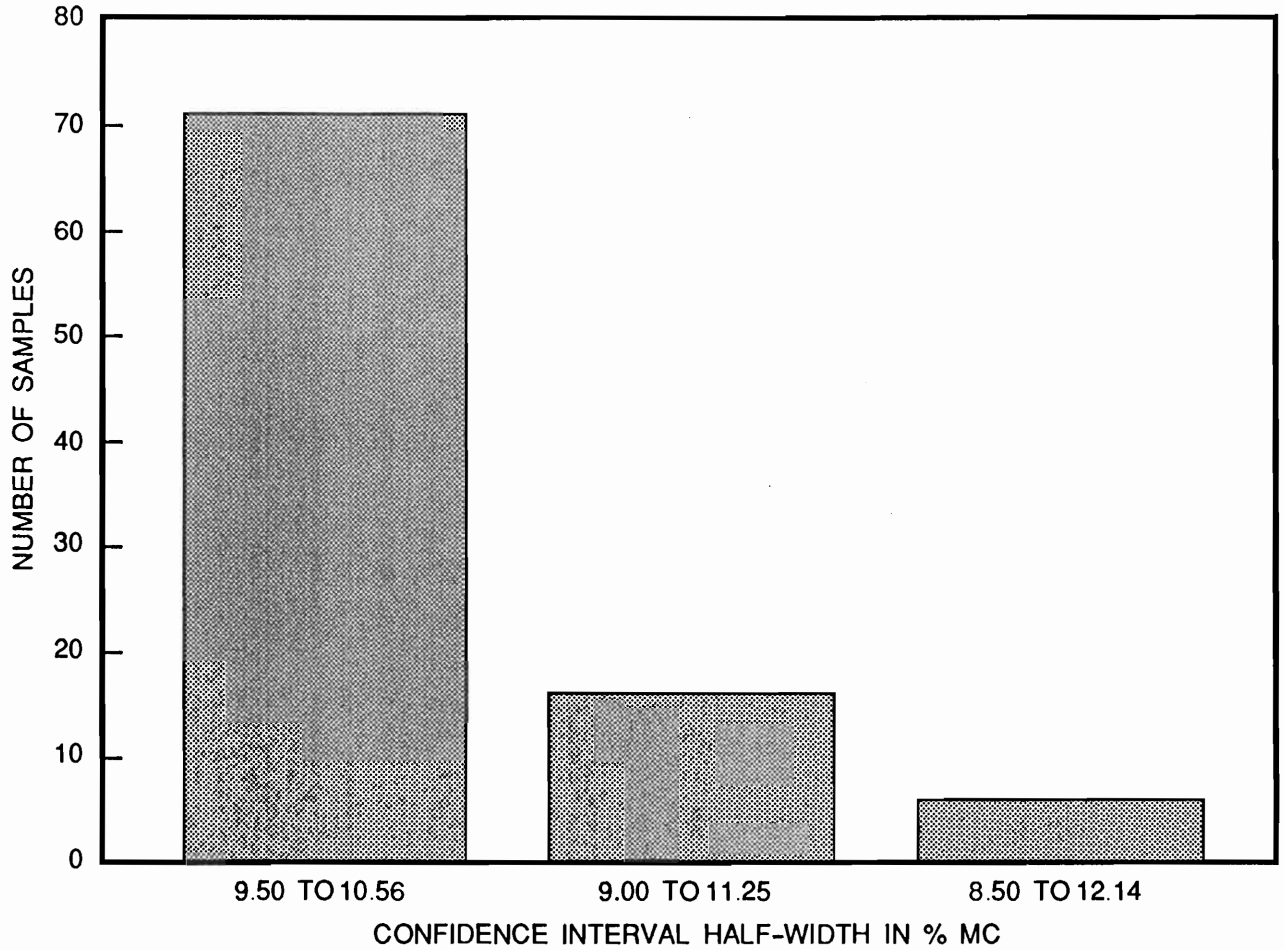


Figure 25. Bar chart comparing required sample sizes to estimate a target MC of 10% according to confidence interval half-width for reciprocal transformed MC data.

X-BAR AND RANGE CONTROL CHARTS

The randomly-selected MC data used to generate the X-bar and Range control charts worked well. All of the MC data from which the random samples were taken was generated using the computer model. The results of these data, when used in the control charts, were what was to be expected. The sample size of 16 board MCs, as calculated according to Equation 1, is a realistic size that could be taken from an entire package consisting of 756 boards at the unstacker or dry chain. The small sample size makes this technique especially advantageous to mills that do not use an in-line moisture meter. The randomly selected MC data used in all the control charts were readily transformed when using the reciprocal value of each precent MC sample. The UCL and LCL on each chart are based on the reciprocal values of MC. These are shown on the left vertical axis. The reciprocal of the calculated control limit values in percent MC are shown on the right vertical axis.

In-Control Situation

The X-bar and Range control charts in Figure 26 show a drying process which is in control. These control charts exhibit the 20 in-control drying charges that were used to establish the initial UCL and LCL for all future illustrative control charts. As typical of a process which is in-control, all points are within the upper and lower control limits and are randomly scattered within these limits.

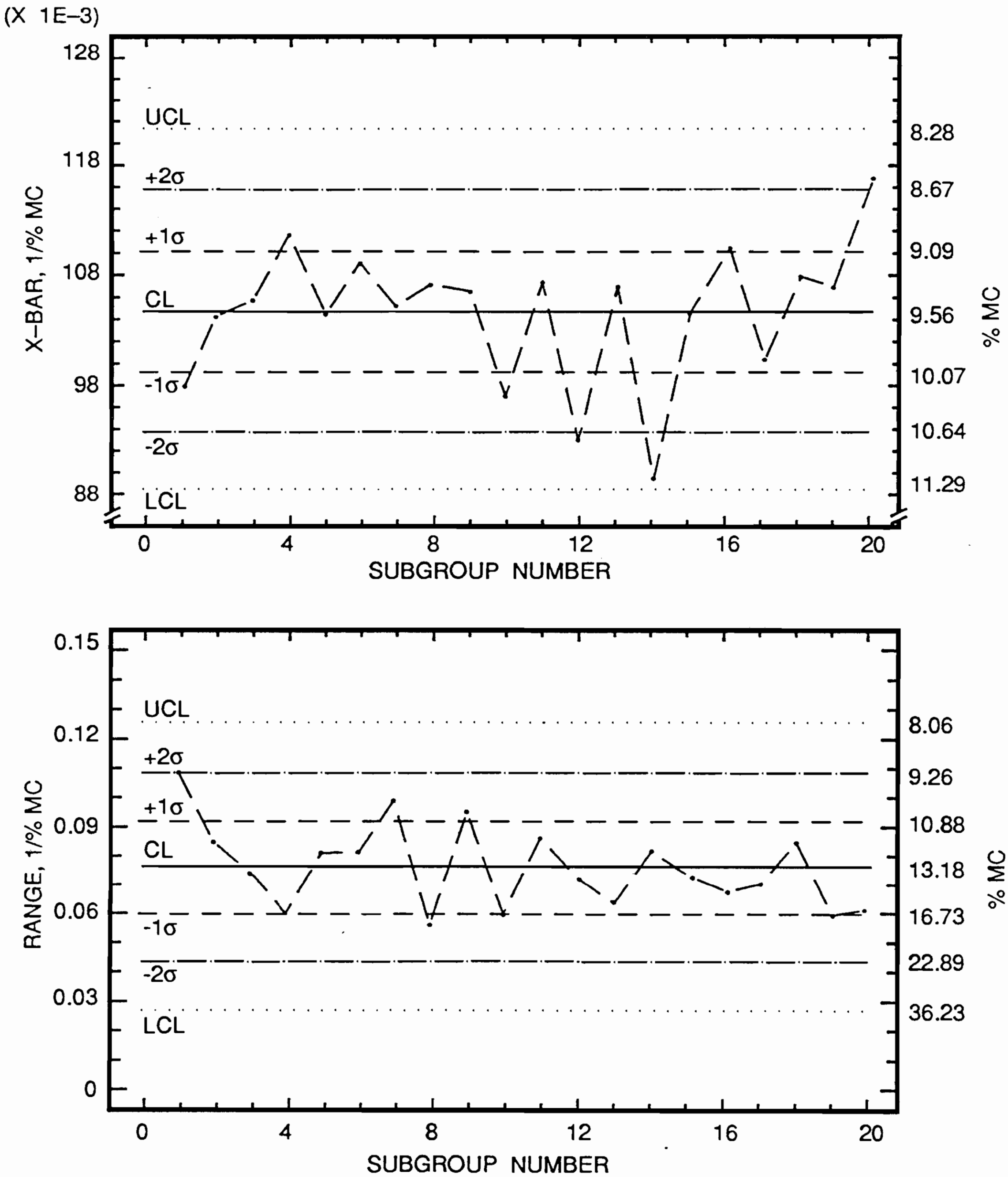


Figure 26. X-bar and Range control charts that are representative of a drying process in control.

Out-of-Control Situations

A control chart that depicts an out-of-control situation is shown in Figure 27. Points lie below the LCL in subgroups (charges) 21, 22, 26, 27, and 30. In addition all points from subgroups 21 to 30 lie below the centerline at 9.56 percent MC or 0.105. This is in contrast to the first 20 subgroups that are all in control. The cause of the out-of-control points was due to too cold of a dry bulb temperature (5° F), which could be the result of insufficient heat inside the kiln. Strangely enough, the associated Range chart for the same conditions gives no indication of an out-of-control situation. See Figure 27. Apparently, there are no assignable causes that seriously alter the range of MC values produced under this drying condition.

Figure 28 shows an X-bar control chart initially under control for the first 20 subgroups. The following nine of 10 subgroups indicate an out-of-control situation, after which the kiln is brought back under control. The out-of-control points were due to too hot of a dry bulb temperature (5° F). The X-bar's companion Range chart (Figure 28) does not give any indication of an out-of-control condition. A kiln with a dry-bulb temperature that is too hot by just 5° F may not be sufficient enough to cause significant changes in the range of MC produced.

An out-of-control situation that is brought back under control is exhibited in Figure 29. The first 20 subgroups are in control. The 10 subgroups that follow show two types of out-of-control situations. First, and most obvious, are the three points that lie below the LCL. These occur at subgroup numbers 22, 23 and 28 and indicate overly wet lumber. The second out-of-control indication is the long run of nine

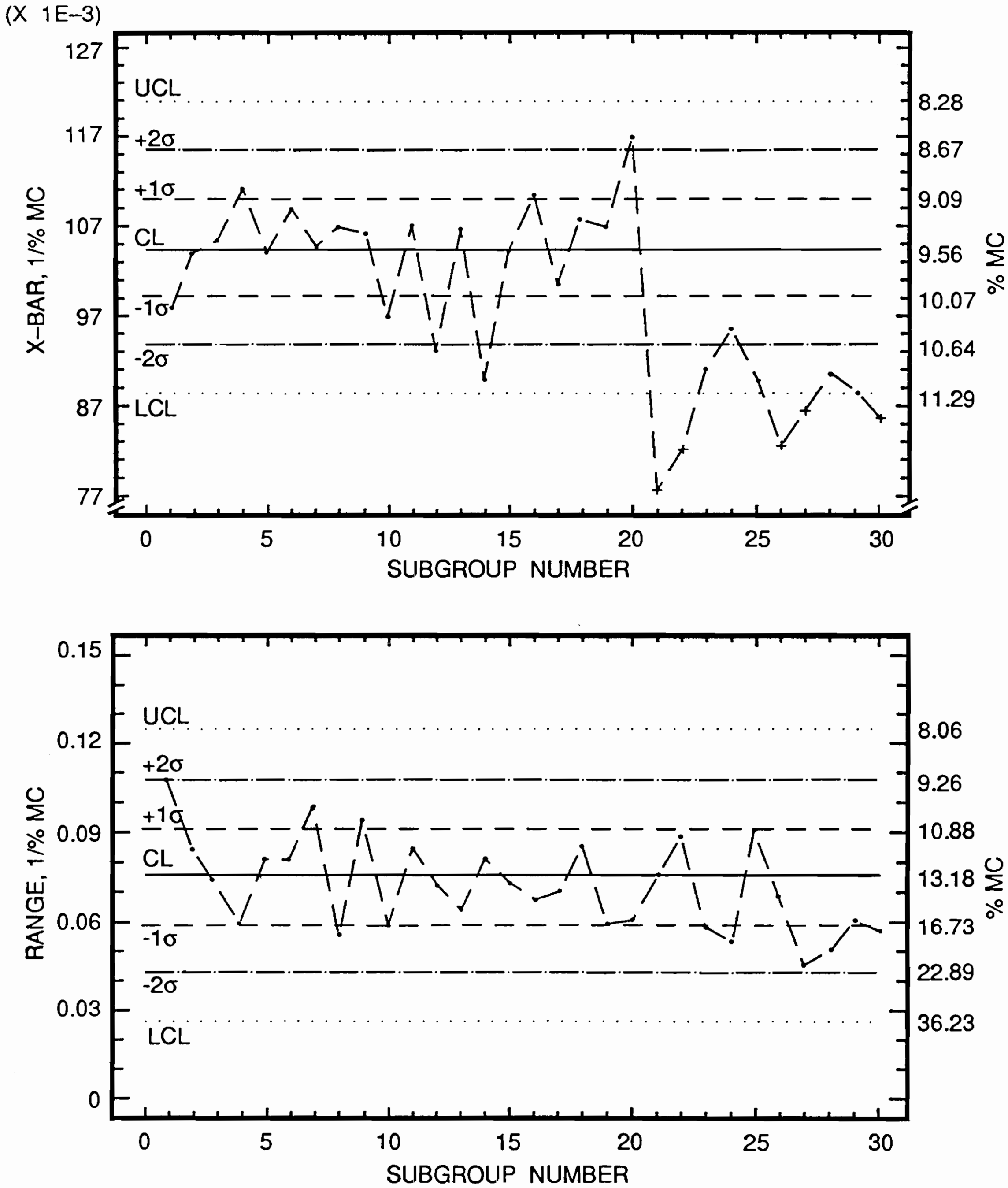
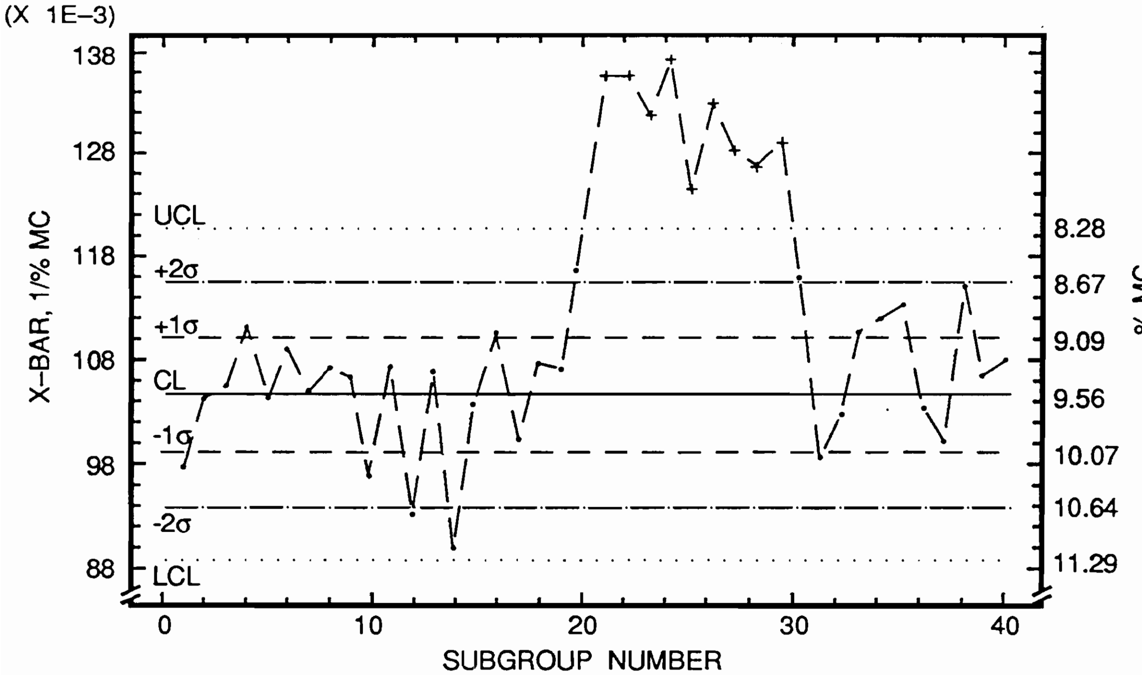


Figure 27. X-bar and Range control charts that are representative of a drying process that is out of control. This was caused by too cold a dry-bulb temperature.



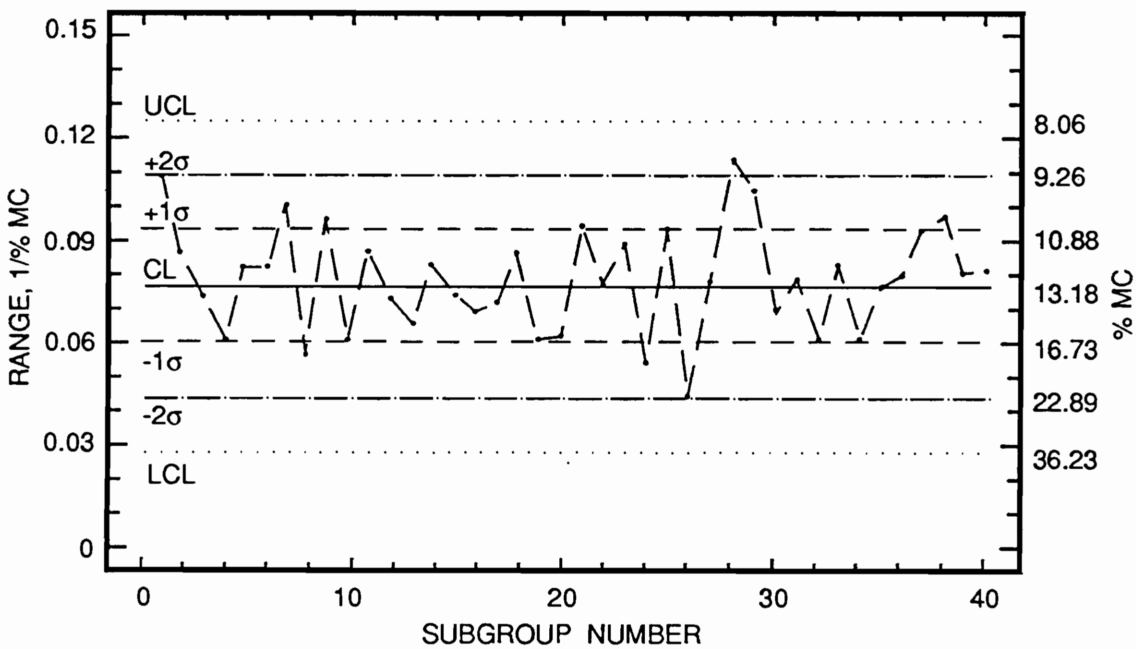
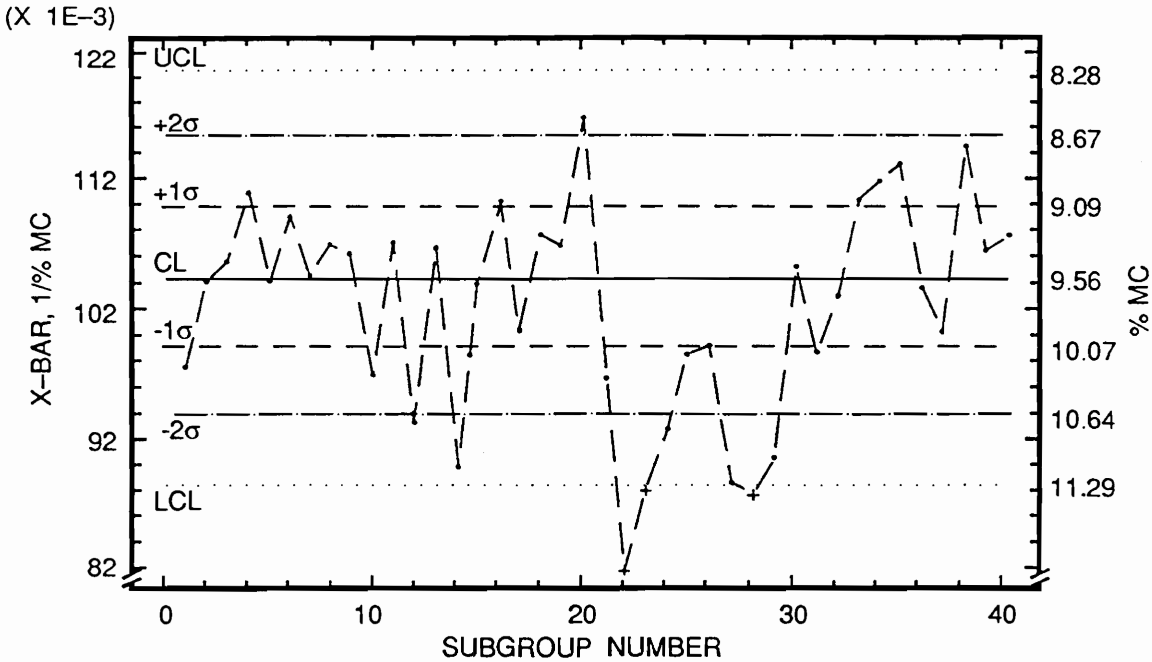


Figure 28. X-bar and Range control charts representative of a drying process brought back under control. The out-of-control points are due to too hot a dry-bulb temperature.



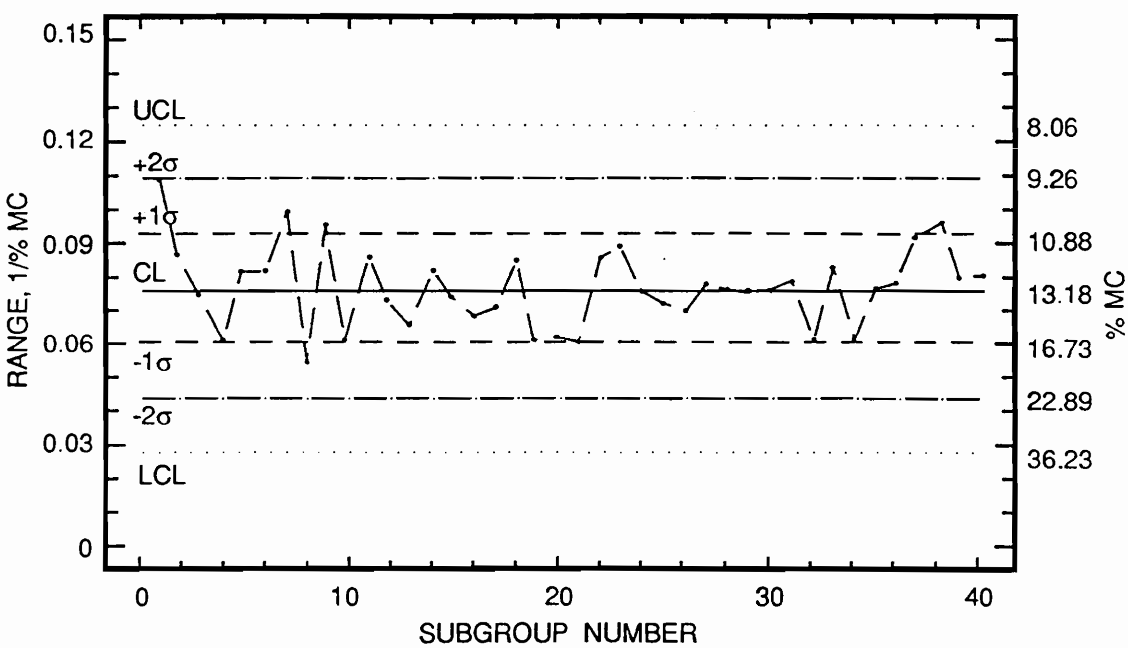
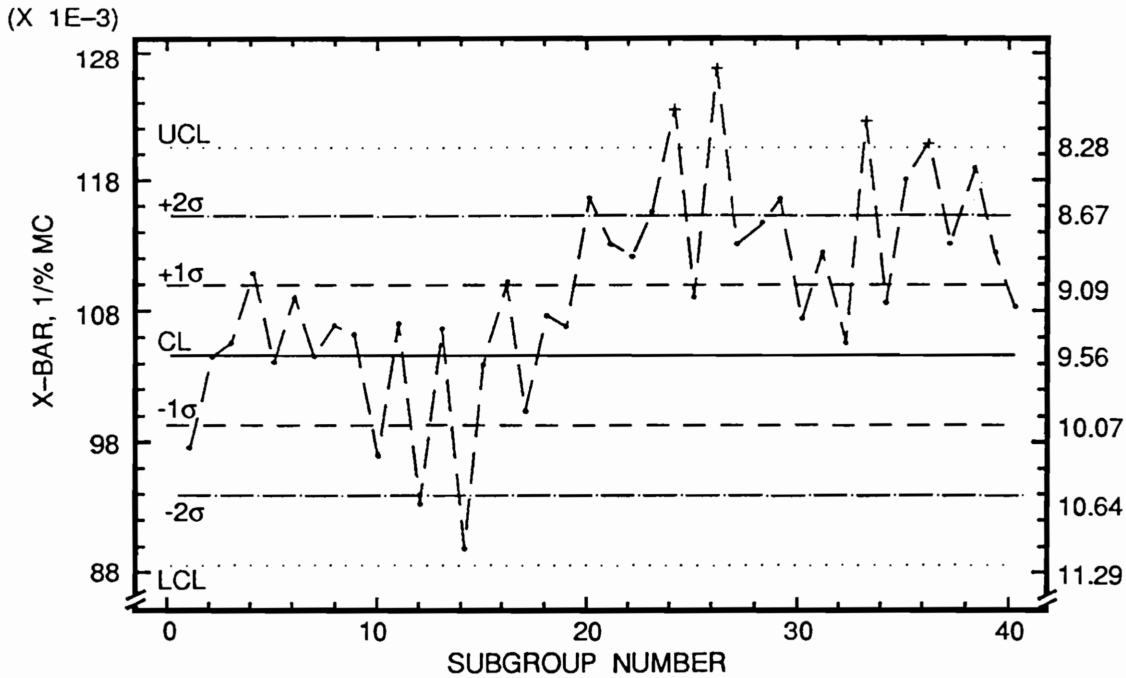


Figure 29. X-bar and Range control charts representative of a drying process brought back under control. The out-of-control points are due to too low a fan speed.

sequential points all lying beneath the centerline. See subgroup numbers 21 to 29. This is not a typical random occurrence common to points within the UCL and LCL, but is due to an assignable cause. The cause was too low of a fan speed. Once the fan speed had been corrected, the following points all lie randomly within the UCL and LCL. The Range chart for the same drying situation is shown in Figure 29. The chart indicates drying trouble with a long series of points all nested close and with very little deviation from the centerline. In particular are subgroups 24 to 30. This phenomenon is not a typical response to a situation that is under control. This occurance is an example of an abnormal arrangement, which was mentioned in the literature review, where a normal random variation among points is not occurring. The low fan speed during this drying period was probably the cause. Too low a fan speed during the initial drying period may not remove enough moisture from the wood, thus possibly causing the plots of subgroups 24 to 30.

An X-bar chart that represents a kiln that is divided into two separate heating zones or quality zones where one end becomes overheated is shown in Figure 30. The first 20 subgroups are all under control, because of correct and even heating throughout the kiln. By subgroup 24, an out-of-control point occurs above the UCL. Three more out-of-control points occur in subgroups 26, 33 and 36. These points were caused by a kiln that has become overheated at one end. Further evidence of an unevenly heated kiln that is out-of-control is the long run of 20 points, all above the centerline, from subgroups 21 to 40. Similarly, a long run of 14 points all above the centerline of the Range chart (Figure 30)



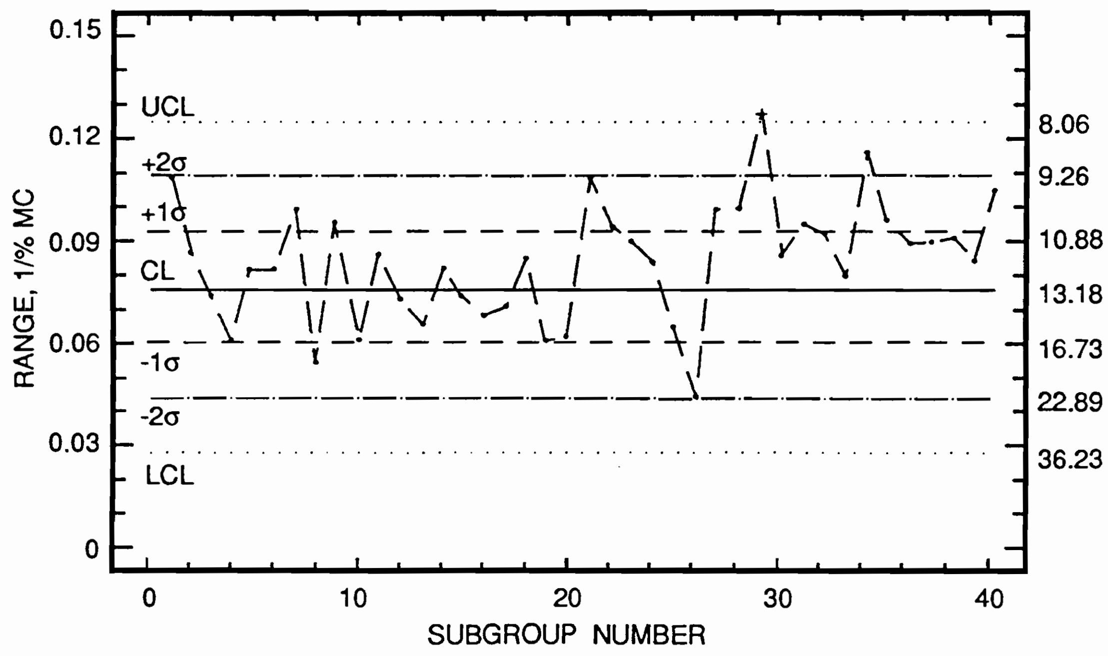


Figure 30. X-bar and Range control charts representative of a drying process that goes out of control. This situation was caused by one end of the kiln becoming too hot.

occurs in subgroups 27 to 40, and a point above the UCL at subgroup 29. This phenomenon is a common occurrence in an out-of-control kiln chart.

GROUP CHARTS

Group control charts representative of a kiln divided into four individual heating zones or quality zones are shown in Figures 31 to 33. A group control chart that is under control is pictured in Figure 31. None of the plotted quality zone numbers fall outside the UCL or LCL. There is a typical fluctuation between the quality zone numbers that are producing the wettest and driest lumber packages.

In contrast, an out-of-control group control chart is shown in Figure 32. This condition was due to a quality zone that was over heated relative to other quality zones inside the kiln. Note that there is one consistent quality zone (number 3) that always occurs as the driest, and in almost all kiln charges lies above the UCL. This quality zone requires adjustment or maintenance. The other three quality zones (1, 2 and 4) all appear to be in control and fluctuate as to which zone produced the wettest lumber. This is typical of quality zones under control.

The third group control chart is shown in Figure 33. This is another example of a group control chart that is out-of-control, but was caused by insufficient heat coming from heating or quality zone 2. Quality zone 2 consistently produces the wettest lumber packages being dried. Most of the points lie below the LCL. This quality zone requires maintenance. Quality zones 1, 3 and 4 exhibit normal conditions, with all points within the control limits. All of these three quality zones

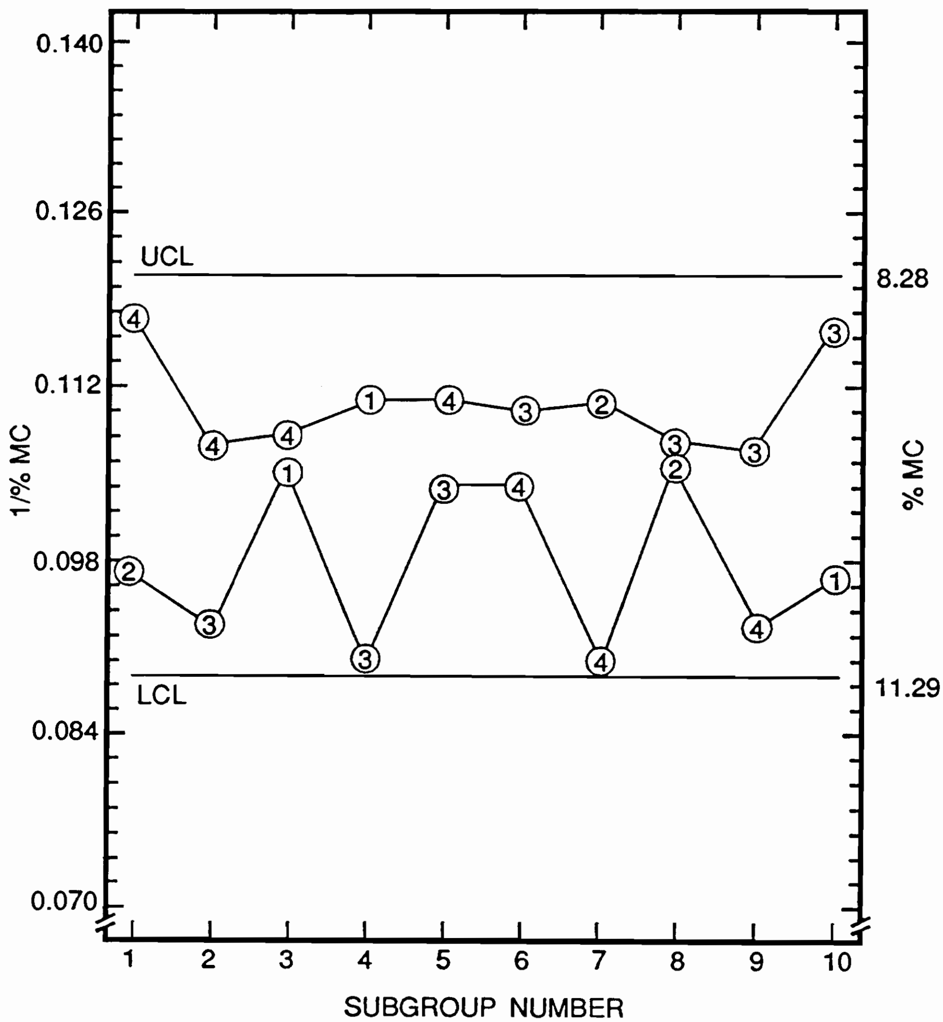


Figure 31. Group control chart of four quality zones inside one kiln. This chart represents a dry kiln that is operating properly.

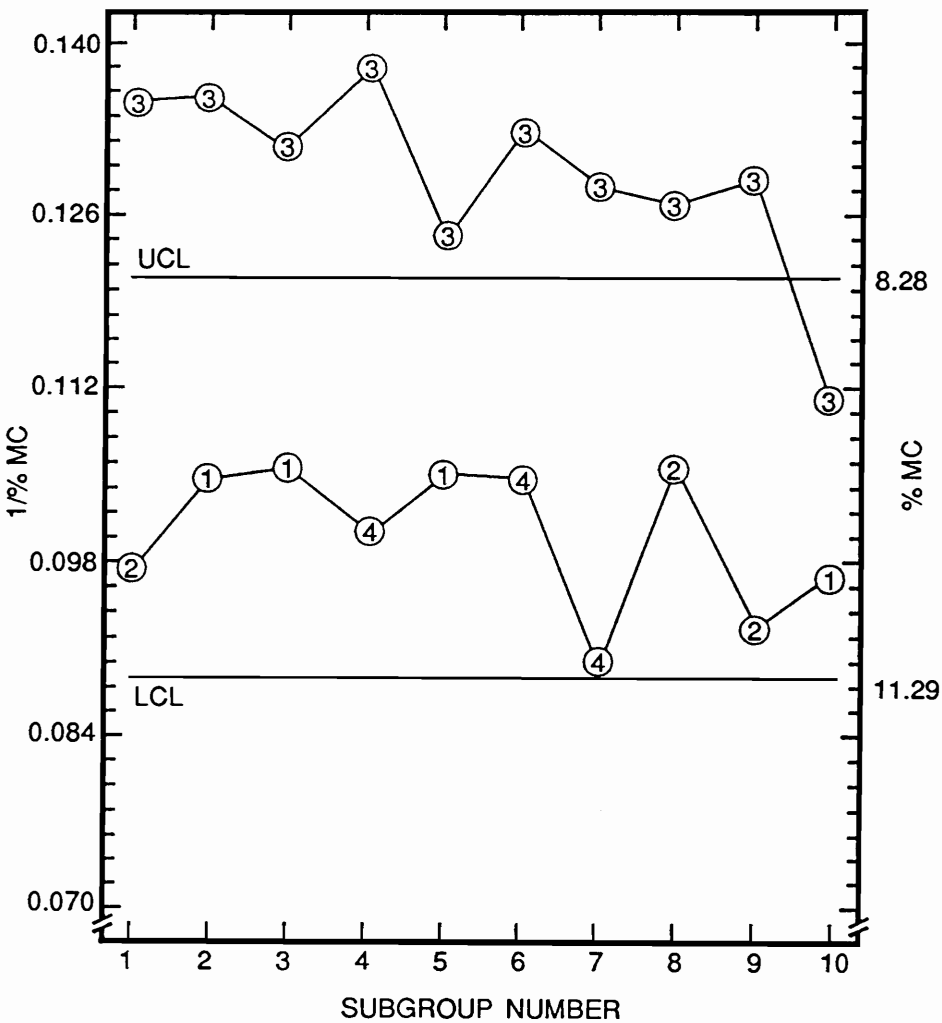


Figure 32. Group control chart of four quality zones inside one kiln. This chart represents a dry kiln that is not operating properly, because quality zone 3 was overheated.

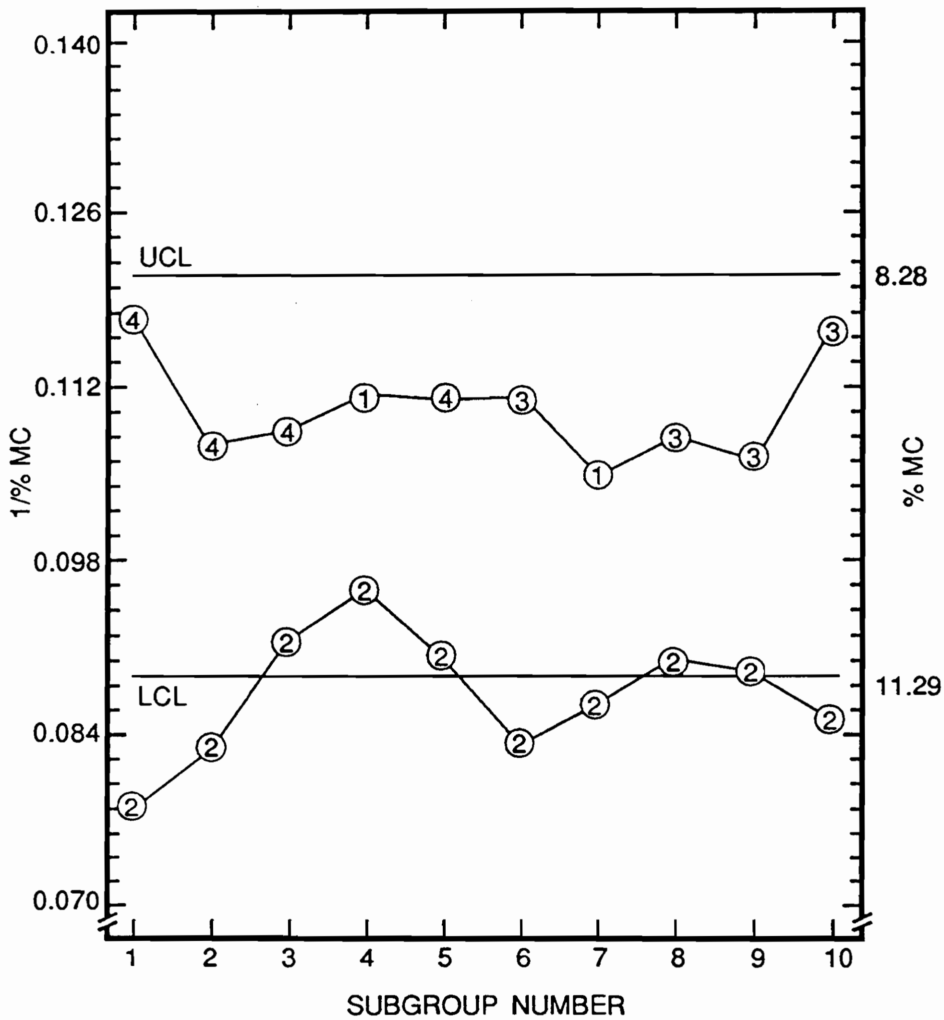


Figure 33. Group control chart of four quality zones inside one kiln. This chart represents a dry kiln that is not operating properly, because quality zone 2 was too cold.

fluctuate as to which zone produces the driest lumber. This random occurance is a typical response from quality zones that are under control.

Group control charts will indicate when a kiln is about to malfunction. This situation typically occurs when a sequential run of the same quality zone occurs on the chart. Points do not need to occur outside of the UCL or LCL to indicate a possible malfunction inside the kiln. An example would be a series of three or more subgroups in which the same quality zone produces the wettest or driest packages. Figure 33 shows an example where quality zone 2 produced the wettest lumber in subgroups 3, 4 and 5, yet none of the points fell below the LCL .

Group control charts are simple quality control tools that will quickly highlight trouble spots inside a kiln. They provide much needed insight into which area or quality zone inside the kiln should be inspected. This information focuses where the maintenance efforts should be directed, thus avoiding wasted time in trying to locate the trouble spot. A group control chart will be an invaluable asset when used either alone or in conjunction with X-bar and Range control charts.

CONCLUSIONS

P charts can be easily produced by randomly examining about 200 stickers or 10 tiers of stickers from a number of stacks of lumber. This will only require approximately 10 minutes per shift or day. The charts can accurately track stacker performance and will indicate if sticker placement by a stacker is occurring within acceptable tolerances or standards (upper and lower control limits).

The most forgiving and realistic technique to evaluate if stickers are in or out of alignment was the use of the widest surface of the vertically aligned sticker. Ideal sticker placements should result in about two percent defective sticker alignments, however, older stackers may not be capable of such accuracy, because of worn parts. This occurance does not mean that control charts can not be used, but rather the average expected percent defect and the upper and lower control limits will be larger.

Regression analysis of the average MC based on hand-held MC readings of outer edge boards versus the actual overall average MC based on an in-line meter did not provide an accurate method by which to predict overall average package MC. This technique can not be used as a quality control measure. The procedure is too time-consuming and arduous a task to be done on a daily basis by mill personnel. Presently, only rough estimates are made as to whether or not a charge of lumber has been correctly dried when just a few randomly-selected, outer edge boards are sampled for MC.

Control charts can be indicators of MC and MC variation for quality control and assess the occurrence of potential drying errors. However, because control charts assume a normal distribution, a transformation of dried MC data is required. One such transformation that has been successful is the reciprocal of board MC values. This may not be a universal transformation to be used on all wood species, as different wood types are known to have different final dried MC distributions. The dry MC distribution for ponderosa pine can be transformed to a normal distribution by using its reciprocal MC value.

The X-bar and Range control charts can be very useful. The single most reliable and responsive control chart was found to be the X-bar chart. In certain circumstances the Range chart was not sensitive enough to detect drying problems. However, the conjunctive use of both charts is very reliable, with many suspect drying errors indicated in the X-bar chart being confirmed in the Range chart. Use of the Range chart alone would be ill advised, due to its lesser accuracy.

Group control charts are another SPC tool that can be used for quality control purposes. The tracking of the wettest and driest package, crib, or zone average MC can visually signal when some malfunction is occurring inside the kiln.

Clearly SPC measures such as X-bar, Range, group, and p charts can be used effectively in any mill to improve and maintain quality control. Mills that do not have an in-line moisture meter to perform a 100 percent MC inspection will benefit the most from using X-bar, Range, and group control charts. However, mills that do use an in-line moisture meter to perform a 100 percent inspection of dried lumber can still benefit by using control charts. This benefit is because of the predictive nature found in control charts. In addition the charts need not be a mechanism by which to affix blame, but rather a tool to maintain quality and be a source of information to be used to verify a job well done.

NOMENCLATURE

Symbol	Definition	First Equation Used	Units
A_2	multiplier of R for 3 sigma control limit	6	-
D_3	multiplier of R for 3 sigma lower control limit	9	-
D_4	multiplier of R for 3 sigma upper control limit	8	-
E	max. allowable error in est.	1	1/%
k	number of subgroups	3	-
K	normal distribution coef. 95% C.I.	1	-
LCL_p	lower control limit on p chart	12	-
LCL_R	lower control limit on R chart	6	1/%
$LCL_{\overline{X}}$	lower control limit X-bar chart	7	1/%
n	subgroup size	2	-
N	sample size required	1	-
n_i	number of articles inspected in subgroup	10	-
$\overline{p}$	average fraction rejected	10	-
p	uniform random deviate between 0 and 1	13	-
r_i	number of nonconforming items in subgroup	10	-
R_i	range for subgroup i	4	1/%
$\overline{R}$	average of set of ranges, central line of R chart	5	1/%
t	intermmediate variable of normal deviate	13	-
UCL_p	upper control limit on p chart	11	-

UCL_R	upper control limit on R chart	8	1/%
$UCL_{\overline{X}}$	upper control limit on X-bar chart	6	1/%
$\overline{\overline{X}}$	avg. of a set of $\overline{X}$ values	3	1/%
$\overline{X}_i$	avg. for subgroup i	2	1/%
$X_{i,max}$	largest value subgroup i	4	1/%
$X_{i,min}$	smallest value subgroup i	4	1/%
x_p	normally distributed random deviate	13	-
α	level of significance	1	-
σ	standard deviation of population	1	1/%

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APPENDICIES

APPENDIX A

Drying Schedules

Table 3. Base case drying schedule.

Schd. Step #	Time hr	Dry-bulb F	Wet-bulb F	Vel-ocity ft/min
1	.0	90.0	70.0	600.0
2	.5	102.0	82.0	600.0
3	1.0	112.0	92.0	600.0
4	2.0	120.0	100.0	600.0
5	3.0	126.0	106.0	600.0
6	4.0	131.0	111.0	600.0
7	5.0	137.0	107.0	600.0
8	6.0	141.0	121.0	600.0
9	8.0	144.0	124.0	600.0
10	10.0	146.0	127.0	600.0
11	14.0	148.0	127.0	600.0
12	20.0	148.0	127.0	600.0
13	36.0	155.0	130.0	600.0
14	44.0	160.0	125.0	600.0
15	50.0	167.0	125.0	600.0
16	60.0	170.0	125.0	600.0
17	65.0	170.0	145.0	600.0
18	66.0	175.0	155.0	600.0
19	67.3	180.0	165.0	600.0
20	91.3	180.0	165.0	600.0

Table 4. Drying schedule when dry-bulb is too cold

Schd. Step #	Time hr	Dry-bulb F	Wet-bulb F	Vel-ocity ft/min
1	.0	85.0	70.0	600.0
2	.5	97.0	82.0	600.0
3	1.0	107.0	92.0	600.0
4	2.0	115.0	100.0	600.0
5	3.0	121.0	106.0	600.0
6	4.0	126.0	111.0	600.0
7	5.0	132.0	107.0	600.0
8	6.0	136.0	121.0	600.0
9	8.0	139.0	124.0	600.0
10	10.0	141.0	127.0	600.0
11	14.0	143.0	127.0	600.0
12	20.0	143.0	127.0	600.0
13	36.0	150.0	130.0	600.0
14	44.0	155.0	125.0	600.0
15	50.0	162.0	125.0	600.0
16	60.0	165.0	125.0	600.0
17	65.0	165.0	145.0	600.0
18	66.0	170.0	155.0	600.0
19	67.3	175.0	165.0	600.0
20	91.3	175.0	165.0	600.0

Table 5. Drying schedule when dry-bulb is too hot.

Schd. Step #	Time hr	Dry-bulb F	Wet-bulb F	Vel-ocity ft/min
1	.0	95.0	70.0	600.0
2	.5	107.0	82.0	600.0
3	1.0	117.0	92.0	600.0
4	2.0	125.0	100.0	600.0
5	3.0	131.0	106.0	600.0
6	4.0	136.0	111.0	600.0
7	5.0	142.0	107.0	600.0
8	6.0	146.0	121.0	600.0
9	8.0	149.0	124.0	600.0
10	10.0	151.0	127.0	600.0
11	14.0	153.0	127.0	600.0
12	20.0	153.0	127.0	600.0
13	36.0	160.0	130.0	600.0
14	44.0	165.0	125.0	600.0
15	50.0	172.0	125.0	600.0
16	60.0	175.0	125.0	600.0
17	65.0	175.0	145.0	600.0
18	66.0	180.0	155.0	600.0
19	67.3	185.0	165.0	600.0
20	91.3	185.0	165.0	600.0

Table 6. Drying schedule when fan speed is too low.

Schd. Step #	Time hr	Dry-bulb F	Wet-bulb F	Vel-ocity ft/min
1	.0	90.0	70.0	300.0
2	.5	102.0	82.0	300.0
3	1.0	112.0	92.0	300.0
4	2.0	120.0	100.0	300.0
5	3.0	126.0	106.0	300.0
6	4.0	131.0	111.0	300.0
7	5.0	137.0	107.0	300.0
8	6.0	141.0	121.0	300.0
9	8.0	144.0	124.0	300.0
10	10.0	146.0	127.0	300.0
11	14.0	148.0	127.0	300.0
12	20.0	148.0	127.0	300.0
13	36.0	155.0	130.0	300.0
14	44.0	160.0	125.0	300.0
15	50.0	167.0	125.0	300.0
16	60.0	170.0	125.0	300.0
17	65.0	170.0	145.0	300.0
18	66.0	175.0	155.0	300.0
19	67.3	180.0	165.0	300.0
20	91.3	180.0	165.0	300.0

APPENDIX B

MC Data for Group Control Charts

Table 7. Group control chart data when all four quality control zones inside the kiln are under control.

CHARGE NUMBER	AVG. M.C.% ZONE #1	AVG. M.C.% ZONE #2	AVG. M.C.% ZONE #3	AVG. M.C.% ZONE #4
1	0.0977	0.0972	0.1073	0.1170
2	0.1041	0.1064	0.0935	0.1072
3	0.1056	0.1071	0.1069	0.1079
4	0.1111	0.1051	0.0900	0.1006
5	0.1045	0.1091	0.1042	0.1104
6	0.1091	0.1045	0.1104	0.1042
7	0.1051	0.1111	0.1006	0.0900
8	0.1071	0.1056	0.1079	0.1069
9	0.1064	0.1041	0.1072	0.0935
10	0.0972	0.0977	0.1170	0.1073

Table 8. Group control chart data when quality control zone #3 inside the kiln is hotter by 5°F dry-bulb temperature.

CHARGE NUMBER	AVG. M.C.% ZONE #1	AVG. M.C.% ZONE #2	AVG. M.C.% ZONE #3	AVG. M.C.% ZONE #4
1	0.0977	0.0972	0.1356	0.1170
2	0.1041	0.1064	0.1357	0.1072
3	0.1056	0.1071	0.1318	0.1079
4	0.1111	0.1051	0.1376	0.1006
5	0.1045	0.1091	0.1245	0.1104
6	0.1091	0.1045	0.1329	0.1042
7	0.1051	0.1111	0.1283	0.0900
8	0.1071	0.1056	0.1269	0.1069
9	0.1064	0.1041	0.1291	0.0935
10	0.0972	0.0977	0.1162	0.1073

Table 9. Group control chart data when quality control zone #2 inside the kiln is colder by 5°F dry-bulb temperature.

CHARGE NUMBER	AVG. M.C.% ZONE #1	AVG. M.C.% ZONE #2	AVG. M.C.% ZONE #3	AVG. M.C.% ZONE #4
1	0.0977	0.0779	0.1073	0.1170
2	0.1041	0.0825	0.0935	0.1072
3	0.1056	0.0916	0.1069	0.1079
4	0.1111	0.0957	0.0900	0.1006
5	0.1045	0.0903	0.1042	0.1104
6	0.1091	0.0830	0.1104	0.1042
7	0.1051	0.0868	0.1006	0.0900
8	0.1071	0.0909	0.1079	0.1069
9	0.1064	0.0888	0.1072	0.0935
10	0.0972	0.0860	0.1170	0.1073

Appendix C

Computed Values Used in Calculations

P Charts

Figure #	$\bar{p}$	$\bar{n}$
5	0.12634	408.0
6	0.121044	394.643
7 & 10	0.1728	200.0
8 & 11	0.1080	200.0
9	0.2135	200.0

X-bar and Range Charts

$\bar{R} = 0.0758641$ $\qquad$ $A_2 = 0.21$

$\bar{\bar{x}} = 0.104649$ $\qquad$ $A_3 = 0.36$

$D_4 = 1.64$